Regulating intra-annual agricultural water use under climate and price uncertainty.[1]

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3èmes journées de recherches en sciences sociales

INRA SFER CIRAD

09, 10 & 11 décembre 2009 –Montpellier, France

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[1] This work is a part of the project *Appeau* funded by the program "Agriculture and Développement Durable" from the Agence Nationale pour la Recherche (ANR). The authors gratefully acknowledge support from the ANR grant that has made this study possible.

Abstract

We propose a framework allowing to optimize land allocation across crops and intra-annual water use for a farmer facing both climate and price uncertainty. Agricultural production technologies are represented through climate-contingent crop yield functions estimated using data generated by a biophysical crop growth model. These crop yield functions are then integrated into a decision model under uncertainty. An empirical application is developed for a region located in Southwest of France. We analyze in particular how the timing of climatic uncertainty modifies farmer's optimal decisions.

JEL CODES: Q12, Q15, Q25

1. Introduction

There exists a vast literature on water use by the agricultural sector, mostly oriented toward the identification and the regulation of the water demand. The problem of evaluating irrigation water demand is not new but it has become a growing field of research in the last few years. As mentioned by Bontemps and Couture (2002), there are two distinct approaches. The first one, based on econometric modeling of the production function, relies on the fact that reliable information about agricultural water use exists. Groom et al. (2008) is a recent example of econometric estimation of an agricultural water demand under uncertainty. A second direction consists in using mathematical programming models where the water demand is derived from simulations of profit maximizing behavior. Those static microeconomic approaches provide useful theoretical frameworks for characterizing the optimum resource use in a timeless environment. However, decisions to apply alternative quantities of irrigation water under uncertain weather conditions are *per se* dynamic and complex. Indentifying optimal irrigation decision requires to know the relationships between soil and water content, growth stress of the plant, and the stage of the crop development. Integrating those complexities into a framework allowing to optimize land allocation across crops and intra-annual water use for a farmer facing both climate and price uncertainty is one of the objective of our paper.

Focusing on intra-annual agricultural water consumption is relevant from a policy point of view for several reasons. The first reason is that the social value of water may vary according the period of the year. In particular, it is likely that the social value is higher in summer when high competition across water users results in scarcity rents.[2] As a result, it makes economic sense to charge more at these times since the opportunity cost of water consumption is higher. Another motivation for focusing on intra-annual water use is that many countries which are not considered as being explicitly water-stressed experience however some scarcity problems at some specific period of the year. France is a typical example of such a country. Since the water exploitation index (WEI)[3] is for France lower than 10%, it should not be considered as a water-stressed country.[4] However, French public authorities

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[2] For instance, the marginal benefit of instream water flow in rivers is typically higher during periods of low flow like summer, justifying a higher price for other uses where they compete with instream flow.

[3] The WEI is defined by the European Environment Agency (EEA) as the mean annual total abstraction of fresh water divided by the long-term average freshwater resources.

[4] According to the EEA, a country is water-stressed if the WEI is greater than 20%. A country is said to experience a severe water-stressed situation if the WEI is greater than 40%. European Environment Agency (2009) indicates that six European countries are currently water-stressed (Cyprus, Bulgaria, the former Yugoslav Republic of Macedonia, Malta, Italy and Spain). At a more local scale, the WEI for some overexploited river

are more and more often required to implement water use restrictions, especially during the summer season. The number of French administrative districts ("départements") having implemented those kind of restriction has increased from 25 on average over the period 1998-2002 to 51 between 2003 and 2004. But, on important characteristic of the water use restrictions is that they mainly occur during the summer where agricultural and other water demands peak at a time when the natural water resource reaches a minimum.[5] From a public policy point of view, this means that intra-annual water consumption matters and that reallocation of water consumption from a peak toward an off-peak period should be promoted. This is especially true in a context of climate change since, according to European Environmental Agency (2007), we can expect "more frequent summer droughts" in Europe.

If the agronomical literature on intra-annual water use is abundant,[6] the economic literature is more limited. McGuckin et al. (1987) have developed a dynamic programming model of irrigation scheduling which account for stochastic weather conditions. The decision to irrigate or not to irrigate is based on two state variables, namely soil moisture and potential evapotranspiration. The general recursive equation is solved numerically. The dynamic programming decision rules significantly outperform nonstress irrigation strategies. Bontemps and Couture (2000) have developed an optimal control approach in order to explain the optimal irrigation management plan of a risk neutral farmer. The discrete irrigation decision is based on three state variables: the water soil content, the crop biomass and the remaining water quota. Shani et al. (2004) have used an analytical optimal control approach to derive the optimal irrigation scheme based on the dynamic response of the biomass yield to soil moisture. The optimal policy consists in driving the water content towards the turnpike as quickly as possible, and then to irrigate at the rate required to maintain the soil water content at that level. Shani et al. (2004) demonstrate that this type of policy is robust to various situations. Peterson and Ding (2005) have specified an irrigated corn production function in western Kansas by including four water inputs corresponding to water applied at different stages of growth (preplant, vegetative,

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basins can even be greater than 100%. This is the case for instance of the Sado river basin in Portugal and the Segura river basin in Spain.

[5] In 2005, the number of French administrative districts having implemented water use restrictions was 19, 50, 71, 66, 33 respectively in June, July, August, September and October.

[6] Agronomists have typically modelled crop yield by characterizing the detailed biophysical processes related to plant growth. An important contribution of these experiments is the finding that crop yields are more sensitive to changes in evapotranspiration at certain times in the growing season than at others, see Norwood and Dumier (2002). This led to modelling frameworks that explicitly account for different plant growth stages in the yield-evapotranspiration relationship. The most recent approach in agronomy to solve irrigation scheduling problems relies on liking daily-loop plant growth simulators with decisional models in order to identify the optimal irrigation decision rules, see Bergez et al. (2002).

flowering, ripening). They estimate a Just-Pope production function using data generated from a daily-loop plant growth simulator designed for western Kansas conditions. Interestingly, they show that water is a risk decreasing input in some growth stages (flowering, ripening) and a risk increasing input in others (preplant, vegetative). Considering different water inputs is then relevant from an economic point of view. Although this framework constitutes a step towards a more realistic representation of crop yield function, it does not take explicitly into account the sequentiality of the irrigation scheduling problem. It neither integrates the timing of climate uncertainty resolution.

Considering farmer's intra-annual decision is relevant for managing agricultural water use for two main reasons. First, the timing of the cropping calendar can also be used as a technique to reduce irrigated water use, see European Environment Agency (2009). Early sowing, for example, can help capture winter rains so that the need for supplementary irrigation is reduced. Early sowing also helps avoid the extreme evapotranspiration rates typical of Mediterranean summers. Second, typically the crop growth process is time dependant. This is particular true concerning the impact of water. For example, regarding maize irrigation, experiments show that a single irrigation at tasselling can increase yield by 29%. Additional irrigations during the vegetative and grain filling stages increased yield an additional 11% and 13%, respectively Norwood and Dumier (2002).

Compared to the existing literature, we propose to include explicitly uncertainty on climate and on crop prices into the decision problem of a farmer. Second we develop a framework allowing to assess the value of water at any date of the irrigation campaign. This is for instance especially important for a water agency wishing to implement peak-load pricing. Third, we introduce the choice of sowing date as a decision of the farmer. Sowing is a particularly important technical operation since it determines the timing of crop cycles, Maton (2007). Last, we simultaneously consider the optimization of land shares and water use.

The paper is organized as follows. In the next section we present the theoretical model of agricultural land and water use under climate and price uncertainty. Section 3 provides an empirical application of this model using French data where we analyze, in particular, how the timing of climatic uncertainty modifies the optimal decisions of the farmer.

2. A model of land use and intra-year water allocation under uncertainty

2.1 Characterization of the representative farmer

We consider a representative farmer that may potentially produce K different crops indexed by $k \in \{1,...,K\}$ on a total land area L (in ha). The farmer faces both a climate risk and an output price risk. The farmer's utility function is denoted by $U(.)$ with $U'>0$ and $U''<0$. The farmer can take three types of decisions. He allocates the available land across all possible crops (*land use choices*), he chooses a sowing date for each crop (*sowing date choices*) and he allocates for each crop at each date of the growing season some water (*water use choices*).

2.1.1 Output price and climate uncertainty

Climate is viewed as a stochastic event $\tilde{\varepsilon}$ characterized by a discrete probability distribution function known by the farmer. The possible climate realizations are indexed by $c = 1,...,C$. We denote by $\lambda_c \in [0,1]$ with $\sum_c \lambda_k = 1$ the probability associated to the realization of climate state of the nature *c*. Crop prices at the harvesting date are also assumed to be stochastic. We denote by $\tilde{p} \in \mathbb{R}^K$ the stochastic vector of crop prices. $\tilde{p}$ is characterized by a discrete distribution where each possible realization is indexed by $n = 1,...,N$. We denote by $\mu_n \in [0,1]$ with $\sum_n \mu_n = 1$ the associated probability distribution.

2.1.2 Timing of farmer's decisions

At the beginning of the year, the farmer chooses the share of land to be allocated to each crop and decides which amount of this share may be eventually irrigated. The land use choice is taken before observing the realization of climate and price risks, see Figure 1. The farmer knows however the probability associated to each possible climate and price realization.

Having made the land use choice, the farmer can choose for each crop (either irrigated or non-irrigated) a sowing date among a set of possible dates. This choice is made ex-ante that is given the probability distribution associated to climate and price risks.

Then the farmer may starts to irrigate from June 1st. Some irrigation decisions are taken before observing the climate risk realization and are based on the probability distribution of this risk. However, from a given date, the climate realization is observed by the farmer and then all the remaining irrigation decisions are taken conditionally to this realization. This reflects the view that, at the beginning of the irrigation campaign, the farmer has an imperfect knowledge of the type of climate that will be realized. However, this knowledge increases with time and becomes perfect from a given date.

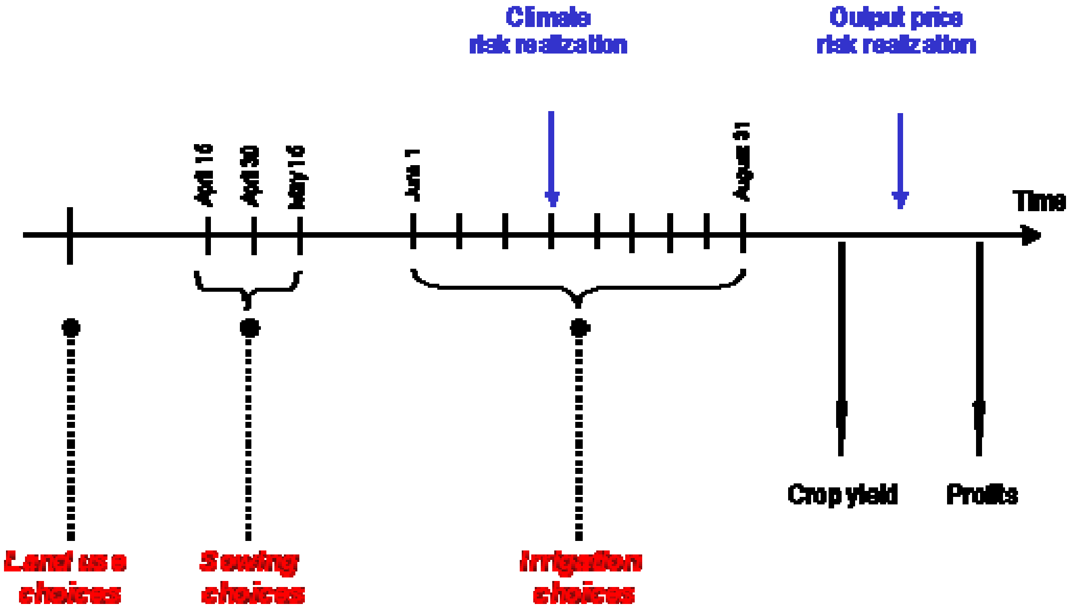

Figure 1: Timing of the model

The realization of the climate risk and the irrigation decisions taken by the farmer result in a given yield for each crop. Finally, the crop price risk is realized which determines the final farmer profit.

2.1.3 A climatic-contingent agricultural production technology

We denote by $t = 1,...,T$ the time index for the intra-annual irrigation dates (typically t may index days or weeks). As a result, the climatic-contingent yield function for crop k with a sowing date s writes:

$$Y_{ks}^{\tilde{\varepsilon}} = f_{ks}^{\tilde{\varepsilon}}(w(1),...,w(t),...,w(T)) \tag{1}$$

where $w(t)$ is the quantity of irrigation at time t. This function is contingent to the realization of the climate risk $\tilde{\varepsilon}$. It gives for any crop and any sowing date given a climate realization, the agricultural product that may be obtained from this crop by unit of area if the vector of irrigation $w = w(1),...,w(t),...,w(T)$ is implemented.[7] Notice that this yield function requires a precise representation of the relationship between water and yield, which is usually not available from

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[7] We don't want to postulate a priori that the production technologies are the same whatever the climate year.

national agricultural production databases. As we will discuss in the next section, we estimate this relationship using biophysical crop growth model simulations.

2.1.4 Farmer's decision variables

Land use choice, land irrigation choice, sowing date choice

Ex-ante, that is before observing the realization of the climatic and the price risks, the farmer allocates his agricultural land among the *K* possible crops (irrigated or not) and choose a sowing date for each crop. We denote by δ_{kis} the share of land allocated by the farmer to crop *k*, if the sowing date *s* is chosen with $s \in \{1,...,S\}$. Index *i* corresponds to the decision to irrigate (*i*=1) or not to irrigate (*i*=0) the crop considered. By definition, we have:

$$\delta_{kis} \geq 0 \quad \forall k,i,s \tag{2}$$

$$\sum_{kis} \delta_{kis} \leq 1 \tag{3}$$

Since the last constraint may not be binding, we allow the farmer not to use all the agricultural land available. Hence, we implicitly introduce the possibility of fallow.

Irrigation decisions and timing of climatic risk uncertainty resolution

We denote by $\overline{t}$ with $\overline{t} \in \{1,...,T\}$ the date from which the climate risk realization is observed by the farmer. From date 1 to $\overline{t}$, irrigation decisions are taken using the probability distribution of price and climate risks. From, $\overline{t}+1$ the irrigation decisions are conditional to the climate risk realization. We denote by $\omega_{ks}(t,\tilde{\varepsilon})$ the quantity of water applied at date *t* to an irrigated crop *k* with a sowing date *s* if climate risk $\tilde{\varepsilon}$ is realized. The fact that the climate realization is only observed by the farmer after date $\overline{t}$ means that we must impose the following constraint in the farmer optimization program:

$$\omega_{ks}(t,\tilde{\varepsilon}) = \omega_{ks}(t) \quad \forall t \in \{1,...,\overline{t}\} \tag{4}$$

which simply states that the quantity of water applied at date *t* to crop *k* with a sowing date *s* cannot depend upon $\tilde{\varepsilon}$ for $t \in \{1,...,\overline{t}\}$.

2.2 The farmer optimization program under climate and price uncertainty

2.2.1 Farmer's profit

For a given crop *k* and a land irrigation choice $i \in \{0,1\}$, we denote by Ψ_{ki} the unit cost of production per unit of area and by Δ_{ki} the coupled payment received by the farmer. We denote by μ the unit water price. We can then write the unit profit from a crop *k* with a sowing date *s* if climate risk $\tilde{\varepsilon}$ and price risk $\tilde{p}$ are realized as:

$$\pi_{kis}(.) = \begin{cases} \tilde{p} \cdot f_{ks}^{\tilde{\varepsilon}}(\omega_{ks}(1,\tilde{\varepsilon}),...,\omega_{ks}(t,\tilde{\varepsilon}),...,\omega_{ks}(T,\tilde{\varepsilon})) - \Psi_{k1} + \Delta_{k1} - \mu \cdot \sum_{t} \omega_{ks}(t,\tilde{\varepsilon}) & \text{if } i=1 \\ \tilde{p} \cdot f_{ks}^{\tilde{\varepsilon}}(0,...,0,...,0) - \Psi_{k0} + \Delta_{k0} & \text{if } i=0 \end{cases} \tag{5}$$

With irrigation (i=1), the farmer uses an irrigation vector $(\omega_{ks}(1,\tilde{\varepsilon}),...,\omega_{kc}(t,\tilde{\varepsilon}),...,\omega_{kc}(T,\tilde{\varepsilon}))$ which involves a water cost. Without irrigation (i=0), the only cost paid by the farmer is the unit production cost Ψ_{k0}.

We have denoted by δ_{kis} the share of land allocated by the farmer to crop k, if the sowing date s is chosen and if the land irrigation choice (irrigated versus non-irrigated) is i . We denote the total profit by $\Pi(.)$ which is defined as follows:

$$\Pi(.) = \sum_{k,i,s} L \cdot \delta_{kis} \cdot \pi_{kis}(.) \tag{6}$$

where L is the total agricultural land of the farmer. The total profit conditional to the climate risk $\tilde{\varepsilon}$ and the price risk $\tilde{p}$ is simply the sum of the conditional unit profit weighted by the land area.

2.2.2 The farmer optimization program

We can now derive the optimization program of the farmer under price and climate uncertainty. The optimization problem P writes:

$$Max\ EU = \sum_{c,n} \lambda_c \cdot \eta_n \cdot U\left[D + \Pi(.)\right] \tag{P.1}$$

with respect to:

$$\delta_{kis}\ \forall k,i,s \tag{P.2}$$

$$\omega_{ks}(t,\varepsilon_c)\ \forall k,s,t,c \tag{P.3}$$

subject to:

$$\delta_{kis} \geq 0\ \forall k,i,s \tag{P.4}$$

$$\sum_{k,i,s} \delta_{kis} \leq 1 \tag{P.5}$$

$$\omega_{ks}(t,\varepsilon_c)\ \geq 0\ \ \forall k,s,t,c \tag{P.6}$$

$$\omega_{ks}(t,\varepsilon_c)\ \leq \overline{\omega}\ \ \forall k,s,t,c \tag{P.7}$$

$$\omega_{ks}(t,\tilde{\varepsilon}_c) = \omega_{ks}(t)\quad \forall t \in \left\{1,...,\overline{t}\right\}\quad \forall k,s,c \tag{P.8}$$

with:

$$\Pi(.) = \sum_{k,i,s} L \cdot \delta_{kis} \cdot \pi_{kis}(.)$$

$$\pi_{kis}(.) = \begin{cases} \tilde{p}_n \cdot f_{kc}^{\tilde{\varepsilon}_c}(\omega_{ks}(1,\tilde{\varepsilon}_c),...,\omega_{ks}(t,\tilde{\varepsilon}_c),...,\omega_{ks}(T,\tilde{\varepsilon}_c)) - \Psi_{k1} + \Delta_{k1} - \mu \cdot \sum_{t} \omega_{ks}(t,\tilde{\varepsilon}_c) & \text{if } i=1 \\ \tilde{p}_n \cdot f_{ks}^{\tilde{\varepsilon}_c}(0,...,0,...,0) - \Psi_{k0} + \Delta_{k0} & \text{if } i=0 \end{cases}$$

where D represents the decoupled aid received by the farmer.

The criterion (P.1) of this program simply corresponds to the expected utility of the total profit of the farmer. The expectation is taken with respect to the climate risk and to the price risk. This criterion is optimized with respect to δ_{kis} that is the share of agricultural that must be allocated to any irrigated or non-irrigated crop with any sowing date. Constraints (P.4) guaranty that those land share are non negative. The next set of constraints (P.5) corresponds to a land availability constraint.

For irrigated crops, the farmer also optimizes the water applied at any date of the irrigation campaign (P.3). The water applied at each date must be non negative (P.6) and is bounded by $\bar{\omega}$, equations (P.7). This upper limit may be viewed as a technical constraint resulting from irrigation equipments or infrastructures. Constraints (P.8) capture the fact that the climate realization is only observed by the farmer after date $\bar{t}$. Hence, the quantity of water applied at date t to crop k with sowing date s cannot depend upon the climate state of the nature for period 1 to $\bar{t}$.

3. An Empirical Application to Southwest of France

3.1. Specification and calibration of the model

The model has been calibrated for representing a typical farmer located in Southwest of France in the Neste system.

3.1.1 Characteristics of the farmer

The total agricultural land to be allocated across crops is 40 ha which corresponds to the average size of a typical farm in that area. For the purpose of the application, we have considered the three main crops produced in that area, *k=corn, sunflower, soy.* The irrigation season (from June 1st to August 1st) is divided into 9 slots, that is there are 9 potential dates for a water application ($T=9$). A slot corresponds here to 10 days. Typically, is Southwest of France, we observe between 5 to 6 water applications on an irrigated crop during the whole growing season.

Farmer's preferences are represented by a constant absolute risk aversion (CARA) utility function. As mentioned in Hardaker and Lien (2007), a CARA utility function is relevant in the case of moderated risks, such as risks affecting only one year farmer's income. Moreover, the CARA utility function has been extensively used in the applied agricultural economics[8] since it is easily tractable and has a single parameter for representing risk aversion. Farmer's preferences write:

$$U(\Pi) = \frac{1}{\alpha} e^{-\alpha\Pi} \qquad (7)$$

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[8] A CARA utility function has been recently used by Oude Lansink (1999) to analyse land allocation decisions of Dutch arable crop farms.

where α is the coefficient of absolute risk aversion. The calibration of α is problematic since at our best knowledge there is no published study having estimated farmer's risk aversion in France. Our calibration must then rely on studies published in countries where farmers face a similar context. For instance, Groom et al. (2008) have estimated a production model for Cypriot farmers producing cereals. They report an Arrow-Pratt risk aversion parameter equal to 0.34. Following this empirical literature, we have chosen to consider a moderately risk-averse farmer. The CARA parameter has been fixed to 0.2.

3.1.2 Climate and price risks

The farmer faces an uncertainty with respect to the type of climate year that could be realized. We observe 20 years of daily weather records from 1986 to 2005. Each year will then be viewed as a possible realization of the climate risk, namely *c=1986,…, 2005*. Initially, we consider the case of equal probabilities across years that is $\lambda_c = 1/20$. Output prices are also stochastic. For each crop, we fit a normal distribution based on 10 years of price observations. We then discretize the distribution considering three possible values for each crop, *n=1,2,3*. The probabilities associated to these values are respectively 0.25 for the extremes and 0.5 for the median (corresponding to the average crop price).

3.1.3 Limitation of irrigation vectors

Corn and soy are typically intensively irrigated during the summer in Southwest of France. At each date t=1,…,9, we assume that the farmer may choose one of the three following water doses {0,20,40} where water doses are measured in mm per ha. As a result, there are $3^9 = 19,683$ possible irrigation vectors for corn and soy. Sunflower irrigation is typically more limited in practice. We limit the total irrigation to be 160 mm/ha or less. Hence there are 14,318 possible irrigation vectors for sunflower.

3.1.4 Economic calibration of the model

The optimization problem of the farmer requires a certain number of economic parameters to be calibrated including crop prices, unit production costs and decoupled payment per crop. The values for those parameters come from various statistical publications. They reflect the 2005 economic conditions, see Table 1.

Table 1: Output prices and unit production costs

		corn		sunflower		soy	
		irrigated	non-irrigated	irrigated	non-irrigated	irrigated	non-irrigated
Average output price	euros/kg	0.095	0.095	0.21	0.21	0.19	0.19
Decoupled payment	euros/ha	346	230	346	230	346	230
Coupled payment	euros/ha/kg	115.4	76.7	115.4	76.7	115.4	76.7
Unit production cost	euros/ha	530	400	347	227	315	228
Unit water cost	euros/mm/ha	0.640	0.640	0.640	0.640	0.640	0.640

Sources: Arvalis, Institut du Végétal.

3.1.5 Crop yield functions

For a given climate realization, for a given crop, we wish to estimate a crop yield function corresponding to the relationship between an irrigation vector (quantity of water applied by the farmer at various dates of the growing season) and the crop yield.

To establish this relationship, we first use a crop growth model to generate a set of experimental data (irrigation vector / crop yield) and second, we estimate econometrically some yield functions based on this dataset.

There are several crop growth models that could be used. We have used the crop growth model STICS[9] developed by Brisson et al. (2002) and adapted to our context in Poupa (2006). SITICS has been chosen first because it allows to realize efficiently a large number of simulations and second, because it has been used in a large number of situations in France and in other countries, Brisson et al. (2002). Then for a given crop, a given irrigation vector and a given climate realization, the crop simulation model gives the resulting yield to be expected by the farmer. The STICS simulations allow us to build a dataset giving for each crop, each climate realization and each vector of irrigation the corresponding yield.

The next step consists in estimating the crop yield function based on this dataset. Simple quadratic forms have been estimated based on these databases. All the crop yield functions (climate × year) have been estimated using Stata, see Appendix A for an example. We get a very good fit of the quadratic approximations with adjusted R2 greater than 0.9 for all climatic years and all crops. This

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[9] STICS is a crop growth model developed by the French National Institute of Agronomic Research (INRA).

means that the quadratic form offers enough flexibility for approximating the unknown yield functions. Moreover, most of the estimated parameters are significant at 1%.

3.2 Characterizing the optimum

In this section, we characterize the optimal decisions of a farmer that may produce corn, sunflower and soy. We particularly focus on the impact of climatic uncertainty resolution on the optimum by distinguishing three cases: a late resolution corresponds to $\overline{t}=9$ (August 30), an early resolution to $\overline{t}=1$ (June 10) and an average resolution to $\overline{t}=4$ (July 10).

Table 2: Characteristics of the optimum and resolution of climatic uncertainty

Resolution of climatic uncertainty	**Expected utility of total profit**[a]	**Expected unit profit**[a] **euros/ha**	**Optimal decisions**				
			crop	**sowing date**	**land irrigation**	**land share**	**expected use of water mm/ha**
Late	-0.053	690.1	corn	15/05	irrigated	0.723	158
			sunflower	30/04	irrigated	0.277	87
Average	-0.036	682.8	corn	15/05	irrigated	0.649	98
			sunflower	30/04	irrigated	0.351	27
Early	-0.029	765.8	corn	15/05	irrigated	0.820	113
			sunflower	30/04	irrigated	0.180	22

[a]: total profit including decoupled payment

First, it should be notice that it is optimal for the farmer to produce corn and sunflower although the expected profit from sunflower is lower than the expected profit from corn. This decision results from a strategy of risk diversification. Second, an early resolution of climate uncertainty is always preferable to a late one and the gain to be expected (both in terms of expected utility and expected total profit) is significant. Third, the crop portfolio appears to be quite stable with respect to the resolution of the climatic uncertainty. Hence, in the three cases, the farmer only produces corn and sunflower with irrigation. The optimal sowing date is not affected by the time at which the climatic uncertainty is resolved. Finally, land shares are similar in the three scenarios of climate uncertainty resolution.

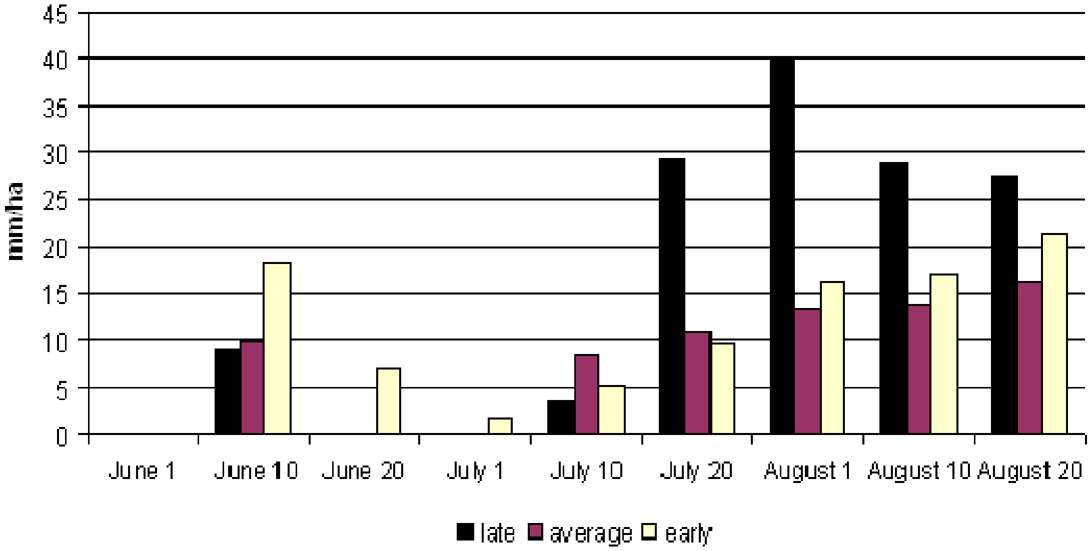

Figure 2: Expected irrigation per date according to the resolution of climatic uncertainty

The timing of the climate uncertainty resolution has however a more important impact on water consumption. If uncertainty is resolved at the first period, the quantity of water used for irrigating corn is 113 mm/ha, compared to 158 mm/ha in the case of a late resolution. With a late resolution of climatic uncertainty, the farmer uses more water. This may be viewed as a precautionary behavior.

In Figure 2, we have plotted the expected use of water as a function of the date. As it can be seen, the intra-annual water use distributions strongly differ according to the timing of climate uncertainty resolution.

3.3 The value of an early resolution of climate uncertainty

An interesting question that emerges from the previous analysis is to determine the value for the farmer of an early resolution of climate uncertainty. In other words, we wish to determine the level of the risk premium a farmer is ready to pay for being in a situation where the climatic uncertainty is resolved earlier. We denote by $RP_{e\to l}$ the risk premium a farmer is ready to pay in order to remain in a situation with an early resolution of climatic uncertainty compared to a late resolution situation. This risk premium is the maximal $RP_{e\to l}$ such that:

$$EU\left[\tilde{\Pi} - RP_{e\to l} \mid early\right] = EU\left[\tilde{\Pi} \mid late\right] \qquad (8)$$

where the left handside term is the expected utility of the farmer in the case of an early resolution of climatic uncertainty with a payment $RP_{e\to l}$ in all climatic states of the nature and the right handside term corresponds to the expected utility for a late resolution. These non-linear equations have been numerically solved with GAMS.

The risk premium $RP_{e \to l}$ is estimated to be 80.3 euros/ha which represents around 10% of the profit/ha in the case of an early resolution of the climatic risk. For $RP_{e \to a}$, the risk premium is equal to 27.3 euros/ha. This lower value is consistent with the fact that an average resolution is always preferred by the farmer to a late resolution of the climatic uncertainty. Those values confirm the fact that the timing of climatic uncertainty resolution is an important determinant of the risk premium of the farmer. Such determinants should be taken into account by an assurance wishing to propose climatic assurance contracts.

4 Regulating agricultural water demands

In this last section, we analyze the impact of some instruments that can be used by public authorities for regulating water use. We will in particular assess the impact of those instruments both on land use choice and intra-annual water use.

4.1 Implementing water quotas

A first possible way to regulate agricultural water demands is to impose quantitative restrictions on water use. We consider here a water quota defined at the farm level. The farmer is allocated an annual water quota $\overline{W}$ (mm/ha) for each unit of land and is free to use it at any period and for any crop.[10] The optimization program of the farmer is solved by introducing the following additional constraints:

$$L \cdot \sum_{k,s,t} \delta_{ks1} \cdot \omega_{ks}(t, \varepsilon_c) \leq \overline{W} \quad \forall c \tag{9}$$

which simply states that whatever the climate year, the water allocated to irrigated crops must remain lower than the annual water quota.

In Figure 3, we compare the optimal land use share for various levels of water quotas varying from 125mm/ha to 0mm/ha.

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[10] We may have considered climate-dependent quotas that is quotas implemented only in the case of a dry year. There are some examples of those types of quotas in Southwest of France were farmers directly contract with a water operator. Such a contract defines a quantity of water that will be guaranteed to the farmer height years over ten. In case of a dry year, the water operator is then allowed to reduce the quota of water.

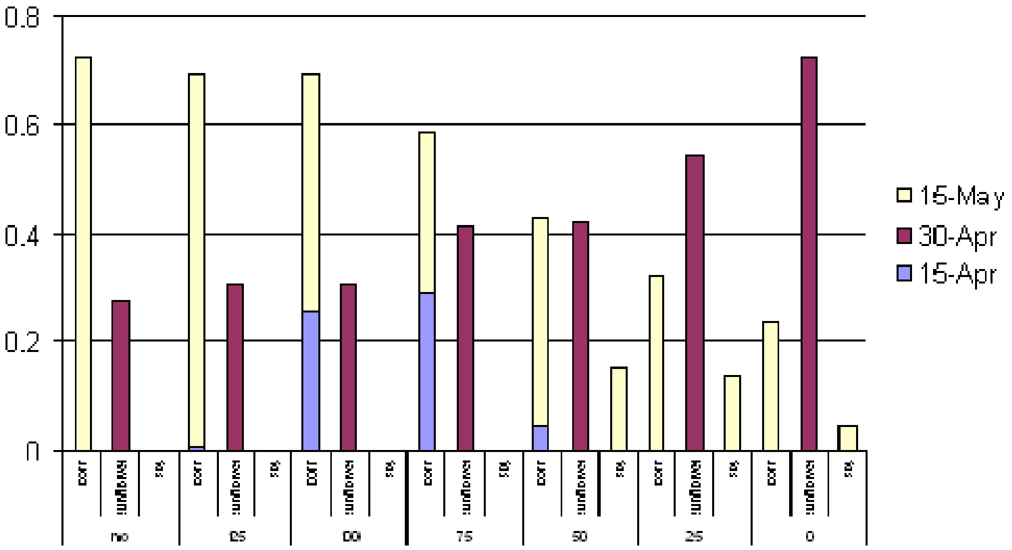

Figure 3: Impact of water quotas on optimal land use share (late resolution of uncertainty)

Without any quota, the optimal crop portfolio consists in allocating 72.3% of the available land to an irrigated corn with a sowing date equal to May 15th and to allocate the remaining land to an irrigated sunflower. In such a case, the expected average irrigation level is 158 mm/ha. Next, we assume that the farmer faces a quota equal to 125 mm/ha. The farmer slightly increases the land share allocated to the irrigated sunflower (from 0.277 to 0.308). Interestingly, corn is now produced with two different sowing dates (April 15 and May 15). A more stringent water quotas (100mm/ha) does not significantly modify the allocation of land between corn and sunflower. However, within the corn share, the weight of corn with an April 15 sowing date increases very substantially. At a quota equal to 50 mm/ha, soy enters into the optimal crop portfolio of the farmer (we observe a transition from irrigated corn toward irrigated soy). Under very limited water quotas (25mm/ha or 0 mm/ha), sunflower emerges has the main crop alternative.

4.2 Changes in the water price

Another possible way to regulate agricultural water demands is to increase (or to decrease) the water price in order to transmit to the final users a signal of water scarcity. The initial unit price of water is 0.64 euros/mm/ha (corresponding to 6.4 cents per m3). In what follows, we derive the optimal crop portfolio of the farmer and the resulting water consumption if the water price is modified by a given coefficient (from 0.5 for a decrease by 50% to 3 for an increase by 200%).

4.2.1. Impact on land use and sowing dates

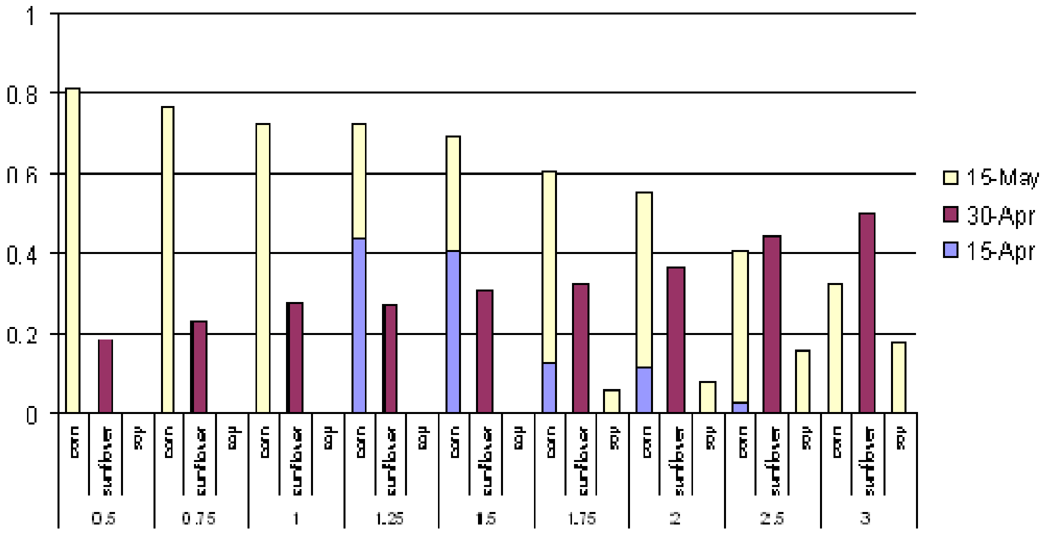

Figure 4: Impact of water price on optimal land use shares (late resolution of uncertainty)

In the previous figure, the benchmark case (price multiplying coefficient equal to 1) results in allocating 72.3% of the available land to an irrigated corn with a sowing date equal to May 15th and to allocate the remaining land to an irrigated sunflower. Facing a unit water price reduction (price multiplying coefficient equal to 0.5 or 0.75), the optimal land use strategy is to allocate more land to corn. On contrary, as the unit water price increases, more land is allocated to sunflower. From a unit water price equal to 1.12 euros/mm/ha (price multiplying coefficient equal to 1.75), soy enters into the optimal farmer crop portfolio.

4.2.2 Impact on water consumption

Table 3 : Impact of water price on annual water use

Unit water price in euros/mm/ha (multiplicative coefficient)	0.32 (0.5)	0.48 (0.75)	0.64 (1)	0.80 (1.25)	0.96 (1.5)	1.12 (1.75)	1.28 (2)	1.60 (2.5)	1.92 (3)
Expected water consumption in mm/ha	163.4	150.6	138.3	129.6	113.2	80.9	68.8	45.3	32.5

Table 3 gives the expected level of water consumption as a function of the unit water price. The main result to notice is that modifying the water price has a significant impact on the annual water consumption.

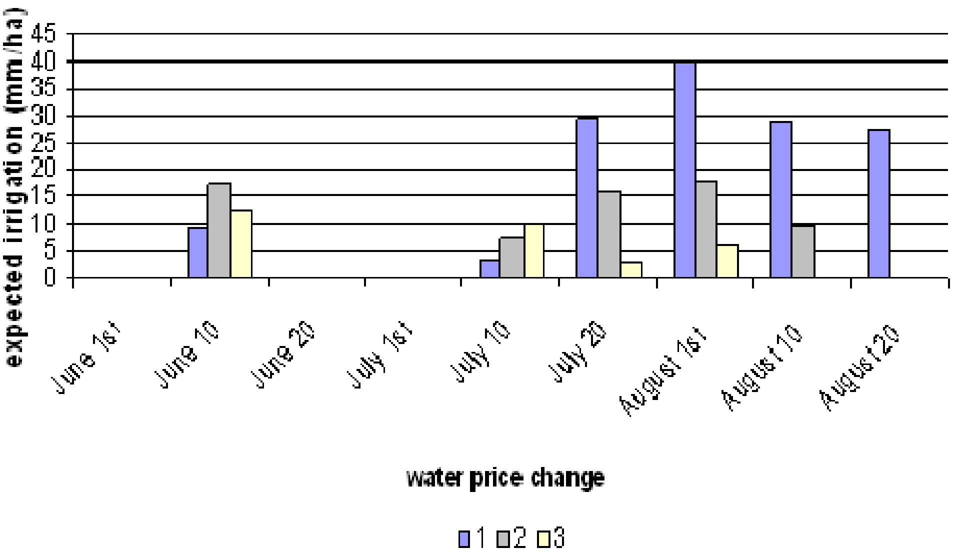

Figure 5: Impact of water price on intra-annual water use

In Figure 5, we have represented the expected intra-annual water use for the benchmark case (multiplicative coefficient equal to 1) and for a water price multiplied by two and three. For the last four slots, as expected, the price increase results in a decrease in the water used. Interestingly, we observe a non-linear relationship between the price and the water consumption for the second slot, and even an increasing relationship for the fifth slot. The fact that, facing a uniform price increase, the farmer increases the water consumption at the fifth slot can be understood based on agronomical consideration. This slot corresponds to the period of corn silking in Southwest of France, period known as critical in terms of hydric stress.

The main result here is that modifying the water price has a non-uniform impact on the intra-annual water consumption. Compared to the benchmark case, the price increase may result in an increase in the water consumption at some slots. From a policy point of view, this is particularly important since the water consumption increase may occur at a period of time where the pressure on the resource is very high due to competitive users.

4.3 Implementing peak prices

In this paragraph we wish to evaluate the impact of implementing a peak water pricing. In the context of agricultural water use, the main motivation for implementing peak prices is that the social value of water is likely to vary according the period of the year. In particular, it is likely that the social value is higher during the summer where the high competition across water users might result in scarcity rents.

As a result, it makes economic sense to charge more at these times since the opportunity cost of water consumption is higher.

Table 4 Impact of peak pricing (late climatic uncertainty resolution)

Peak price coefficient	**Expected utility of total profit**	**Average water use (mm/ha)**	**Share of peak water use (%)**	**Irrigation date**								
				June 1	**June 10**	**June 20**	**July 1**	***July 10***^{a}	***July 20***^{a}	***August 1***^{a}	**August 10**	**August 20**
1	-0.053	138.5	53	0.0	9.2	0.0	0.0	*3.5*	*29.5*	*40.0*	28.9	27.4
1.25	-0.056	138.3	49	0.0	21.5	0.0	2.1	*2.6*	*26.6*	*38.4*	26.0	21.2
1.5	-0.061	130.8	41	0.0	21.8	0.0	5.4	*1.0*	*20.3*	*31.7*	29.4	21.0
1.75	-0.062	122.4	27	0.0	29.1	0.0	10.9	*0.0*	*17.6*	*16.1*	34.6	14.2
2	-0.065	114.4	21	0.0	28.3	0.0	11.7	*0.0*	*11.3*	*12.8*	35.9	14.3
2.25	-0.067	107.4	15	0.0	27.2	0.0	12.8	*0.0*	*5.8*	*9.9*	37.6	14.1
2.5	-0.068	102.6	11	0.0	26.6	0.0	13.4	*0.0*	*3.0*	*8.3*	37.2	14.1
2.75	-0.069	98.4	8	0.0	26.0	0.0	14.0	*0.0*	*1.3*	*6.1*	36.6	14.3
3	-0.069	96.2	6	0.0	25.7	0.0	14.3	*0.0*	*0.5*	*4.9*	36.5	14.4

^{a}: peak period (July 10, July 20, August 1)

The peak period we have considered corresponds to slots 5, 6 and 7 (from July 10 to August 10). For these periods, we have simulated a multiplicative price coefficient varying from 1.25 to 3.

In the benchmark case, the expected water consumption during the peak period represents 53% of the expected annual water consumption. Increasing the peak price by 25% does not result in a significant change in the average expected water use (138 mm/ha) or in the share of the peak water use to total water use (around 50%). From a peak price increase of 50%, a process of reallocating water from the peak period toward adjacent decades starts. Implementing peak price allows to reallocate water from the peak period toward the off-peak period at a reasonable cost for the farmer (measured in term of expected utility loss).

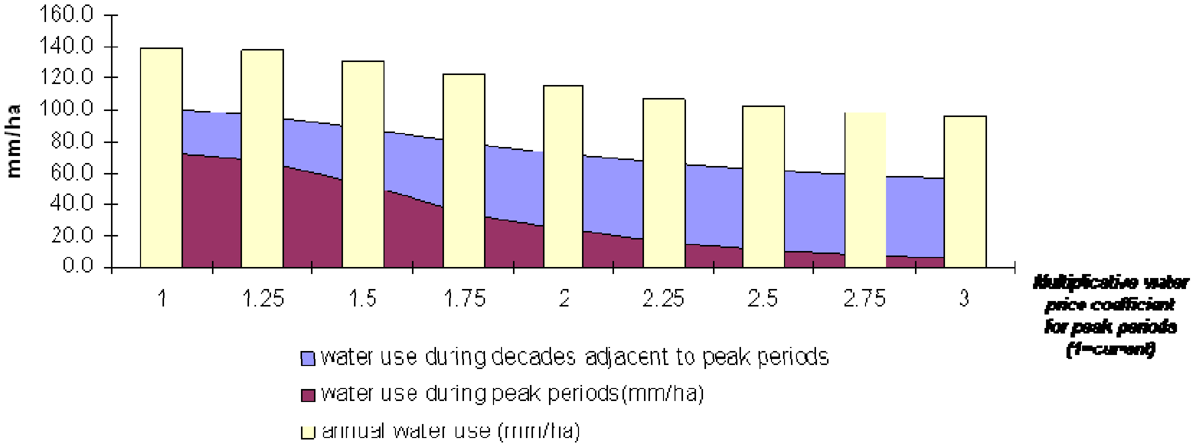

Figure 6: Impact of peak pricing on intra-annual water use

The main result is here that implementing peak water prices has a moderate impact on annual water use and on the expected utility of the farmer but a significant impact of intra-annual water use. Peak pricing appears to be an interesting instrument for a public authority wishing to transmit to farmers some incentives to reallocate water use from the peak-period towards the off-peak period. The social gains to be expected from peak pricing include the water saved during the peak period which is now available for alternative uses. One should however take into account the cost of installing meters in order to measure water consumption during the peak and the off-peak periods.

5. Conclusion

We have proposed a framework allowing to optimize land allocation across crops and intra-annual water use for a farmer facing both climate and price uncertainty. Agricultural production technologies are represented through climate-contingent crop yield functions estimated using data generated by a biophysical crop growth model. These crop yield functions are then integrated into a decision model under uncertainty allowing to optimize both land and water use. An empirical application has been developed for a region located in Southwest of France. We have shown that the timing of climatic uncertainty is a significant determinant of farmer optimal decisions.

We have also assessed the impact of various economic instruments aiming at regulating intra-annual water use by farmers. We have in particular shown that peak pricing appears to be an interesting instrument for a public authority wishing to transmit to farmers some incentives to reallocate water use from the peak-period towards the off-peak period.

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Appendix A: Post-estimation of crop yield functions for selected years

In this appendix, we present some example of yielf functions estimated using the data produced by the crop simulation model STICS.

year = 1987, 2003
sowing date = April 15
functional form = quadratic
STIC calibration = Midi-Pyrénées with Toulouse climate
crops = corn, sunflower, soy
irrigation for corn : 9 possible dates (from June 1st to August 31st), 3 possible doses (0, 20, 40 mm) with a max of 360 mm
irrigation for sunflower : 9 possible dates (from June 1st to August 31st), 3 possible doses (0, 20, 40 mm) with a max of 120 mm
irrigation for soy : 9 possible dates (from June 1st to August 31st), 3 possible doses (0, 20, 40 mm) with a max of 300 mm

Table A.1: Estimated crop yield functions for selected years

	Corn				**Sunflower**				**Soy**			
	1987		**2003**		**1987**		**2003**		**1987**		**2003**	
wat1	29.63	**	2.88	**	1.18	**	19.40	**	-9.25	**	1.50	**
wat2	45.36	**	4.97	**	1.91	**	23.45	**	-1.51	**	0.06	
wat3	46.51	**	10.76	**	1.68	**	32.89	**	0.01	**	-0.04	
wat4	37.66	**	18.60	**	0.99	**	27.29	**	-0.65	**	0.77	**
wat5	40.22	**	13.72	**	0.71	**	24.93	**	-0.19	**	1.44	**
wat6	38.84	**	9.15	**	0.29	**	23.02	**	0.00	**	-0.64	**
wat7	31.40	**	3.57	**	-0.06		15.38	**	0.00	**	5.36	**
wat8	34.62	**	1.67	**	-0.25	**	8.14	**	0.00	**	-0.16	**
wat9	38.04	**	3.15	**	-0.25	**	0.37		0.00	**	-0.06	
wat1_2	0.11	**	0.15	**	0.00	*	-0.03	**	0.16	**	0.02	**
wat2_2	-0.12	**	0.30	**	-0.02	**	-0.05	**	0.03	**	0.04	**

wat3_2	-0.12	**	0.12	**	-0.01	**	-0.16	**	0.00	**	0.04	**
wat4_2	-0.05	**	-0.09	**	-0.01	**	-0.12	**	0.01	**	0.03	**
wat5_2	-0.08	**	-0.01	**	-0.01	**	-0.09	**	0.00	**	0.01	**
wat6_2	-0.06	**	0.03	**	0.00		-0.07	**	0.00		0.04	**
wat7_2	-0.02	**	0.11	**	0.00		-0.06	**	0.00		-0.05	**
wat8_2	-0.14	**	0.11	**	0.00		-0.06	**	0.00		0.01	**
wat9_2	-0.10	**	-0.02	**	0.00		0.00		0.00		0.00	
wat1_wat2	-0.25	**	0.14	**	-0.04	**	-0.10	**	0.00	**	0.00	
wat1_wat3	-0.24	**	0.03	**	-0.03	**	-0.14	**	0.00	**	-0.01	**
wat1_wat4	-0.19	**	0.02	**	-0.01	**	-0.11	**	0.00	**	-0.01	**
wat1_wat5	-0.19	**	0.01	**	-0.01	**	-0.11	**	0.00	**	0.00	
wat1_wat6	-0.17	**	0.00		0.00	**	-0.11	**	0.00		0.02	**
wat1_wat7	-0.11	**	0.00		0.01	**	-0.06	**	0.00		-0.01	**
wat1_wat8	-0.09	**	0.00		0.01	**	-0.03	**	0.00		0.00	**
wat1_wat9	-0.11	**	0.01	**	0.01	**	0.00		0.00		0.00	
wat2_wat3	-0.33	**	-0.16	**	-0.03	**	-0.18	**	0.00	**	0.00	**
wat2_wat4	-0.25	**	-0.08	**	-0.02	**	-0.15	**	0.00	**	0.00	**
wat2_wat5	-0.24	**	0.00		-0.01	**	-0.15	**	0.00	**	0.00	**
wat2_wat6	-0.21	**	0.03	**	0.00	**	-0.15	**	0.00		0.02	**
wat2_wat7	-0.14	**	0.05	**	0.00	**	-0.08	**	0.00		-0.01	**
wat2_wat8	-0.10	**	0.05	**	0.00	**	-0.04	**	0.00		0.00	*
wat2_wat9	-0.12	**	0.05	**	0.00	**	-0.01	**	0.00		0.00	
wat3_wat4	-0.25	**	-0.13	**	-0.01	**	-0.23	**	0.00	**	0.00	
wat3_wat5	-0.25	**	-0.06	**	-0.01	**	-0.21	**	0.00	**	0.00	**
wat3_wat6	-0.22	**	-0.03	**	0.00	**	-0.19	**	0.00		0.02	**
wat3_wat7	-0.15	**	-0.03	**	0.00	*	-0.11	**	0.00		-0.01	**
wat3_wat8	-0.11	**	-0.03	**	0.00	**	-0.06	**	0.00		0.00	*
wat3_wat9	-0.13	**	-0.03	**	0.00	**	-0.01	**	0.00		0.00	
wat4_wat5	-0.18	**	-0.06	**	0.00	**	-0.18	**	0.00	**	0.01	**
wat4_wat6	-0.18	**	-0.05	**	0.00	**	-0.15	**	0.00		0.02	**
wat4_wat7	-0.14	**	-0.03	**	0.00		-0.09	**	0.00		-0.01	**
wat4_wat8	-0.10	**	-0.02	**	0.00	*	-0.04	**	0.00		0.00	*
wat4_wat9	-0.13	**	-0.02	**	0.00	*	-0.01	**	0.00		0.00	

wat5_wat6	-0.18	**	-0.03	**	-0.01	**	-0.14	**	0.00		0.04	**
wat5_wat7	-0.14	**	-0.02	**	0.00		-0.08	**	0.00		-0.02	**
wat5_wat8	-0.10	**	-0.01	**	0.00		-0.04	**	0.00		0.00	
wat5_wat9	-0.13	**	0.00	*	0.00		-0.01	**	0.00		0.00	
wat6_wat7	-0.13	**	-0.01	**	0.00		-0.08	**	0.00		-0.03	**
wat6_wat8	-0.10	**	-0.02	**	0.00		-0.03	**	0.00		0.00	**
wat6_wat9	-0.13	**	-0.01	**	0.00		0.00		0.00		0.00	
wat7_wat8	-0.11	**	-0.01	**	0.00		-0.03	**	0.00		0.00	**
wat7_wat9	-0.12	**	-0.02	**	0.00		0.00		0.00		0.00	
wat8_wat9	-0.13	**	-0.03	**	0.00		0.00		0.00		0.00	
_cons	5419.61	**	2767.64	**	1858.13	**	2159.67	**	2659.23	**	362.19	**
R2	0.91		0.93		0.90		0.92		0.87		0.92	

** significant at 1%

* significant at 5%