ARTICLE

Deficit irrigation management for rice using crop growth simulation model in an optimization framework

B. Soundharajan · K. P. Sudheer

Received: 9 February 2009/Revised: 12 March 2009/Accepted: 12 March 2009/Published online: 29 March 2009 © Springer-Verlag 2009

Abstract Optimization of irrigation water is an important issue in agricultural production for maximizing the return from the limited water availability. The current study proposes a simulation-optimization framework for developing optimal irrigation schedules for rice crop (Oryza sativa) under water deficit conditions. The framework utilizes a rice crop growth simulation model to identify the critical periods of growth that are highly sensitive to the reduction in final crop yield, and a genetic algorithm based optimizer develops the optimal water allocations during the crop growing period. The model ORYZA2000, which is employed as the crop growth simulation model, is calibrated and validated using field experimental data prior to incorporating in the proposed framework. The proposed framework was applied to a real world case study of a command area in southern India, and it was found that significant improvement in total yield can be achieved by the model compared to other water saving irrigation methods. The results of the study were highly encouraging and suggest that by employing a calibrated crop growth model combined with an optimization algorithm can lead to achieve maximum water use efficiency.

Keywords Deficit irrigation management · Rice crop · Crop growth models · ORYZA2000 · Genetic algorithm

Introduction

The relation between water and food is a real struggle for over two-third of world's 850 million under-nourished

B. Soundharajan · K. P. Sudheer (⊠) Indian Institute of Technology Madras, Chennai 600036, India e-mail: sudheer@iitm.ac.in people, where water is a key constraint to food security. The per capita water availability in India is declining continuously, and is likely to reach the stress/scarcity levels in some regions within the next few years. This has lead to injudicious abstraction of surface and ground water resulting in several problems including rapidly declining water table levels and salt water intrusion in coastal areas. The increased frequency of extreme events (especially drought) may further lead to unavailability of water to meet current irrigation demands. Irrigation water demand is still increasing because the area being irrigated continues to expand. The great challenge for the coming decades will be the task of increasing food production with less water, particularly in countries with limited water and land resources.

Water stress affects crop growth and productivity in many ways. Most of the responses have a negative effect on production, but crops have different and often complex mechanisms to react to shortages of water. While agricultural water supply is increasingly limited, many irrigation schemes are routinely operated according to maximum supply conditions, and lack appropriate procedures and mechanisms to adjust supply and cropping pattern to water availability. In India, most of the irrigation systems follow rotational water supply, in which each farmer's field gets water at a definite interval throughout the growing period. In this case, irrigation frequency is fixed, but the depth of application depends on the water availability at the reservoir. When the available water is limited, the area that can be irrigated with full water supply becomes limited, and consequently the food production is constraint by the area being irrigated. However, increasing the irrigated area by imposing certain stress level of water supply might help to increase the food production, and this is the key objective in any deficit irrigation management. The philosophy behind deficit irrigation management is that marginal stress, except during critical reproductive stages, may not significantly affect the crop yield (Boggess and Ritchie 1988). Nonetheless, the imposed stress levels have to be scientifically identified so that the reduction in crop yield (compared to full irrigation) is minimal. Therefore, accurate knowledge on the impact of reduced water supply on crop yield is required to define appropriate strategies to schedule crop water supply. Hence, there is a clear need to provide more accurate, and in particular, dynamic tools to analyze and evaluate the crop yield responses to suboptimal water conditions.

Optimal irrigation scheduling under deficit conditions is highly complex since it depends on the interaction of physical constraints of the irrigation system, soil moisture availability at the time of irrigation, growth stage of the crop, effect of previous and subsequent irrigations on crop growth and yield, and nature of weather conditions. Traditionally, yield reduction models based upon evapotranspiration (ET) ratios (e.g., Doorenbos and Kassam 1979; Jensen 1968) have been employed by many researchers for deficit irrigation management (Vedula and Mujumdar 1992; Kumar et al. 2006). However, these models have two major limitations: (1) they cannot provide crop yield in absolute terms and (2) they do not have endogenous optimization capacity (Brumbelow and Georgakakos 2007). Yet another concern is that most of the ET ratio based yield reduction models consider crop vield reduction as a linear function of crop ET. Researchers have integrated optimization schemes with ET ratio based yield reduction models to arrive at optimal deficit irrigation schedules (Rao et al. 1988; Paul et al. 2000; Prasad et al. 2006). These methods employ crop water production functions on different crop growth stages, which can optimize the total water requirement for different stages of crop growth. Therefore, identification of the timing of irrigation application becomes difficult.

Recent developments in crop growth simulation models have given the opportunities for simulating the field conditions. Adequately calibrated and validated agricultural system models provide a systems approach and a fast alternative method for developing and evaluating agronomic practices that can utilize technological advances in limited irrigation agriculture (Saseendran et al. 2008). A few researchers have employed crop growth simulation models for irrigation scheduling (Rao and Rees 1992; Talpaz and Mjelde 1988). However, in most of the crop growth simulation model based irrigation scheduling, the irrigation triggering condition is uniform for the entire crop period and is mostly based on the simulated soil moisture level. Further, most of these models suggest uniform irrigation amount, though the frequency of application may vary. In the case of deficit irrigation management, it is appropriate to schedule the irrigation based on the effect of water stress on crop yield and the water availability. This is normally achieved by splitting the irrigation requirement between different growth stages (splitting ratio) based on their sensitivity to crop yield, and uniform irrigation within each growth stage (Saseendran et al. 2008). However, the splitting ratio in this case is highly subjective. With the advancements in physiologically based crop growth simulation models in terms of inclusion of many specific processes and localized factors, one is able to efficiently identify the critical period of growth that are highly sensitive to crop yield reduction. Therefore, integrating these simulation models in an optimization framework would help achieving improved water use efficiency by eliminating the concerns of uniform application of water in each growth stage as well as the concern about the splitting ratio.

In this study, a novel approach for deficit irrigation water management is proposed that employ ORYZA2000 model (Bouman et al. 2001) for developing optimal irrigation schedules for rice crop(*Oryza sativa*) by integrating it within an optimization framework. The parameters of ORYZA2000 model are optimized and validated using the data collected from field experiments conducted in three seasons. The calibrated (and validated) ORYZA2000 was integrated in a genetic algorithm (GA) based optimization framework to derive the optimal irrigation schedules that maximizes the crop yield. The results are compared with traditional water saving irrigation techniques such as alternate wetting and drying. ORYZA2000 is selected for the current research since paddy is the major crop cultivated in the study area.

Materials and methods

Simulation-optimization framework

A block diagram of the proposed simulation–optimization framework is presented in Fig. 1. The framework has three different components: (1) optimizer, which develops the irrigation schedules and irrigated area; (2) reservoir simulation, which simulates the operation of reservoir by maintaining water balance in the reservoir system, and (3) crop growth simulation model, which determines the total crop yield for a given irrigation scenario. All the three components interact with each other and produce the optimal irrigation schedules for maximum water use efficiency for rice crop with limited available water.



Fig. 1 Optimal irrigation scheduling using crop growth in simulation-optimization framework

Description of the models employed

Crop growth simulation model—ORYZA2000

ORYZA2000 is an eco-physiological crop growth model that simulates the growth, development and water balance of rice in situations of potential, water limited, and nitrogen limited conditions on a daily basis. Since rice is the major crop cultivated in the study area, we selected this model for our study. While there are a few other crop growth models for rice that are available [e.g., RICEMODE (McMennary and O'Toole 1985), WOFOST (Boogaard et al. 1998)], the ORYZA2000 has been extensively used and tested for its efficiency in water limited conditions, and the results were encouraging (Belder et al. 2007; Feng et al. 2007; Arora 2006; Belder et al. 2004), and therefore is considered in the current study.

A detailed explanation of the model along with the program source code is given in Bouman et al. (2001). The model assumes that the crop is well protected against diseases, pests and weeds, and consequently the model does not consider the yield reduction due to these factors. The model computes the rate of phenological development of rice on a daily time scale based on the daily average temperature and photoperiod. The dry matter at plant organs is computed considering the daily heat units. The detailed scientific description of dry matter production can be obtained from Bouman et al. (2001). The simulated total dry matter is partitioned by the model among various parts of the crop (roots, leaves, stems, and panicles) using partitioning factors, which are to be determined through calibration.

The model requires inputs of management practices, soil properties and weather data in addition to crop parameters. The required management practices are crop variety, spacing or plant population, transplanting depth, nursery duration, and fertilizer and irrigation application. Soil properties required are volumetric soil water content at saturation, field capacity and wilting point and corresponding soil water potential, depth of puddled soil, and saturated hydraulic conductivity of the soil. The weather data include the rainfall and temperature during the growing season. The crop parameters include phenological development parameters and many other parameters related to the process of crop growth, and most of them can be obtained from literature. However, the cultivar specific parameters such as development rates, partitioning factors, relative leaf growth rate, specific leaf area, and leaf death rate are to be calibrated using experimental data (Bouman et al. 2001). In the case of deficit irrigation management, the daily soil water dynamics is to be determined. This enables the computation of effect of water stress on the crop yield, and to affect this, soil water balance module of the ORYZA2000 was considered in this study.

Optimizer—genetic algorithm

As discussed earlier, the proposed framework is a highly constrained, nonlinear optimization problem. The objective of the optimizer in the current study is to identify the optimal allocation of irrigation application which would produce maximum yield of rice under water deficit condition. The major concern here is that the objective function of maximizing the yield is not a direct function of the decision variables. Therefore, despite the existence of a large number of traditional nonlinear programming (NLP) techniques for solving this kind of optimization problem, a search based optimizer is appropriate. In the current study we employed genetic algorithm (Holland 1975; Goldberg 1989; Michalewicz 1992) as the optimizer because of its various advantages, which includes their potential to search the solution from a population of points (not a single point), use objective function information itself but not any derivatives, and use probabilistic transitions rules but not deterministic rules. GA has found a large number of applications in complex optimization problems in various branches of science and engineering (Kohler 1990; Bickel and Bickel 1990; Suckley 1991; Cook and Wolfe 1991). Ines et al. (2006) employed GA to optimize the components in a water balance model, 'Soil Water Atmosphere Plant (SWAP)'(Van Dam et al. 1997) to develop optimal water management plans for wheat. In the recent past, a few researchers have used GA for irrigation water management under deficit condition by using the ET ratio based crop productions functions (Wardlaw and Bhaktikul 2004; Raju and Kumar 2004; Kumar et al. 2006; Kuo et al. 2000; Wardlaw and Bhaktikul 2001; Wardlaw and Sharif 1999), and reported promising results.

Genetic algorithm (GA) is a random search optimization algorithm inspired by biological evolution that provides a robust method for searching of the optimum solution to complex problems. In a GA, the solution set is represented by a population of strings, which comprises of a number of blocks each representing the individual decision variables of the problem. Strings are processed and combined according to their fitness (objective function value evaluated using the components in the string), in order to generate new strings that contain the best features of two parent strings. Strings with the highest fitness have the greatest chance of contributing to future generations, similar to the process of natural selection. Initially GA suggests a set of candidate solutions to the problems, evaluates the fitness function that is to be optimized, and arrives at the optimal solution by the genetic operations in subsequent generations. A detailed description about the GA is beyond the scope of this paper, and the readers are referred to Goldberg (1989) and Michalewicz (1992).

Calibration of ORYZA2000

Field experiments

The ORYZA2000 model was calibrated using the data from field experiments conducted at Tamil Nadu Agricultural University, Coimbatore, India during 2 years (1999 and 2000). The experiments were laid out in a split plot design with three replications of three different water applications by growing medium duration rice variety. The

Table 1 Details of irrigation experiments on Rice (Oryza sativa)

experiments were continued in three consecutive seasons (June–October 1999, September 1999–February 2000; June–October 2000) in the 2 years of study (Luikham 2001). The water applications considered for the experiment were (1) application of 5 cm irrigation water depth as and when the standing water has disappeared—no deficit condition (IR1), (2) application of 5 cm irrigation water depth 1 day after the standing water has disappeared (IR2), and (3) application of 5 cm irrigation water depth 3 days after the standing water has disappeared (IR3). Details of the experiments and crop period are presented in Table 1, which also includes the information about rainfall during the crop growth period.

The nutrient supply for the crop was done at full recommended levels as per the Crop Production Manuel for the area (TNAU 1994) in order to ensure that the crop will not have any nutrient deficiency during the experiment. Soil information collected during the experiment were fraction of sand, silt and clay, textural class, organic matter (%), soil pH, electrical conductivity (dS m^{-1}), volumetric water content at field capacity (FC), and permanent wilting point (PWP), and infiltration rate. Using this information, the soil properties such as saturated hydraulic conductivity, volumetric water content at saturation, and soil moisture tension at different moisture levels were determined using the pedotransfer function proposed by Saxton and Rawls (2006). It may be noted that the computed values of moisture content at FC and PWP were closely matching with the measured values. The major properties of the soil in which the crop was grown is presented in Table 2.

During the experiments, the dates of sowing, emergence, transplanting, active tillering, panicle initiation, flowering and physiological maturity were recorded in each

Location	Coimbatore (11°N 77°E)–Altitude 426.7 m					
Cropping season	Khariff 1999 (June–October)	Rabi 1999-2000 (October-February)	Khariff 2000 (June-October)			
Water application	IR1, IR2, IR3	IR1, IR2, IR3	IR1, IR2, IR3			
Cultivar	ADTRH 1	CORH 2	ADTRH 1			
Sowing date	June 10	September 30	June 9			
Transplanting date	July 6	October 29	July 4			
Panicle initiation date	August 10	December 8	August 4			
Flowering date	September 4	January 3	September 7			
Maturity date	October 10	February 8	October 6			
Duration (days)	120	130	118			
Seedlings per hill	1	1	1			
Plant population (hills m ⁻²)	50	50	50			
Seasonal rainfall (mm)	190.9	439.5	407.5			

IR1: application of 5 cm irrigation water depth as and when the standing water has disappeared—no deficit condition

IR2: application of 5 cm irrigation water depth 1 day after the standing water has disappeared

IR3: application of 5 cm irrigation water depth 3 days after the standing water has disappeared

Table 2 Properties of the soil in the experimental site

Parameter	Value
Texture class	Clay loam
Clay:silt:sand	39.5:18.5:40.6
$\theta_{wp} (\psi_{wp})$	0.236 (1,463 kPa)
$ heta_{fc} (\psi_{fc})$	0.357 (33 kPa)
$\theta_s (\psi_s)$	0.441 (5 kPa)
K _s	1.51 mm h^{-1}

 θ , volumetric soil water content (fraction); ψ , soil water potential (kPa). wp, fc, and *s* are wilting point, field capacity and saturation, respectively; and K_s, saturated hydraulic conductivity

experimental plot. In order to determine the total crop biomass and leaf area index at different stages of crop growth, crop samples were collected at active tillering, panicle initiation, flowering, and maturity. At the time of harvest, yield components were measured in terms of total crop yield, weight of 1,000 grains and the straw weight. During the period of experiment, the climatic parameters such as values of minimum and maximum temperature, minimum and maximum relative humidity, sunshine hours, wind speed and rainfall on each day were recorded.

Parameter estimation of ORYZA2000

The data from the experiments described above corresponding to maximum production condition (no deficit condition—IR1) was used for estimation of ORYZA2000

 Table 3 Calibrated parameter values of ORYZA2000 model

model parameters. As mentioned earlier, five model parameters, viz. dry matter partitioning factors, development rates, relative leaf growth rate, leaf death rate, and specific leaf area are estimated during calibration of the model. All of these parameters except relative leaf growth rate vary at different stages of growth and therefore calibrated values were determined for each of these parameters corresponding to different growth stages. Phenological development parameters (first four parameters in Table 3) were directly estimated from effective temperature and observed phenology (dates of transplanting, panicle initiation, flowering and maturity) following Bouman et al. (2001). As mentioned earlier, the data observed during the field experiment were leaf area index and total bio mass at four different stages of growth and the crop yield at the time of maturity. Since, these information alone were not sufficient to estimate the parameters, an automatic calibration procedure is employed in the current study using GA, with the objective to minimize the sum of squared error (relative) between measured and simulated values of leaf area index, dry biomass and total yield.

The fitness function evaluated by GA is:

$$Fitness(z)_{min} = \sum_{i=1}^{5} \left(\frac{\text{LAI}_{o}^{i} - \text{LAI}_{s}^{i}}{\text{LAI}_{o}^{i}} \right)^{2} + \sum_{i=1}^{5} \left(\frac{\text{TBM}_{o}^{i} - \text{TBM}_{s}^{i}}{\text{TBM}_{o}^{i}} \right)^{2} + \left(\frac{Y_{o} - Y_{s}}{Y_{o}} \right)^{2}$$
(1)

Parameter	Value
Phenological development parameters	
Development rate in juvenile phase (°C day ⁻¹)	0.000818
Development rate in photoperiod sensitive phase (°C day ⁻¹)	0.000758
Development rate in panicle development (°C day ⁻¹)	0.000577
Development rate in reproductive phase (°C day ⁻¹)	0.002006
Leaf growth parameters	
Maximum relative growth rate of leaf area (°C day ⁻¹)	0.0076
Minimum relative growth rate of leaf area (°C day ⁻¹)	0.0030
Specific leaf area, biomass partitioning and leaf death rate	

DVS	SLATB	FLVTB	FSTTB	FSOTB	DRLVT
0.00	0.0035	0.70	0.30	0.0	0.0
0.43	0.0032	0.70	0.30	0.0	0.0
0.65	0.0028	0.40	0.60	0.0	0.0
1.00	0.0024	0.0	0.50	0.5	0.01
2.10	0.0013	0.0	0.0	1.0	0.06

DVS, crop development stages; SLATB, specific leaf area, ha leaf Kg^{-1} ; FLVTB, fraction shoot drymatter partitioned to leaves; FSTTB, fraction shoot drymatter partitioned to the stems; FSOTB, fraction shoot drymatter partitioned to the panicles; DRLVT, leaf death coefficient, day⁻¹

Subject to

$$(FLVTBi + FSTTBi + FSOTBi) = 1 \quad \text{for } i = 1, 2, \dots, 5$$
(2)

where, LAI, leaf area index; TBM, total biomass (kg ha⁻¹); *Y*, yield (kg ha⁻¹); with subscript variables 'o' and 's' corresponding to the observed and simulated values, respectively; 'i' refers to the stage of crop growth, i = 1, 2, 3, 4, and 5 are corresponding to the growth stages sowing, active tillering, panicle initiation, flowering, and maturity, respectively; FLVTB, fraction shoot dry matter partitioned to the leaves; FSTTB, fraction shoot dry matter partitioned to the stems and FSOTB, fraction shoot dry matter partitioned to the panicles.

The procedure of auto-calibration of the model is presented in Fig. 2 in the form of a flow chart. Initially, the GA generates candidate models for the decision variables (parameters) from the feasible region. Using these values for the decision variables, the ORYZA2000 model simulates the crop growth and yield. The model is provided with the soil properties observed during the experiment. The simulated values are used in evaluating the fitness function, based on which the GA develops the next generation candidates. The optimization of fitness function is continued till the maximum number of generation is reached. The lower and upper bounds of the parameters were fixed to be -10% and +10% from the default values for a medium



Fig. 2 Parameter estimation of ORYZA2000 model using GA

duration crop (parameter values corresponding to rice variety IR64). In addition, a constraint was enabled in the GA that the sum total of portioning parameters should be equal to unity for each stage of growth. The average daily percolation rate was fine tuned after the calibration of the model in order to represent the actual field conditions by considering the measured values of water balance components in the experimental field. The contribution of water through capillary pores to the crop root zone was not considered, since the water table of the experimental field is significantly deep. The effective rainfall during the period of crop growth was computed using the procedure outlined by Bouman et al. (2001), in which the any amount of rainfall above the field bund height is considered to be not supplementing the irrigation.

The calibrated model is evaluated for its performance using the data corresponding to the irrigation treatments IR2 and IR3 from all the three seasons. The results are discussed in later sections of this paper.

Optimal irrigation scheduling under deficit condition

Model formulation

As discussed earlier, the calibrated ORYZA2000 was integrated in an optimization framework along with a reservoir simulation model to determine the optimal irrigation releases under water deficit situations. The objective function of the optimization scheme was to maximize the total yield from the irrigation command area. The model aims to optimally allocate the available water in the reservoir throughout the cropping season in maximum possible cropped area. The mathematical form of the fitness function considered by GA is:

Fitness function
$$(Z)_{\max} = \left\{ \sum_{s=1}^{n} A_s \times Y_s \right\}$$
 (3)

where, Z, sum of total seasonal rice yield, kg; A_s , cultivated area of rice crop during the season 's', ha; Y_s , rice crop yield during the crop season 'n', kg ha⁻¹; n, crop season [Khariff (June–October) and Rabi(October–February]. Note that the decision variables of the optimizer are the weekly irrigation depths and the area that can be irrigated. Crop yield (Y_s) in the objective function for the specific irrigation schedule is simulated by the ORYZA2000 model. The command area specific soil parameters and climatic parameters are input to the rice crop growth simulation model. The candidate models of reservoir releases generated by the GA are subject to the constraints of the water availability and water balance of the reservoir, considering the storage continuity equation (Loucks et al. 1981):

$$(1 + a_t)S_{t+1} = (1 - a_t)S_t + Q_t - R_t - O_t - A_0e_t a_t = \frac{A_{\alpha}e_t}{2} for t = 1, 2, ..., T$$
 (4)

$$\begin{cases} S_t \le S_{\max} \\ S_t \ge S_o \end{cases} \quad \text{for } t = 1, 2, \dots, T$$

$$(5)$$

where, S_t , reservoir storage, m³; Q_t , inflow to the reservoir, m³; R_t , gross release from the reservoir, m³; O_t , spill from the reservoir, m³; A_0 , water spread area at dead storage level, m²; A_{α} , water spread area per unit volume of live storage, m² m⁻³; e_t, evaporation loss from the reservoir, m; the subscript 't' specifying the value of each variable during time period t; S_o , minimum reservoir storage, m³ and T, total number of time periods (number of sub-timings in the crop period) and S_{max} , maximum reservoir storage capacity, m³. The reservoir simulation is performed on a daily time scale. Note that the seepage from the reservoir is considered to be insignificant in this study and therefore is not considered in the reservoir storage continuity equation.

In order to account for the overall efficiency of the irrigation system, the amount of water that is reaching the field and the corresponding irrigation depth are computed as:

$$\left.\begin{array}{l} \operatorname{NR}_{t} = \eta . R_{t} \\ I_{t} = \frac{\operatorname{NR}_{t}}{10A_{s}} \end{array}\right\}$$

$$(6)$$

where, NR_t, net reservoir release during the time period 't', m^3 ; η , overall irrigation efficiency, fraction; A_s, area under rice crop during the season 's', ha; I_t , irrigation depth at time period 't', mm.

The maximum irrigation depth proposed to be given at any irrigation event is 10 cm (I_{max}) of water (TNAU 1994) and the maximum area that can be irrigated during any season is the total cultivable command area. Accordingly, the upper and lower bunds for the decision variables are:

$$\begin{array}{l}
0 \le I_t \le I_{\max} \\
0 < A_s \le A_{\max}
\end{array} \tag{7}$$

where, I_{max} , maximum depth of irrigation, cm; A_{max} , maximum cultivable command area, ha.

The algorithm

The flow chart of computations performed in the optimization framework is provided in Fig. 3. The algorithm works as follows:

1. The GA component initializes the decision variables (weekly reservoir releases and the cropping area for all cropping seasons.



Fig. 3 Optimal irrigation scheduling using ORYZA2000 model

- 2. The reservoir releases are fed in to the reservoir simulation module of the framework, wherein the feasibility of the candidate solutions are evaluated by examining the water balance of the reservoir. In order to compute the water balance of the reservoir, the data pertaining to inflow to the reservoir, rainfall, and evaporation from the reservoir are used. If any solution set generated by the GA component violates the reservoir water balance, that solution is fine tuned to maintain water balance in the system.
- 3. The reservoir releases are converted in to irrigation depth by appropriately accounting for the overall irrigation system efficiency.
- 4. The irrigation depths along the crop growing season are input to the crop growth simulation model, which simulates the crop growth and production. This will be performed for all the seasons considered in the analysis.
- 5. The fitness function of the GA is evaluated using the simulated crop yield and the cropping area.
- 6. Based on the fitness function, the GA generates the population in the next generation through its operations like selection, cross over and mutation.

- 7. The steps 2–6 are continued till the maximum number of generations in the GA are over.
- 8. The framework outputs the optimal irrigation schedules and the cropping area for each season.

In the case of other irrigation scheduling methods (IR1, IR2 and IR3 considered for comparison in this study), the corresponding optimal cropping area was arrived at using linear programming. The objective was to maximize the cultivable area without violating the irrigation schedule and reservoir storage continuity.

Details of the study area and data

The proposed framework for optimal irrigation scheduling under water deficit condition is applied on cultivable command area of Karupanadhi reservoir in Chittar river basin, Tamil Nadu, India. Chittar River, which originates from the Western Ghats, is the largest tributary of the river Tambaraparani in India (Fig. 4). The reservoir has a storage capacity of 5.24 Mm³. Karupanadhi command area has six control schemes (anicuts) along the river course downstream of the reservoir. The overall efficiency of the Karupanadhi irrigation system is considered to be 60% in the current study based on discussions with the field engineers. Irrigation water is supplied to agricultural fields (direct command area of 1,552 ha) and also to 72 irrigation tanks (indirect command area of 1,298 ha) through these anicuts. Karupanadhi reservoir gets inflow during southwest monsoon (June-September) and northeast monsoon (October-December) periods. Based on the current practice of cropping pattern, the command area of Karupanadhi is divided in to two zones (Centre for water resources 2001). The Zone I, which is the upper part of the command area, primarily grows rice during two seasons using irrigation

water. The tail end parts of the Zone I, frequently experiences water shortage in Khariff season, and therefore in such situations grows upland crops. The Zone II, lies in the down stream parts of the command area and cultivates rice (October–February) and dry crop (June–September) in rotation. Zone II experiences severe water shortage in both the seasons, and therefore practices conjunctive use of surface and ground water together for agriculture. As mentioned earlier, rice is the major crop in this area, which occupied 79–93% of the gross cropped area in Zone I, and 60–70% of the gross cropped area in Zone II. The predominant soil groups in the study area are deep red loamy soils and river alluvium.

The study area falls in semi arid climatic condition. It is noted that in a given year the potential evapotranspiration exceeds the rainfall in most of the months except a few. The maximum temperature ranges between 30 and 37.5° C and the minimum temperature ranges between 20 and 27° C. The normal rainfall in Karupanadhi is 621 mm. The temporal distribution of rainfall on an average in an year is, 25% during southwest monsoon (June–September), 53%during northeast monsoon (October–December), 9% during winter (January–February) and 13% during summer (March–May).

During October to February, the command area generally does not experience any water stress since it received sufficient amount of rainfall and inflow to the reservoir. However, during June to September season, acute water shortage is experienced in total command area. Therefore, the command area of first three anicuts only will grow rice crop, and the remaining downstream areas will be grown with rainfed/irrigated dry crop. The current operating policy of the reservoir is to release a constant rate of ten cusecs during June to September, and 25 cusecs during



October to February. No releases are made during the summer season.

Results and discussions

Calibration and validation of ORYZA2000

As mentioned earlier, the data pertaining to irrigation treatment IR1 for all the three season of the field experiments were used for calibrating the ORYZA2000 model. The data corresponding to other irrigation treatments (IR2 and IR3) were employed to evaluate the performance of calibrated ORYZA2000. The calibrated values of model parameters are presented in Table 3.

The results of calibration and validation of the model in terms of simulated and measured crop yield is presented in Table 4. The calibration of model parameters was performed using GA so as to minimize the deviation between the simulated and measured values of crop yield, biomass and leaf area index. It can be observed from Table 4 that the calibrated model satisfactorily predicts the expected crop yield. This is evident from the fact that the deviation between measured and simulated crop yield is within $\pm 5\%$ during calibration. During the validation period, the model

Table 4 Observed and simulated crop yield for calibration and validation for different seasonal and irrigation treatments experiments

Season	Irrigation treatment	Yield (observed), kg ha ⁻¹	Yield (simulated), kg ha ⁻¹	Error (%)
Calibration				
Khariff 1999	IR1	4,646	4,434.0	-4.80
Rabi 1999–2000	IR1	3,637	3,754.8	3.10
Khariff 2000	IR1	4,316	4,249.2	-1.60
Validation				
Khariff 1999	IR2	4,475	4,357.1	-2.70
	IR3	4,069	4,071.4	0.10
Rabi 1999–2000	IR2	3,502	3,710.7	5.60
	IR3	3,202	3,607.4	11.20
Khariff 2000	IR2	4,232	4,234.7	0.10
	IR3	3,935	4,094.9	3.90

is able to predict the crop yield with reasonable accuracy, which is mostly within a band of -2.70% to 5.60%, except one set of experiment (during Rabi 1999–2000 with irrigation treatment IR3).

It is to be noted that the yield reduction due to water stress is higher in irrigation treatment IR3 compared to IR2, as expected, since IR3 imposes longer days of water stress compared to IR2. The percentage reduction in yield due to water stress is presented in Table 5 for comparison. During Khariff 1999, the reduction in measured crop yield for treatment IR3 compared to the treatment IR1 is 12.42%, while that for IR2 is 3.68%. The yield reduction is found to be consistent in other seasons also. The calibrated ORYZA2000 is found to be able to effectively simulate the trend of yield reduction due to water stress in all the three seasons.

Table 6 presents a comparison of the amount of water applied actually during the experiment and that simulated by the crop growth model. It can be observed from the Table 6 that the ORYZA2000 model simulated quantity of water application is not significantly different from the amount that is actually applied in the field, except for Rabi season. The larger amount of water application simulated during the Rabi season may be plausibly due to the high amount of rainfall during this period. These results during the validation period indicate that the calibrated model is able to simulate the experimental set up effectively.

The biomass production simulated by the model is also found to be very good. The measured biomass values were available at four different stages of growth, as explained earlier. The measured and simulated biomass is presented in Fig. 5a through Fig. 5f. It is evident from these figures that the ORYZA2000 is capable of simulating the biomass production efficiently. The scatter plots of measured and simulated crop yield as well as biomass during the data used for validation of the model are presented in Figs. 6 and 7, respectively. It is clear from these figures that the data points do not significantly deviate from the ideal 45° line, and confirms the model's efficiency.

From the foregoing discussions it is clear that the calibrated ORYZA2000 model is capable of simulating the water stress condition of rice crop effectively, and can be used to develop deficit irrigation management schedules.

Table 5 Observed and simulated crop yield reduction (percentage) of irrigation treatments IR2 and IR3 compared to IR1

Irrigation treatment	Khariff 1999		Rabi 1999–2000		Khariff 2000	
	Observed	Simulated	Observed	Simulated	Observed	Simulated
IR2	3.68	1.73	3.71	1.17	1.95	0.34
IR3	12.42	8.18	11.96	3.92	8.83	3.63

Season	Irrigation Treatment	Observed		Simulated		Error (%)
		Irrigation (mm)	Effective rainfall (mm)	Irrigation (mm)	Effective rainfall (mm)	
Calibration						
Khariff 1999	IR1	1,050	118.4	1,050	167.0	4.2
Rabi 1999–2000	IR1	900	141.0	950	439.5	33.5
Khariff 2000	IR1	900	310.8	950	412.7	12.5
Validation						
Khariff 1999	IR2	950	118.4	900	167.0	-0.1
	IR3	800	118.4	700	167.0	-5.6
Rabi 1999–2000	IR2	850	141.0	850	439.5	30.1
	IR3	700	141.0	650	439.5	29.5
Khariff 2000	IR2	800	310.8	750	412.7	4.7
	IR3	650	310.8	550	412.7	0.2

Table 6 Observed and simulated total water used (irrigation and effective rainfall) for crop growth

Deficit irrigation management

The optimal deficit irrigation schedules were prepared using the proposed framework that incorporated the calibrated ORYZA2000 model, for Karupanadhi command area. The model was applied during Khariff (June-October) of year 2005. The observed records of inflow to the reservoir, rainfall, and evaporation were utilized for this purpose. The optimal schedules were compared with other water saving alternatives available according to Belder et al. (2007). The water saving alternatives considered in this study were very similar to that done in the field experiment: (1) continuous submerged (irrigation of 5 cm the day when the standing water disappears—IR1), (2) application of irrigation water depth of 5 cm 1 day after the standing water disappeared (IR2), and (3) application of irrigation water depth of 5 cm 3 days after the standing water disappeared (IR3).

The results of the simulation exercise are presented in Table 7, from which it is evident that the water use efficiency is highest for the proposed simulation-optimization model. The proposed model results in a production of 8.79 kg per unit quantity (ha mm) of water applied. This was possible since the model triggered sufficient irrigation only during high sensitive periods of the crop growth, thereby saving water which in turn helped to increase the cultivated area. The no deficit irrigation treatment (IR1) was able to irrigate only 334.8 ha of command area, while the proposed model suggested irrigating 1,194.3 ha of the command area. It may be noted that during initial part of the growing season, the inflow to the reservoir was less compared to the later parts of the season (Fig. 10). Therefore, the IR1 scheme of irrigation was not able to suggest cropping in large area for irrigation, while the proposed model suggested cropping in larger areas since the initial period of crop growth was relatively less sensitive to final crop yield. Even though irrigation treatments IR2 and IR3 are water saving schemes, the imposed water stress during the crop growth is uniformly distributed (without considering the sensitivity of crop growth stage to water stress), and therefore could not save much water to increase the area of cultivation. A marginal increase in cultivated area of 401 and 539 ha were suggested by IR2 and IR3, respectively.

It should be noted that the total crop yield per unit area is lowest for the proposed model as it imposes water stress at different stages of growth. However, this imposed water stress helped the model to save large quantity of water resulting in increased cropped area. Consequently, the total yield from the command area is highest for this model (4,399.6 Tonnes). Comparison of the total crop yield from IR2 and IR3 indicates that increasing the length of water stress uniformly to irrigate larger areas, do not significantly improve the total crop production (only an increase of approximately 500 Tonnes).

The variation of actual evapotranspiration (AET) along the growing season of the crop for different irrigation treatments along with the potential evapotranspiration (PET) is presented in Fig. 8. It can be observed from Fig. 8 that the difference between AET and PET is not significant in irrigation treatments IR1 and IR2, indicating that the crop is not subjected to major water stress during this irrigation treatment. This is evident from the results that yield per unit area produced by IR2 is only 100 unit different from that produced by IR1 (Table 7). In the case of the irrigation treatment IR3, the crop is subjected to water stress at some periods of the growing season, but relatively much less than the irrigation schedule suggested by the **Fig. 5** Observed and simulated dry biomass. (Observed points corresponding to active tillering, panicle initiation, flowering and maturity). *DAT* days after transplanting



proposed model. Therefore, the water saving is much more efficient in the case of the proposed model, thereby facilitating coverage of larger area for cropping.

The irrigation schedules suggested by all the irrigation schemes (including the proposed model) are presented in Fig. 9. The uniform distribution of water stress by IR2 and IR3 model is clearly visible from Fig. 9. On the contrary, the pattern of irrigation is not uniform in the case of the proposed model. The quantity of irrigation water triggered by the proposed model is based on the sensitivity of the crop growth stage to the final yield as well as the water available in the reservoir.

Figure 10 presents the inflow, release suggested by the proposed model and storage in the Karupanadhi reservoir during the crop growing season of Khariff 2005. It is evident from Fig. 10 that the inflow to the reservoir is very



Fig. 6 Simulated and observed crop yield



Fig. 7 Simulated and observed biomass

less during the initial period of the season, which makes a constraint on the available water immediately after transplanting. In other words, the irrigation water is to be supplied to the crop mainly from the storage during this period. Consequently, the irrigation treatments IR2 and IR3 may not be able to suggest larger cropping area; on other hand, the proposed model imposes maximum water stress to the crop during this period and hence is able to suggest

larger cropping area. Nonetheless, it is advisable to keep a minimum amount of standing water in the initial period to control weed. While this can be incorporated in the proposed model by putting a constraint on water application during this period, which was not considered in this study. Towards the tail end of the season, though larger inflow and higher storage is possible, the irrigation treatments IR2 and IR3 are not able to utilize this available water since initially suggested cropped area is less. However, the proposed model is able to provide minimum water stress during the tail end of the season.

Summary and conclusions

In the current study, a simulation–optimization framework is proposed to develop optimal irrigation schedule for rice crop under water deficit conditions. The framework utilizes a rice crop growth simulation model to identify the critical periods of growth that are highly sensitive to the reduction in final crop yield, and a genetic algorithm based optimizer develops the optimal water allocations during the crop growing period. The water allocation by the optimizer is performed in such a way that the reduction in total crop yield is minimal during the season. The model ORYZA2000, which is employed as the crop growth simulation model, is calibrated and validated using field experimental data prior to incorporating in the proposed framework.

The results of the study indicate that the calibrated ORYZA2000 model was able to effectively simulate the crop growth under water deficit conditions. During the validation of the model, it is observed that the simulated yield closely matches with the measured yield under water deficit experiment. The model was found to be efficiently simulating the biomass production at various stages of crop growth. It is also noted that the utilization of water under deficit condition simulated by the model was also close to the actual amount of water applied during the experimental study.

The proposed simulation-optimization framework was applied to develop optimal irrigation schedules for Karupanadhi command area in southern parts of India. The

Table 7 Crop production and water use efficiency for different irrigation scenarios

Model	Suggested cultivable area, ha	Simulated yield, kg ha ⁻¹	Suggested total irrigation, mm	Simulated total crop yield, Tonnes	Water use efficiency, kg ha ^{-1} mm ^{-1}
Proposed Model	1,194.3	3,683.9	419	4,399.6	8.79
IR1	334.8	4,316	950	1,445.0	4.54
IR2	401.0	4,232	850	1,697.0	4.98
IR3	539.0	4,057	650	2,186.7	6.24

Fig. 8 Comparison of potential evapotranspiration and actual evapotranspiration for different irrigation treatments and proposed optimal irrigation schedule

Fig. 9 Irrigation scheduling

optimal irrigation scheduling

treatments and proposed

model



effectiveness of the framework was compared with that of traditional water saving irrigation plans. The results indicated that a nonuniform distribution of water stress during the growing period of the crop, imposed by the proposed model, was able to increase the cultivable area of the crop with minimum reduction in crop yield, thereby facilitating maximum crop production under deficit condition. The major advantage of the proposed model is that it eliminates the limitation of triggering irrigation at fixed levels of soil moisture content, which is followed in the traditional

Fig. 10 Karupanadhi reservoir storage, inflow and release towards irrigation for the khariff season 2005

methods. The model also eliminates the subjective decisions about the splitting of irrigation requirement between different growth stages based on their sensitivity to crop yield. It is noted that the traditional methods of water saving irrigation for rice since imposes uniform water stress over the growing season, was not able to suggest increased cultivable area due to limited water availability. Overall, the results of the study suggest that by employing a calibrated crop growth model combined with an optimization algorithm can lead to achieve maximum water use efficiency.

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