Dynamics and Uncertainty in Irrigation Management.*

Dynamique et incertitude dans la gestion de l'irrigation.

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Abstract

Water supply for irrigation is limited in the southwestern France as in many regions of the world. Many conflicts between users highlight the fact that efficient irrigation scheduling is needed. The aims of this study are twofold. First we identify optimal irrigation strategies under stochastic weather conditions. Second we evaluate the economic losses due to uncertainty and risk aversion. The agronomic crop growth model, EPIC-PHASE, generates yield data which are incorporated into a dynamic programming model for the determination of optimal irrigation scheduling under risk and limited water supply, in the southwestern France. The results indicate that optimal dynamic irrigation strategies produce higher profits, and utilities, and required less irrigation water than the optimal agronomic irrigation strategies.

Key-words : irrigation scheduling, uncertainty, risk aversion, bioeconomic simulation model, optimization.

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Résumé

Dans le Sud-ouest de la France, comme dans de nombreuses régions du monde, l'offre d'eau à usage agricole est limitée. De ce fait, une gestion efficace de l'irrigation s'impose. L'objectif de cette étude est double. Premièrement, nous identifions les conduites d'irrigation optimales sous des conditions climatiques aléatoires. Deuxièmement, nous évaluons les pertes économiques dues à l'incertitude et à l'aversion pour le risque. Le modèle agronomique de simulation de croissance de la plante, EPIC-PHASE, engendre des données relatives au rendement qui sont ensuite incorporées dans un modèle économique de programmation dynamique. Ce modèle permet de déterminer la conduite d'irrigation optimale en univers aléatoire, dans un contexte de ressources en eau limitées, pour la région du Sud-ouest de la France. Nous montrons que les conduites dégagées par le modèle engendrent des niveaux de profit et d'utilité plus importants que ceux obtenus pour des conduites "agronomiquement" optimales malgré l'offre en eau limitée.

Mots-clés : conduite d'irrigation, incertitude, aversion pour le risque, modèle de simulation bio-physique et économique, optimisation.

1 Introduction

Irrigation water in the southwestern France, as in many regions of the world, is limited. In this area, farmers generally intake water from streams. These intakes are difficult to regulate because irrigation water consumptions are rarely metered, and therefore unobserved. Moreover, the stochastic weather conditions can induce water scarcity and limit water available for irrigation. These conditions place a premium on irrigation scheduling management. Determining the optimal timing of irrigations over a season in an uncertain environment is a significant problem when water is scarce.

We deal with the specific problem of finding the optimal allocation of a finite quantity of water over an irrigation season on a particular area of crop in the face of stochastically varying rainfall. We address two questions : When and how much to irrigate ? What are the economic losses due to the risks the farmer has to face ?

A wide range of modeling procedures has been used for economic evaluation of irrigation scheduling. These methods principally include the use of dynamic programming (Yakowitz, 1982; Rao *et al.*, 1988) or control theory (Zavaletta *et al.*, 1980). They provide a potential tool in defining optimal allocation of intraseasonal irrigation water. No analytic results appear in these studies. They only compute numerical models in order to obtain solutions. One way to improve and adapt these models is to incorporate bio-simulation models.

Crop growth simulation models integrated in a dynamic economic analysis of irrigation under limited water supply become frequently used as research tools (Zavaletta *et al.*, 1980 ; Epperson *et al.*, 1993). The way farmers make irrigation decisions under stochastic conditions has been best explored in the literature. However the latter studies of economically optimal irrigation water schedule were based on the strong assumption that the producer is risk neutral (Zavaletta *et al.*, 1980) while it is recognized in the literature that many farmers are risk averse (Binswanger, 1980). Boggess and Ritchie (1988) address an issue to this problem; they define means and standard deviations of net returns, and stochastic dominance is used to evaluate the risk associated with the alternative irrigation strategies. Botes *et al.* (1995) define expected utility as criteria but impose a Constant Absolute Risk Aversion (CARA) utility function. Chavas and Holt (1990), Pope and Just (1991) proved that farmers exhibit significant aversion to downside risk (higher moments of crop yields modify the optimal decisions of farmers). A Constant Relative Risk Aversion (CRRA) and Decreasing Absolute Risk Aversion (DARA) function is preferable to CARA functions. No works assume CRRA utility function.

Moreover, to our knowledge, no studies investigated this framework as an irrigation management tool. Specifically, no applications of this problem on the southwestern France area with economic criteria guiding decisions exist; there only exist agronomic studies (Cabelguenne *et al.*, 1995).

To overcome these limitations, the objective of this study is to select irrigation plans within irrigation scheduling strategies. We use a crop growth model, EPIC-PHASE[1], to generate crop yields. This information is incorporated in an economic model whose objective function is the expected utility, subject to a number of technical constraints. This integrating model is used to find irrigation decision rules in both a deterministic and an uncertain context under limited water supply. In a deterministic environment, the farmer knows climatic conditions. In an uncertain environment, the farmer has some expectations of weather conditions and may incorporate some information during the season.

Our paper makes two contributions to the literature on irrigation scheduling under risk. First, we conceive an economic model integrating a crop growth simulation tool. We use this model to define appropriate irrigation under limited water supply and uncertain climatic conditions. The advantage of our approach is that it uses accurate definition of production and decision making model. It also assumes that weather conditions are unknown. Second, our framework assumes risk aversion and sequential input decisions. Many existing sequential decision models assume risk neutrality. To our knowledge, there are no studies in the literature proposing models of irrigation decisions under risk, without imposing restrictive or inconsistent assumptions on the farmer's utility function. We use a CRRA utility function that is recognized in the literature to describe the farmer's risk attitude with a fixed risk

[1]EPIC-PHASE : Erosion Productivity Impact Calculator - PHASE

aversion parameter.

The results show that irrigation strategies that maximize profits per hectare of corn under perfectly known environment give high yields and associated profits with quotas smaller than those needed to obtain optimal agronomic yields. We emphasize the impact of the risk on irrigation both from a qualitative and a quantitative point of view.

The theoretical model is presented in section 2. In section 3, we present the highlights of the numerical method and data used to solve the problem. The results are given in section 4. Section 5 concludes the paper.

2 The model

As a useful benchmark, we first consider the problem of an optimal irrigation scheduling in a deterministic context, the weather being known for the whole irrigation period (section 2.1). We then introduce random considerations in the section 2.2.

2.1 The deterministic framework

Consider a farmer facing a sequential decision problem of irrigation. At date 1, the farmer knows the water quota available for the season, Q, the initial water stock in soil, $\bar{V}$, and the state of crop biomass, $\bar{M}$. The farmer has to take decisions on irrigation at each date $t = 1, ..., T-1$, and must choose the quantity of irrigation water denoted q_t. Therefore, we have a dynamic model of sequential choice under limited water supply, with three state variables $(M_t, V_t, Q_t) \quad for \quad t = 1, ..., T-1$.

$$M_{t+1} - M_t = f_t(M_t, V_t) \tag{1}$$

$$V_{t+1} - V_t = g_t(M_t, V_t, q_t) \tag{2}$$

$$Q_{t+1} - Q_t = -q_t \tag{3}$$

The change in the level of the biomass at any date (equation 1) is a function (f_t) of the present date state variable and water stock in soil. The change in water stock in soil (equation 2) depends moreover on the decision taken at the current date. The quota has a simple decreasing dynamic (equation 3).

Given the complexity of the production function, we made here assumptions regarding the dynamic of the soil-plant continuum, as well as simplifications. Notice that these assumptions do not modify the numerical resolution of the problem, as we will see in the section 3.

The difficulty of applying small and high quantities of irrigation water is included in the model as an additional constraint:

$$\underline{q} \leq q_t \leq \bar{q} \qquad for \quad q_t > 0 \tag{4}$$

There are technical (irrigation practice, capacity) as well as economic motivations for this constraint (4). For example, during water crisis in summer, the regulator can fix to $\bar{q}$ the maximum amount of water to be intaken for irrigation.

The final date ($t = T$) corresponds to harvesting when actual crop yield becomes known. Let Y denote the crop yield function ; that quantity depends only on the final biomass at date T and is denoted $Y(M_T)$.

The profit per hectare of the farmer can be written as:

$$\Pi = p \cdot Y(M_T) - C_{FT} - \sum_{t=1}^{T-1} (c \cdot q_t + \delta_t \cdot C_F) \tag{5}$$

where p denotes output price; C_{FT} denotes fixed production costs; c is water price; δ_t is a dummy variable taking the value 1 if the farmer irrigates and 0 if not. C_F represents fixed costs for each irrigation due to labour and energy costs. We assume in the following that there is no uncertainty on output price.

The farmer is represented by a strictly monotonic, increasing and concave Von-Neumann-Morgenstern utility function, denoted U. We chosed the most common CRRA utility function ; it has the form :

$$U(\Pi) = \frac{\Pi^{(1-r)}}{(1-r)} \tag{6}$$

with r ($r \neq 1$), the relative risk aversion coefficient. We have assumed a risk aversion coefficient of 0.001, in accordance with the literature (Jayet, 1992).

The model formulation is conceptually similar to the dynamic models used in Zavaleta *et al.*(1980), Johnson *et al.*(1991) and Vickner *et al.*(1998) but these studies do not take into account risk aversion among other aspects of the problem that we consider.

The farmer sequential problem is the following :

$$Max_{\{q_t\}_{t=1,\dots,T-1}} \quad U\Big(p \cdot Y(M_T) - C_{FT} - \sum_{t=1}^{T-1} (c \cdot q_t + \delta_t \cdot C_F)\Big) \tag{7}$$

$$s/c \qquad \begin{cases} M_{t+1} - M_t = f_t(M_t, V_t) \\ V_{t+1} - V_t = g_t(M_t, V_t, q_t) \\ Q_{t+1} - Q_t = -q_t \end{cases} \tag{8}$$

$$and \quad s/c \qquad \begin{cases} \delta_t = \begin{cases} 0 & si \quad q_t = 0 \\ 1 & si \quad q_t > 0 \end{cases} \\ \underline{q} \leq q_t \leq \bar{q} \qquad iff \quad q_t > 0 \\ M_t \geq 0, \quad V_t \geq 0, \quad Q_t \geq 0 \\ M_1 = \bar{M}, \quad V_1 = \bar{V}, \quad Q_1 = Q \end{cases} \tag{9}$$

The equations (8) are the main dynamics while (9) are technical, and physical constraints. We will solve numerically this problem in section 3.

2.2 The stochastic framework

The model under uncertainty is conceptually the same than the deterministic model. The difference lies in the dynamic behavior of the system that now incorporates stochastic weather variables, $\tilde{\omega}_t$. The dynamics of biomass and water stock in soil (equations 1 and 2) become:

$$M_{t+1} - M_t = f_t(M_t, V_t, \tilde{\omega}_t) \tag{10}$$

$$V_{t+1} - V_t = g_t(M_t, V_t, q_t, \tilde{\omega}_t) \tag{11}$$

From now on, the farmer's objective will be the expected utility. We have to define now how the farmer does (or does not) incorporate the information he gets during the season. We focus here on two main procedures known as "*feedback*" and *"open-loop"* .

2.2.1 The feedback strategy

In this framework, the farmers incorporates all the information he gets during the decision process. At date 1, the farmer takes the decision q_1 according to his weather expectations. On date 2 he integrates the decision made at date 1 and actual climat, he may revise his weather expectations. The decision taken at date t clearly depends on the weather conditions observed during the period $[t-1, t]$ and on the past decisions $q_1, \cdots, q_{t-1}$. This procedure is repeated up to date $T-1$.

Formally, the producer sequential problem is :

$$Max_{q_1} E_{\omega_1} Max_{q_2} E_{\omega_2/\omega_1} ... Max_{q_{T-1}} E_{\omega_{T-1}/\omega_{T-2}} E_{\omega_T} \quad \left[U\Big(p \cdot Y(M_T) - C_{FT} - \sum_{t=1}^{T-1} (c \cdot q_t + \delta_t \cdot C_F)\Big)\right] \tag{12}$$

$$s/c \qquad \begin{cases} M_{t+1} - M_t = f_t(M_t, V_t, \omega_t) \\ V_{t+1} - V_t = g_t(M_t, V_t, q_t, \omega_t) \\ Q_{t+1} - Q_t = -q_t \end{cases} \tag{13}$$

and subject to the unaltered constraint (9).

E_{ω_1} denotes the expectation on ω_1. $E_{\omega_t/\omega_{t-1}}$ represents the conditional expectation on ω_t given ω_{t-1}.

2.2.2 The open-loop strategy

The farmer's decision program is an *"open-loop"* one if he decides to choose all irrigations, $\{q_t\}_{t=1,\ldots,T-1}$, before observing stochastic variables. In this case, all the decisions are made at date 1. At each period, the farmer does not revise his expectations. This procedure serves as benchmark since no information is incorporated during the season.

The problem is the following:

$$Max_{\{\{q_t\}_{t=1,\dots,T-1}\}} E_{\omega_1} E_{\omega_2} .... E_{\omega_T} \quad \left[U\Big(p \cdot Y(M_T) - C_{FT} - \sum_{t=1}^{T-1} (c \cdot q_t + \delta_t \cdot C_F) \Big) \right] \tag{14}$$

$$s/c \qquad \begin{cases} M_{t+1} - M_t = f_t(M_t, V_t, \omega_t) \\ V_{t+1} - V_t = g_t(M_t, V_t, q_t, \omega_t) \\ Q_{t+1} - Q_t = -q_t \end{cases} \tag{15}$$

and subject to the unaltered constraint (9).

$E_{\omega_1} E_{\omega_2} .... E_{\omega_T}$ represents the expectation on the whole information set $(\omega_1, \cdots, \omega_T)$.

Under uncertainty, the two classes of strategies, open-loop and feedback, can be distinguished by the amount of information used and the anticipation of future knowledge. Note that the optimal stochastic control belongs to the feedback class.

3 Empirical application, procedure and data

The complexity involved in modeling and in deriving analytical solutions leaves numerical solutions as a viable alternative.

3.1 Empirical application and procedure

We use a crop growth model to generate information relating to state variables, and previously denoted by functions f_t and g_t. The use of this model allows new ways of implementing the engineering production function approach. Using the EPIC-PHASE[2] model it is possible to simulate yields for a large variety of agricultural techniques. The model allows us to represent the effects on yields arising from changes in the levels and timing of irrigation

[2]The agronomic model, EPIC-PHASE (Cabelguenne and Debaeke, 1995), is a version of EPIC (Sharpley and Williams, 1990 ; Williams *et al.*, 1990) which has been adapted by INRA (Toulouse). It has been developed to estimate crop yields for various irrigation scheduling, involving alternative irrigation timing. The EPIC-PHASE model predicts crop growth and water use in daily increments. This modified version of the model, EPIC, simulates more precisely the effects of water stress on crop growth and yield.

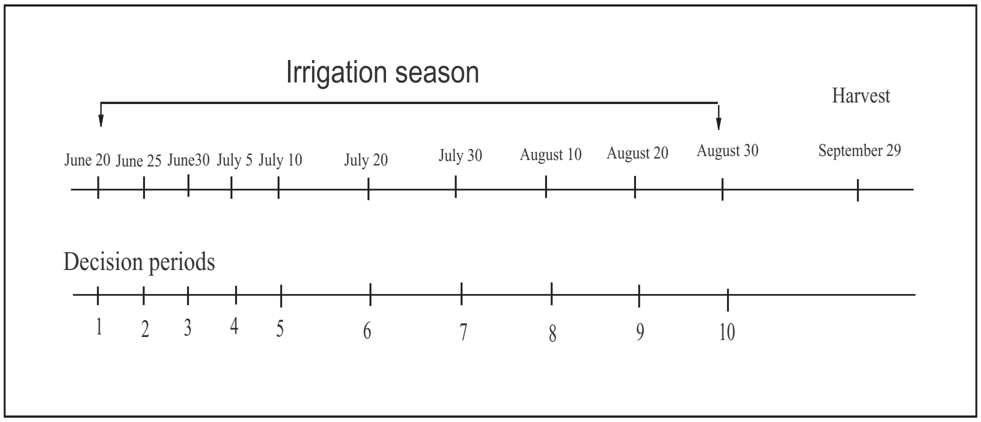

Figure 1: **Decision process.**

and climat conditions. It is considered as a sophisticated and powerfull tool for generating agricultural production surface. It has been validated by agronomists in the studied region for the crop considered, that is corn (Cabelguenne and Debaeke, 1995). The outputs from the plant simulation model are used as input in the economic model.

We make different assumptions in order to solve the problem. We assumed that the irrigation season is not endogenous and begins on June 20th. The whole irrigation season is subdivided into ten irrigation intervals of 5 or 10 days duration which is a common practice (Figure 1). The maximum number of irrigations[3] is 5 over the 10 decision dates. The quantity of water in each watering is calculated as an uniform repartition of the total quantity of water[4] that is a fifth of the quota. The weather expectations are simulated by using daily average values from a sample of 14-year observed weathers .

In the feedback case, the procedure used to find the solutions is an approximation of the "*pure feedback*" defined in section 2.2.1. We define it as an "*open-loop feedback*" procedure, and is very similar[5] :

[3]The average number of irrigations realized in Toulouse area is 5 (Enquête Agreste, 1996).

[4]This assumption is realistic because it is a common practice observed in the considered area.

[5]It can be shown that "*open-loop feedback*" and "*feedback*" strategies are equivalent if the system is linear and the objective function is quadratic (see Bradford and Kelejian (1981)).

At date 1, the farmer takes all the irrigation decisions $\{q_t\}_{t=1,...,T-1}$ according to his weather expectations. Then, he integrates only his optimal decision at date 1 and actual climat. He also uses a Bayesian rule to adjust his expectations for the remaining future periods according to observed past information. At date 2, the farmer defines all remaining irrigation decisions $\{q_t\}_{t=2,...,T-1}$, according to these revised expectations, and keeps only his choice for date 2. This procedure is repeated up to date $T-1$.

The economic model identifies the optimal irrigation schedule by using yields generated by the crop growth model on different irrigation strategies. The formulation of this problem is based on a method of global optimization. By the contraints imposed, the problem can be solved using an algorithm of search on all possible cases since the set of constraints limits the space of available irrigation schedules. Then, we obtain the optimal decision pattern by examining exhaustively the set of simulated utilities.

3.2 Data

The simulation model was initialized with soil and corn[6] parameters typical for production practices in the southwestern France. Data used to run EPIC-PHASE include weather variables (daily values of air temperature, solar radiation, precipitation, wind speed and relative humidity), soil variables, erosion variables, parameter values for crop, fertilization, pesticide and irrigations. The daily weather input file was developped from data collected at the INRA station in Toulouse, for a 14-year series. The average price per ton for corn was 1440 Francs in Toulouse area. The crop price is known for each year. Costs equal the variable cost of irrigation water plus other fixed costs. The per-unit cost of irrigation water is estimated as 0,25 F per hectare. Fixed costs by irrigation are evaluated as 150 F ; they included energy and labour costs. Global fixed costs evaluated at 2150 F per hectare are composed of fertilizer, nitrate, seed, and hail insurance costs.

[6] Corn is the only crop considered in this study. With approximatly 80 % of irrigated area in the southwestern France, corn remains the main irrigated crop.

	Profit (Fr/ha)	**Yield** (T/ha)	**Water quota** (m^3/ha)	**Number of irrigations**
• **No irrigation:**	5529	7,32	0	0
• **Agronomical optimum:**	7291	12,90	4970	19
• **Optimal irrigation scheduling:**	8929	11,63	1500	5

Table 1: **Profits and yields simulated with a fixed total available quantity of water equal to 1500** m^3/ha**.**

4 Results and discussion

We assume that the farmer faces a fixed total available quantity of water[7] of 1500 m^3/ha. We chosed a dry[8] climate for the unknown reference climate in the simulation . The problem of irrigation scheduling is particularly accurate under these stochastic weather conditions and with limited water supply.

In the perfectly known environment case, we use our model to generate optimal irrigation scheduling strategies and we compare these irrigation decision plans to optimal agronomic strategies for the reference year. We illustrate the necessity of economic analysis of irrigation management decisions (see Couture (2000) for details)) and compare the small differences in terms of yield, with the big ones in terms of water and money savings between these strategies.

Under uncertainty, we first compare the strategies with the ones obtained under a known climate ; then we highlight the differences due to the way information is taken into account.

4.1 Optimal irrigation water allocation with deterministic environment

The model is used to analyse the impact of weather variables on yields and profits. The results are presented in Table 1. The table contains water quantity, number of irrigations,

[7]In Toulouse area, the average quota used by farmers is 1800 m^3/ha (Enquête Agreste, 1996).
[8]The reference year is 1989

	Optimal utility (F/ha)	**Yield** (T/ha)
Deterministic case	8854	11,63
Feedback strategy case	8594	11,38
Open-loop strategy	8386	11,18

Table 2: **Simulated optimal utilities and yields with a uniform repartition of the fixed total available quantity of water equal to 1500** m^3/ha**.**

profits and yields for the no-irrigation case, agronomically optimal case (potential case), and so-called *"optimal"* case obtained by the model. The agronomically optimal case with no restriction on water provides a benchmark against which the effects of alternative irrigation procedure strategies can be evaluated. It is clear from Table 1 that moving the optimal timing of irrigations results in less total water consumed, relatively high yield and profit. If the farmer follows the schedule recommanded by the optimization model, he makes important savings of resource and he improves water management. These analyses for managed irrigations with limited water supply can be accomplished with little loss in yield. This result is also due to the fact that the weather is known. Specifically, by optimizing the timing and water rates, profits for the reference year increase despite the limitation on water supply.

4.2 Optimal irrigation water allocation under uncertainty

Under uncertainty, the farmer chooses the optimal irrigation scheduling maximizing expected utility according to weather risk and expectations. Then, we applied the principle of solution generation with the feedback strategy and the open-loop one. In the feedback strategy case, we assume that the farmer revises each period his expectations ; therefore, the expected climate is close to the real one. On the contrary, in the open-loop strategy case, the farmer does not modify his expectations.

The perfectly known environment results provide the optimal irrigation strategy and a benchmark for determining the performance of the stochastic strategies. The primary effects

Optimal irrigation scheduling	Decision periods									
	1	2	3	4	5	6	7	8	9	10
Deterministic	300		300	300		300	300			
Feedback strategy	300	300		300	300	300				
Open-loop strategy		300		300	300	300			300	

Table 3: **Optimal irrigation scheduling under uncertainty with a uniform repartition of the fixed total available quantity of water equal to 1500** m^3/ha**.**

of uncertainty are to reduce yields and therefore utilities (Table 2). With the open-loop strategy and the feedback one, results obtained for yields slightly differ from this obtained in the deterministic case. Therefore, differences between utilities (respectively 8594 F/ha and 8386 F/ha for the feedback strategy and for the open-loop one) are found, representing a decrease of almost 2,9 % and 5,3 % with respect to the perfect knwoledge case (8854 F/ha). The secondary effects of risk concern optimal irrigation scheduling that differs between the three cases (Table 3). The optimal feedback irrigation schedule is more close to the optimal deterministic irrigation strategy than the optimal open-loop one, because of expectation revisions. There appears three common irrigation dates between the feedback case and the perfect knowledge one while there only are two similar ones between the open-loop case and the deterministic one.

The utilities differences between the feedback strategy and the open-loop strategy cases could be considered to be the cost of not revising expectations, and represent the value of information. The farmer always must use information that is available to make decisions although this information is not complete. The difference between deterministic strategy and uncertain strategies represents the cost of not possessing complete information.

5 Conclusion

The uncertain weather conditions surrounding agriculture make irrigation scheduling management difficult. A simulation model that incorporates irrigation, economic and crop growth components, as well as an efficient search optimizer, was used to solve the problem of intraseasonal irrigation water allocation under uncertainty or perfect knowledge environment and under conditions of limited and unlimited water supply. The results exhibit two important conclusions. First, profit maximizing strategies generally make the farmer's profit more important than yield maximizing strategies and call for significantly less water, under deterministic weather conditions. Second, under risk, expected utility maximizing irrigation strategies are modified. They depend on the farmer's expectations and the integration of information in the decision making process. The use of more information improves the farmer's ability to schedule irrigation and increases expected utility due to the attainment of near optimal certain yield.

In our essay, we assumed that the farmer has ten decision times, and for each irrigation decision, quantity applied was uniformly defined. To overcome this assumption, the simulation model can be included within a global optimization program using neural networks or genetic algorithms. Crop simulation models and the strategy evaluation procedure of this study can be generalized to look at other variables affecting irrigation decisions as soil type, or with other management practice decisions such as fertilization, planting and harvesting dates. This model can be used to obtain crop-level irrigation water demand. As mentionned earlier, the farmer faces a fixed and limited quota. Under water scarcity, he can be likely to pay more for having additional water. Irrigation water demand can be evaluated on the basis of the estimation of the farmer's willingness to pay for obtaining an additional unit of water. A final extension of this work may include a method to determine the value of irrigation scheduling information and its dynamic over an irrigation season.

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