



HAL
open science

Sharing data to share water more efficiently? French farmers' preferences

Pauline Pedehour, Marianne Lefebvre

► **To cite this version:**

Pauline Pedehour, Marianne Lefebvre. Sharing data to share water more efficiently? French farmers' preferences. 2024. hal-04536555

HAL Id: hal-04536555

<https://hal.science/hal-04536555v1>

Preprint submitted on 8 Apr 2024

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

Sharing data to share water more efficiently? French farmers' preferences

Pauline Pedehour¹ & Marianne Lefebvre¹

JEL Codes: O32, Q16, Q25, C93

Keywords: Irrigation, Discrete Choice Experiment, Q-method, Smart meter, Water allocation rules

Abstract

Water sharing rules are a key component of water conservation. We evaluate an innovative scheme where water is shared between farmers according to physical irrigation efficiency. Measuring efficiency requires information exchange between farmers and the water manager, as well as a digital architecture to share these data. Relying on a Discrete Choice Experiment with 202 French farmers, we analyse their preferences for this architecture. We find that around half of them are likely to join such a scheme where information is collected and used by the manager to allocate water. But most farmers are reluctant to share automatically through a smart meter their water consumption data. However, they are less reluctant to the transmission of information on cropping patterns, if they remain in charge (as opposed to automatic transmission from satellite observations or link with administrative data).

Acknowledgments: We would like to thank Adrienne Moreau, Thalia Pivert and Yoann Mallard for their help with the survey, the REECAP network for providing initial feedback during the “check before you collect” webinar, as well as participants to the CREM (Rennes), INRAE (Clermont-Ferrand and Rennes), IESEG (Lille), Forum Innovation (Montpellier) and SWELL (Vrije Universiteit Amsterdam) seminars for their thoughtful comments. We also thank Sophie Hémont, Nicolas Pihee and Alexandre Chaigneau from the chamber of Agriculture for providing field comprehension and irrigators at the head of the Aubance and Authion associations. We acknowledge funding by Pays de la Loire Région for the BEHAVE project (Agreement number 221_11615).

¹Univ Angers, GRANEM, SFR CONFLUENCES, F-49000 Angers, France.

1 Introduction

Climate change, population growth, and economic development increase competition for water and exacerbate water scarcity and drought-related losses (IPCC 2023), resulting in the identification of water crises as the greatest global societal threat (WEF 2019). Farming currently accounts for 70% of freshwater use worldwide (FAO 2019) and often constitutes the least productive use (Damania et al. 2017). Securing food production while making more water available to alternative uses requires efficiency improvements in agricultural water management. This entails increasing allocative efficiency through water sharing rules between competing uses, and increasing physical irrigation efficiency through water conservation technologies (WCTs) (Pérez-Blanco, Hrast-Essenfelder, and Perry 2020).

Reviewing available evidence on the impact of WCTs on water conservation, Pérez-Blanco et al. (2020) show that WCTs can worsen rather than alleviate water scarcity. For water conservation to occur, there must be (i) either a reduction in acreage, a shift toward less water-intensive crops, or an intentional reduction of crop water consumption through regulated deficit irrigation (RDI), (ii) a combination of WCTs and water sharing rules. We focus on these last two levers and test the acceptability by farmers of water sharing rules accounting for physical irrigation efficiency and, in particular, the use of RDI as an allocation key.

Regulated deficit irrigation (RDI) has been identified as one of the key water-saving technologies in agriculture (Chai et al. 2016). RDI is generally defined as an irrigation practice whereby "a crop is irrigated with an amount of water below the full requirement for optimal plant growth; this is to reduce the amount of water used for irrigating crops, improve the response of plants to the certain degree of water deficit, and reduce irrigation amounts or increase the crop's water use efficiency" (Chai et al. 2016). By limiting water applications to drought-sensitive growth stages, this practice aims to maximise water productivity and to stabilise – rather than maximise – yields. RDI has been widely investigated as a valuable and sustainable production strategy in dry regions (Geerts and Raes 2009), but its use in less water-scarce area will develop since soil water content will also decline.

Measuring the efficiency in conducting RDI requires information exchange between farmers and water manager: in particular, each farmer water consumption and its cropping pattern to calculate the theoretical water needs for optimal plant growth. It also requires a digital architecture to share these data. We analyse farmers' preferences for

this architecture, and in particular whether farmers agree to share personal data, if they are used to allocate irrigation water in a more sustainable way. A few studies have focused on the acceptability of water saving technologies (Wang et al. 2017; Zekri et al. 2017; Chabé-Ferret et al. 2019; Ouvrard et al. 2023), but none combine water saving technologies and water allocation rules. It is also the first evaluation of a water allocation scheme where water is shared between farmers according to irrigation efficiency, and in particular the adoption of RDI.

We first model farmers' water use decisions in a two-periods framework: a normal period with no water restrictions and a dry period where water is generally banned. Farmers who improve their irrigation efficiency can benefit from derogatory access to water in a dry period. We analyse conditions under which farmers are more likely to join such a scheme. Since preferences towards personal data sharing cannot be captured in this model, we further rely on a Discrete Choice Experiment (DCE) to capture behavioural drivers of decisions. Our methodological contribution is twofold: (i) we couple Q method and DCE to select attributes and triangulate the results; (ii) There is no price mechanism to foster water use reduction. Rather, we analyse willingness to accept with a non-monetary payment vehicle: farmers engaged in RDI can benefit from guaranteed volumes, even when irrigation is restricted.

This paper is structured as follows. In Section 2, we develop a theoretical framework to understand the conditions favourable to scheme adoption. Section 3 details the experimental design. Results are presented in section 4. Finally, the paper ends with a discussion including recommendations for the implementation of the water saving scheme in section 5 and a conclusion.

2 Theoretical modelling of farmers' decisions

The model is developed for f farmers and a water manager, under the assumption of perfect information and risk neutrality. Under this simplified representation, we analyse under which conditions are farmers more likely to join the scheme.

We consider a territory composed by f farmers located around a common water resource managed collectively under the responsibility of a manager. The set of farmers denoted by $F = \{1, \dots, f\}$ shares the total volume of water available for irrigation during the growing season, denoted by Q . The water quota allocated to farmer i by the manager is denoted by Q_i . It is the maximum volume the farmer can use over the K weeks of the irrigation season, with q_{ik} the weekly volume consumed by farmer i during week k such

that:

$$\sum_{k=1,\dots,K} q_{ik} = Q_i.$$

Moreover, the sum of individual water quotas of all farmers $i \in F$ cannot exceed the amount of water available for agricultural use Q during the growing season.

Thus,

$$\sum_{i=1,\dots,f} Q_i \leq Q. \quad (1)$$

In case of drought, water extraction by agriculture can be restricted or purely banned, upon administrative decision taken on a weekly basis, in order to safeguard priority uses (environmental flows and domestic use). In case of such restrictions, the water allocation to farmer i in week k is lower than their needs.

To study this constrained use of water, we focus on decisions taken by farmers and the manager each week. We consider two states of the world: one normal one (N) and one dry one with potential restrictions (D), with p the probability of a dry week.

2.1 Water use without restrictions (normal week)

Farmers claim a water volume at the beginning of the season in order to maximise their utility provided by water use. We assume utility only depends on water use (for simplicity, no other inputs are modelled). Utility of any farmer $i \in F$ is composed by two terms. First, concave benefits from water extraction, as the first water units extracted are important for crops and additional ones are less necessary (as suggested by the RDI concept). Second, a constant marginal cost per unit of water used. This assumption applies in the most frequent case of pure volumetric water tariff, and no investment cost.

The utility function $U_i : \mathbf{R}_+^n \rightarrow \mathbf{R}$ of farmer i is given by:

$$U_i = \alpha_i q_i - \frac{\beta_i}{2} q_i^2 - C q_i \quad (2)$$

where the marginal value of water is defined by the amplitude of benefit α_i and its depreciating slope β_i (function on farm characteristics such as crops and soils), and C is the constant marginal cost. Each farmer maximises his utility, adjusting his level of water extraction. The first-order condition of utility maximisation for agent i with respect to q_i is given by

$$\frac{\partial U_i}{\partial q_i} = \alpha_i - \beta_i q_i - C$$

Then the equilibrium weekly water extraction is given by

$$q_{ik}^* = \frac{\alpha_i - C}{\beta_i}. \quad (3)$$

In a normal week without water restriction, a farmer is entitled the right to use up to their water need. Their weekly water allocation is therefore $q_i^N = q_i^*$, $\forall i \in F$.

Applying deficit irrigation, a farmer can use less water while securing their yields. We assume that an efficient farmer will extract the volume $q_i^N = \epsilon_i q_i^*$ in a normal period, with $0 \leq \epsilon_i < 1$.

2.2 Water use in a dry week

In dry weeks, farmers face restriction and cannot use all their water allocation, such that $q_i^D = \delta_{ik} q_i^*$, with $\delta_{ik} < 1$. For simplicity, we assume water use is totally banned for non-efficient farmers (those who have used $q_i^N = q_i^*$ in the normal period), such that $\delta_{ik} = 0$. For efficient farmers, $0 \leq \delta_{ik} \leq 1$ is set by the manager according to the state of the water resource and their individual irrigation efficiency. A farmer with $\epsilon_i < 1$ in a normal week may not benefit from $\delta_{ik} > 0$ in the following dry week, if the resource is too scarce. Before knowing the state of the world (normal or dry week), farmers are uncertain about δ_{ik} , but can form beliefs on their efficiency, on others' efficiency, on the state of the water resource, and ultimately on the manager decision with regard to δ_{ik} .

2.3 Under which conditions are farmers more likely to join the scheme ?

We analyse whether farmers are likely to join the water saving scheme under which they commit to reduce their water use in a normal week by ϵ in exchange for the right to irrigate in a dry week up to δ of their weekly water needs. We first define the participation and the incentive constraints, before highlighting the conditions under which a farmer is better off participating to the scheme and improving their irrigation efficiency.

2.3.1 Participation constraint

The expected utility of farmer i is given by:

$$EU_i = (1 - p)U_i(q_i^N) + pU_i(q_i^D)$$

Under non adoption, the expected utility EU_i^{NA} comes from water consumption in

the normal period only since water use is banned in dry period.

$$EU_i^{NA} = (1-p) \left[\alpha_i q_i^N - \frac{\beta_i}{2} (q_i^N)^2 - C q_i^N \right]$$

Under adoption, the expected utility EU_i^A increases with the benefits from water use in the dry period but is reduced by the fixed cost T . T includes transaction costs such as the time spent to share the data with the manager or the installation of the meter. We assume water use in the normal period q_i^N is not impacted by participation (this assumption will be modified in the incentive constraint).

$$EU_i^A = (1-p) \left[\alpha_i q_i^N - \frac{\beta_i}{2} (q_i^N)^2 - C q_i^N \right] + p \left[\alpha_i q_i^D - \frac{\beta_i}{2} (q_i^D)^2 - C q_i^D \right] - T$$

Farmers are better-off with participation to the scheme if $EU_i^A \geq EU_i^{NA}$, i.e.

$$(1-p) \left[\alpha_i q_i^N - \frac{\beta_i}{2} (q_i^N)^2 - C q_i^N \right] + p \left[\alpha_i q_i^D - \frac{\beta_i}{2} (q_i^D)^2 - C q_i^D \right] - T \geq (1-p) \left[\alpha_i q_i^N - \frac{\beta_i}{2} (q_i^N)^2 - C q_i^N \right]$$

or equivalently,

$$p \left[\alpha_i q_i^D - \frac{\beta_i}{2} (q_i^D)^2 - C q_i^D \right] \geq T.$$

The participation constraint is binding if the fixed cost is lower than the expected benefits from water use in the dry period.

2.3.2 Incentive constraint

The manager would like farmers not only to participate, but also to make the effort to reduce their water use thanks to deficit irrigation in normal periods. Doing so, they can benefit from derogatory water allocation during dry weeks.

The expected utility of a farmer improving their irrigation efficiency in the scheme framework is given by :

$$EU_i^E = (1-p) \left[\alpha_i \epsilon_i q_i - \frac{\beta_i}{2} (\epsilon_i q_i)^2 - C \epsilon_i q_i \right] + p \left[\alpha_i \delta_i q_i - \frac{\beta_i}{2} (\delta_i q_i)^2 - C \delta_i q_i \right] - T$$

and the expected utility of a farmer participating to the scheme, but not improving irrigation efficiency is given by :

$$EU_i^{NE} = (1-p) \left[\alpha_i q_i - \frac{\beta_i}{2} q_i^2 - C q_i \right] - T$$

The scheme is incentive-compatible if $EU_i^E \geq EU_i^{NE}$, i.e:

$$(IC) : (1-p) \left[\alpha_i q_i - \frac{\beta_i}{2} q_i^2 - C q_i \right] - T \leq (1-p) \left[\alpha_i \epsilon_i q_i - \frac{\beta_i}{2} (\epsilon_i q_i)^2 - C \epsilon_i q_i \right] \\ + p \left[\alpha_i \delta_i q_i - \frac{\beta_i}{2} (\delta_i q_i)^2 - C \delta_i q_i \right] - T$$

or equivalently,

$$(IC) : (1-p) \left[(1-\epsilon_i)(\alpha_i q_i - C q_i) - (1-\epsilon_i^2) \frac{\beta_i}{2} q_i^2 \right] \leq p \left[\alpha_i \delta_i q_i - \frac{\beta_i}{2} (\delta_i q_i)^2 - C \delta_i q_i \right]$$

Farmers have an incentive to be efficient and preserve water in normal period if the gain in dry period exceeds the losses due to irrigation efficiency in normal periods.

2.3.3 Conditions for improvements in irrigation efficiency in the scheme framework

We combine the participation and incentive constraints to determine under which conditions a farmer is better-off implementing RDI in the scheme framework. To do so, we study cases in which $EU_i^{NA} \leq EU_i^E$.

This corresponds to:

$$(1-p) \left[\alpha_i q_i - \frac{\beta_i}{2} q_i^2 - C q_i \right] \leq (1-p) \left[\alpha_i \epsilon_i q_i - \frac{\beta_i}{2} (\epsilon_i q_i)^2 - C \epsilon_i q_i \right] + p \left[\alpha_i \delta_i q_i - \frac{\beta_i}{2} (\delta_i q_i)^2 - C \delta_i q_i \right] - T$$

equivalently, isolating the cost of the scheme :

$$T \leq \underbrace{(1-p) \left[(\epsilon_i - 1)(\alpha_i q_i - C q_i) - (\epsilon_i^2 - 1) \frac{\beta_i}{2} q_i^2 \right]}_{\text{Loss in normal period } (\leq 0)} + \underbrace{p \left[\alpha_i \delta_i q_i - \frac{\beta_i}{2} (\delta_i q_i)^2 - C \delta_i q_i \right]}_{\text{Additional gain in dry period for efficient farmers } (\geq 0)}$$

A farmer is better-off improving their irrigation efficiency in the scheme framework if the fixed cost of the scheme is sufficiently low compared with the difference between the extra gain in the dry period and the loss in the normal period due to RDI implementation.

The manager decision with regard to derogatory water allocation in the dry period δ has a key role in insuring water conservation effort. A farmer with pessimistic expectations with regard to the state of the water resource or their ability to improve their irrigation efficiency may believe they will not be granted any derogatory water allocations in dry periods ($\delta_i=0$). In this case, we show that $EU_i^E \leq EU_i^{NA}$, i.e. they have no interest in participating to the scheme. On the contrary, $EU_i^E \geq EU_i^{NA}$ for more

optimistic farmers with regard to their performance and the state of the resource. They have positive beliefs on derogatory water access in dry period ($\delta > 0$) and can have an interest to adopt the scheme and be efficient according to the value of other parameters such as p and ϵ_i .

This theoretical model presents conditions under which the water-saving scheme can increase farmers' profits. To further understand under which conditions such as water saving scheme can be accepted, we rely on a discrete choice experiment. This stated preference method can better capture obstacles such as the psychological costs of data sharing, pessimism with regard to the state of the water resource or trust in the manager capacity and willingness to grant derogatory access to water in restriction times.

3 Experimental design and Method for data analysis

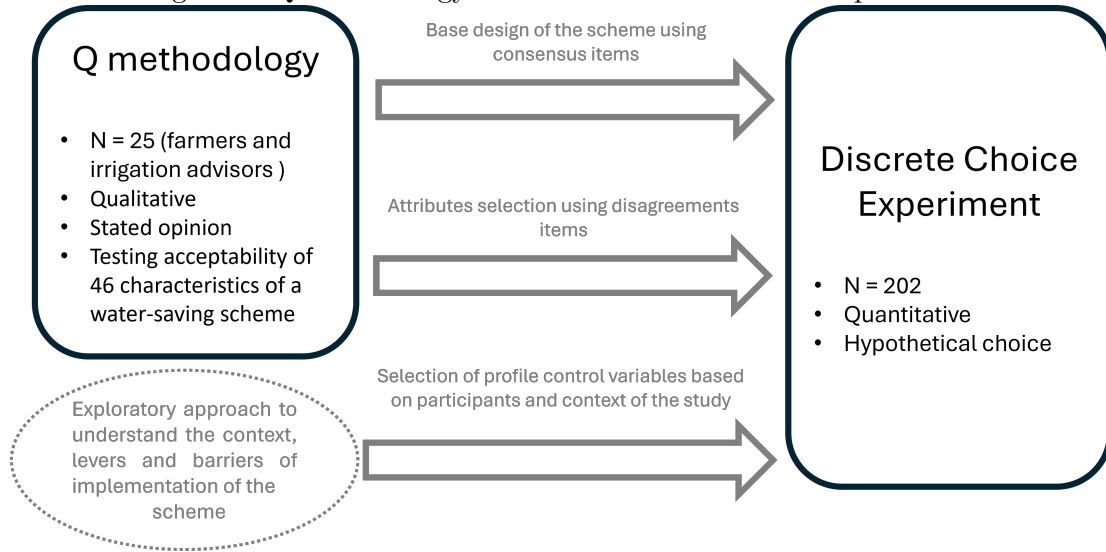
3.1 Q-method and selection of the attributes

We rely on a discrete choice experiment (DCE) to evaluate farmers' preferences for such a scheme combining technologies likely to improve physical irrigation efficiency and rules targeting better allocative efficiency. DCEs are particularly valuable for investigating individuals' preferences in hypothetical decision-making situations (Louviere et al. 2000). Here, adoption data are not available since the scheme is not yet implemented. The method has been previously used in similar contexts, for example to evaluate *ex-ante* programs targeting water conservation (Giannoccaro et al. 2022).

The validity of DCE relies on researcher's ability to identify, select, define and articulate the attributes together in a way that is understandable to the respondents (Armatas et al. 2014). Well-defined attributes can increase the perceived credibility of the valuation scenario and consequentiality of the topic (Welling et al. 2022) and limit the risk of attribute non attendance (Koetse 2017).

Most discrete choice experiment studies rely on focus groups, expert consultations, interviews, literature reviews to choose the right set-up and attributes. This often lacks transparency on the foundations and the process is often poorly documented (Jensen 2019). The Q methodology, developed by Stephenson (1953), can overcome these limitations. In a Q-method study, participants (P-sample) have to sort a list of statements (Q-set) into a pre-defined grid, indicating their affinity for each statement in relation to a given topic (Watts and Stenner 2012). The analysis of the ranking position of statements provides an overview of the main profiles of perception within a population for a

Figure 1: Q methodology to calibrate discrete choice experiment



given topic and main consensus and disagreement statements between these profiles. Q methodology can provide transparency to the design choices made in a DCE framework (Armatas, Venn, and Watson 2014, Jensen 2019). It can also be an interesting complementary tool to choice experiment for triangulation of results (Hampson, Ferrini, and Turner 2022).

As suggested by a limited number of previous studies (Venus and Sauer 2022, Armatas, Venn, and Watson 2014, Jensen 2019), we used results from a Q-method study with 25 farmers and advisors of the case study area to define the basis scheme and select the different attributes to be tested in this DCE study (Figure 1). First, the Q-method study provided us with first inputs on farmers’ perceptions on combining technologies and incentives for water conservation. This exploratory approach is useful to highlight the barriers and levers of intervention for a water manager to foster water conservation.

Second, we use consensus statement as a baseline to define the scheme analysed through the DCE. Main consensus highlighted by the Q methodology concern the material aspect of the scheme: sensors in soils and the mobile app are well accepted. Respondents also agree on the need of transparency on how the system works and score calculation, and information on the state of the water resources. We also observed huge consensus in favor of an in-kind compensation - a derogatory water allocation- rather than a financial payment or a label, which are way more controversial. In the Q-method, all factors (except one for which it is more neutral) sorted the derogatory water allocation in the positive extreme part of the grid indicating that it favors acceptability, while other types of reward were less preferred. This has been confirmed by post-sort interviews.

Following these consensus elements provided by the qualitative study, the baseline of the water-saving scheme for the discrete choice experiment is set-up as follows:

- The calculation of an irrigation efficiency score, which depends on efforts in conducting the most adjusted irrigation to the needs of the crops (RDI), weighted by a merit indicator. The more critical the state of the resource and the less it rains, the more meritorious farmers are if they limit the irrigation.
- The calculation of such a score requires weekly transmission of water consumption data to the manager, either by manual entry into the application or by a smart meter. The manager also needs to have perfect knowledge of the crop rotation.
- A mobile application that aggregates in one place various information: the state of the water resource, farmers' water consumption and the irrigation efficiency score.
- Incentives in the form of derogatory access to water when irrigation is prohibited, conditional to the score, and within the limit of farmers' individual authorised volume.

Third, as in Venus and Sauer (2022), main disagreements are tested in the choice experiment as attributes. Q-study results highlighted that there is no consensus on how the score should be calculated. Then, while weekly metering of water consumption is necessary, farmers do not all agree with the extra workload induced. We selected two attributes that relate to the information the farmers need to provide to the manager in order for the scheme to operate and a monetary attribute.

The first attribute refers to calculation of the score and data required for it. Q study shows that irrigators generally disagree on the communication of farm's data to the manager. More generally, there is no consensus on how the score should be calculated, and whether it should account for weather and climatic conditions. There is a trade-off between collecting precise information to obtain a more robust score, and reducing the need of data exchange between the irrigators and the manager. Thus, we include an attribute on the precision of data requested for the scheme to operate. In the actual system, irrigators declare their irrigated crops **at farm level** and can update this information during the season. Another option is envisaged and consists of a declaration of crops irrigated and soil types **at plot level**. This version would allow the useful water reserve to be calculated, therefore better taking into account for weather and climatic conditions. A last option is **automatic satellite** transmission of crops irrigated and soil types to the manager.

The second attribute concerns how water consumption data are shared with the manager. The Q study has shown that irrigators do not want to compromise to share each week their water consumption with the manager, because it takes too much of their time during the growing season. However, previous evidence has shown that smart meter are not always well accepted. Nevertheless, for the scheme to operate, the manager needs to know (at least) the weekly water consumption of each irrigator. The first level is manual reading: the irrigator can read his meter and enter manually his data consumption in the application each week. The data is then accessible to the manager. Alternatively, a smart meter can be installed on the farm to forward automatically consumption data to the manager in real time.

Lastly, the monetary attribute is presented as a derogatory water allocation in % of weekly needs. Given that all respondents in the Q method were in favor of water derogatory rights, we ensure that this monetary attribute has a non-negative effect on water-saving scheme adoption. When irrigation is prohibited by decree, only irrigators with a high score can benefit from those derogatory volumes of water, corresponding to a percentage of their weekly needs (providing they haven't already consumed all their individual water allocation). The levels have been chosen to encourage irrigators to adopt the scheme but also not to exceed the 50% threshold actually authorised in periods of drought.

These attributes have been validated by experts (advisers from the chamber of agriculture, irrigators representatives, private company selling water-saving scheme) through interviews. Table 1 shows these three attributes and their 2 to 5 levels. The levels were all set at realistic range, as discussed with field partners.

Based on pilot data collection (n=25), we have created a Bayesian D-efficient design, with 2 blocks of 8 choices. Figure 4 shows an example of choice card, with two unlabelled water saving schemes (A and B) and a status-quo option.

3.2 Data collection

The survey was disseminated by the agricultural chamber, through emails and text messages, to 641 irrigators in two water catchments located in Maine-et-Loire, France (77 from Aubance-Sud Loire and 564 from Authion). The survey was also administered face-to-face to 17 farmers, at the end of meetings organized by the agricultural chamber on irrigation-related topics. We filtered persons who are responsible for irrigating decisions on their farm. We obtained 202 complete answers, representing a response rate of 32%.

Table 1: Attributes and levels

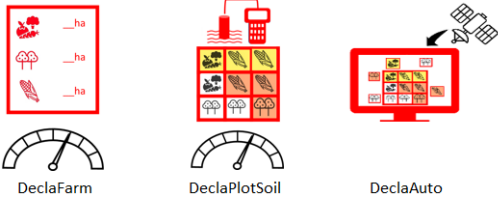

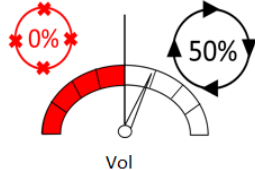






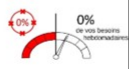
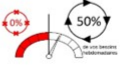
Attributes	Levels	Pictos
Crop declaration : Data needed to calculate the score	- Declaration at farm level of irrigated crops (type, surface) - Declaration at plot level of irrigated crops (type, surface) and soil types (allowing the useful water reserve to be calculated) - Satellite transmission at plot level of irrigated crops (type, surface) and soil types (allowing the useful water reserve to be calculated)	 <p>DeclaFarm DeclaPlotSoil DeclaAuto</p>
Water consumption : Data transmission to the manager	- The irrigator reads his meter every week and enters the data in the application, which is then automatically forwarded to the manager - A smart meter is installed on the farm. This allows for automatic transmission of consumption data to the manager on a continuous basis.	 <p>ManualWeekly Smart</p>
Incentive : Dero- gation to the irriga- tion ban	The percentage corresponds to the derogatory water volume authorised for an efficient irrigator with 5 levels : 0%, 20%, 30%, 40% and 50%.	 <p>Vol</p>

Figure 2: Example of choice card

	Scheme A	Scheme B	Current management
			No efficiency score
Sharing crop data to calculate efficiency score			As currently on your farm
Water consumption data sharing			As currently on your farm
Guaranteed volumes despite restrictions			Restriction apply as currently on your farm

Beyond choices in the DCE, we collected information to characterise the respondent (experience in farming, age, education) and its farm (location, UAA, irrigated UAA, types of soil, number of extraction water points of the farm, water consumption during the last three years, whether the farm has faced water restrictions, irrigation material, whether the farm is involved in production contracts, whether the production is certified (organic, in conversion towards organic production, high environmental value . . .)). We further collected information on reasons why farmers always opted-out and main reason to subscribe to the water-saving scheme for the interested respondents. The full text of the survey is available in Appendix A2.

The French Maine et Loire department was selected as the case study area for several reasons. First, water needs are important due to crop and soil types and weather conditions. While 10% of utilised agricultural area is irrigated (6.9% in France) in 2019, irrigated productions represent 25% of the total economic value from agriculture in the area. Second, there are conflicts of use between water users, with agriculture being the main extractor. Agricultural water withdrawals for irrigation represent 53 millions of cubic meters, i.e. 45% of the total volume of water withdrawn for all uses. In 2022, almost all irrigators in the department of Maine-et-Loire have faced water restrictions during the entire irrigation period.

The water saving scheme under study has been experimented in 2021 and 2022 at small scale on 9 farmers of the Authion watershed (located in the case study area). Smart meters, weather stations and tensiometric sensors were installed on the plots of those farms. The 9 irrigators were trained on the use of an app that provided irrigation recommendations based on plot observations and weather data, and the calculation of their score. Farmers could also see on the app what would be their potential gains if the reward system was implemented (it was hypothetical in the experimentation phase). This experimentation was monitored by the agricultural chamber and a private company developing the app.

For a successful scaling-up of this very small scale experimentation, we analyse the conditions of acceptability of the scheme in two water catchments described in Table 2. This territory is characterised by high heterogeneity in crop types, plots sizes and water availability.

Aubance (joint with southern Loire) area is characterised by a small number of irrigators and rather homogeneous crops. Except during years of strong drought as 2022, water is not yet scarce. Until now, water management stays individual, and irrigators

Table 2: Characteristics of the two water catchments in the case study area

	Aubance	Authion
Number of irrigators	70	600
Number of ha irrigated each year	around 3000	between 16000 and 18000
Volumes of extracted water	around 15 million m^3	between 10 and 30 million m^3
Crops types	Mainly corn, grassland and seeds	Very diversified (corn and other cereals, arboriculture, horticulture, vegetables)
Type of water resources used for irrigation	Mainly retention water	Very diversified (surface and ground water, retention)

can extract water as long as there is no ban.

Authion area represents a much bigger irrigation community, with high diversity of crops, soils, and farm sizes. Water management on this territory is organised collectively and the agricultural chamber acts as manager of the *Single collective management organisation* (OUGC in France). The manager is responsible for sharing a total volume available for irrigation into individual water allocations. Each year, irrigators make a declaration of their expected production and their associated needs in water (requested volume). Given this information, the manager determines individual water allocations, which can be equal or lower than the requested volumes, based on criteria such as match between claims, irrigated surfaces and crops. From now, irrigation efficiency is not taken into account.

3.3 Data Analysis

The econometric estimation of DCE data is in line with the behavioral framework of the random expected profit approach developed by McFadden (1974). Irrigants are assumed to choose their preferred scheme such that their expected utility is greater than either the other option or opting out. For each farmer i the expected utility obtained from alternative s in choice set t can be written as:

$$U_{fst} = V_{ist} + \epsilon_{ist} = X'_{ist}\beta_i + \epsilon_{ist}$$

The expected utility is a function of observable attributes V_{ist} plus an unobserved random component ϵ_{ist} (the stochastic error term). X_{ist} refers to the vector of levels of the attributes, i.e. the scheme characteristics.

We include in X_{ist} an individualized Alternative Specific Constant (ASC) to take into account the respondent's current situation. This ASC captures preferences for scheme's

characteristics not included in our attributes. Accounting for each farmer’s individual SQ situation improves the explanatory power of models, in particular in study settings where: (i) one cannot afford to have a large sample, (ii) there is large heterogeneity in perception of respondents and (iii) the policy is viewed as so contentious that a significant portion of respondents is expected to prefer their current situation to a proposed policy (Barton and Bergland 2010).

The monetary attribute is specified as a continuous variable. For the other attributes, we include one dummy variable for each level of the attribute described in Table 1 except one. This excluded level per attribute represents the reference level for each attribute.

To estimate preferences, we rely on the Random Parameter Logit (RPL) model which allows parameters to vary randomly (with a normal distribution) across respondents (Boxall and Adamowicz 2002). We apply several tests to check the robustness of the results to different specifications of the RPL (Appendix A1). To further understand heterogeneity, we also estimate a latent class model. Latent class models work similarly to mixed logit models, except that the distribution of β coefficients is assumed to follow a discrete rather than normal mixing distribution (Pacifico and Yoo 2013).

From RPL estimates, we obtain individual parameters for each attribute, and can calculate the utility of each respondent for different schemes. We assume that an irrigant would join the scheme if their utility from a given scheme S defined by its X characteristics x_S is higher than their utility from the status-quo (as captured by the coefficient associated to the alternative specific constant ASC). For each respondent, we know whether they would subscribe or not to the scheme for different volumes of derogatory water allocation ranging from 0% to 50%. From this, we can calculate adoption rate at sample level.

The following hypotheses are tested. They have been elaborated based on the literature on water saving scheme acceptability levers and obstacles. They are also in line with results from the Q-study.¹

- H0: Farmers have a preference for the status-quo (with no monitoring of irrigation efficiency and associated incentives)
- H1a: Farmers who have experienced irrigation restrictions in the past are more

¹Numbering differs compare to the pre-registration available here: https://osf.io/jwtnb/?view_only=051b9aee41cb4291a58460e143a257f3. Variables in italic have been added compared to the version of pre-registered hypotheses available on-line. The pre-registration also mentioned the possibility to aggregate variables through a principal component analysis. Given the low measure of sampling adequacy of the PCA over the variables considered to test H1a-d (54.91%), we did not use the PCA dimensions in further analyses

likely to be interested in the scheme.

- H1b: More pessimistic farmers with regard to the frequency of restrictions in the future and those who are more optimistic with regard to their ability to reach frequently a high efficiency score are more likely to be interested in the scheme.
- H1c: Farmers who are highly dependent on irrigation are more likely to be interested in the scheme. Dependence to irrigation is approximated by the following variables: the share of irrigated land in the total surface, being engaged in production contracts, being engaged into certifications including water management requirements, *cultivating specialized production*.
- H1d: Farmers who already use a decision-support tool to manage their irrigation are more likely to be interested.
- H1e: *Farmers already operating under water collective management are more likely to be interested.*
- H2: If the scheme requires providing manually detailed information on crops and soil at the plot level, farmers are less likely to accept it.
- H3: If the scheme imposes smart meters, farmers are less likely to accept it.
- H4: Those preferring smart meters also prefer the automatic transmission of crops and soil information to the manager.
- H5: The larger the incentive (in terms of % of individual weekly water allocation that can be used despite the irrigation ban), the more likely farmers are to join the scheme.

4 Results

We test our pre-registered hypotheses and run complementary exploratory analyses. We first investigate the profile of farmers more likely to join the scheme. We then analyze scheme features more likely to trigger adoption.

4.1 Descriptive statistics

The final sample included in the analysis consisted of 202 responses, whose characteristics are described in Table 3. In light of the online mode of participation, and the distribution

channels, the present sample must be regarded a convenience sample and findings of subsequent analyses may not necessarily hold for the general French farmer population relying on irrigation.

We collected information on who is already equipped with a smart meter (5.94% of the sample) and who is already sharing information on cropping patterns to a water manager (All those under collective management, i.e. 81.6% of the respondents). This information is used to account for the individualised status quo in further analysis.

The average farm size in the sample is 112ha, with 47ha of irrigated area on average but heterogeneity is very high, as the sample includes farm from 0.4 to 600ha of irrigated surface. The average sample size is large compare to the population of French farmers (69ha on average) since we reminded in particular farms with the highest water claims (and water claims are correlated with the total surface). Our sample is highly concerned by irrigation. On average, respondents irrigate 49% of their farm land, while in France only 11% of the utilized agricultural area can be irrigated.

The farmers surveyed used on average 1423 m³ per hectare over the 3-years period 2020-2022 (median 1153 m³), slightly less than the French average (1902 m³ in 2020, according to data from "Banque National des Prélèvements Quantitatifs en Eau"). In France, the most irrigated crop is corn (38% of irrigated land), followed by wheat (12%). Other crops represent less than 10% irrigated land in 2020. In our sample, 40.1% of farmers grow specialised crops (including fruits, grapes for wine, seeds, vegetables and other horticultural plants), who are the more dependant on irrigation. Other farms surveyed are equally divided between field crops, mixed crops and mixed crops and livestock. 20.3% of the farms surveyed are certified organic farming or in transition and 19.3% have High Environmental Value certification, slightly more than in the population (respectively 14% and 8.4% of the French farms).

The median survey completion time was 33 minutes. We checked reading time of attributes and interview time to be sure to avoid questionnaire-surfing in our responses. 75% of the respondents answered correctly to the three quiz questions, suggesting a relatively good understanding of the scheme despite its complexity and the on-line format. 20% of the respondents dedicated less than 4 minutes to the video presenting the attributes, and they have a significantly lower score on average to the three understanding questions (2.36 vs 2.72 correct answers). We therefore include robustness checks to account for potential impact on preferences.

Table 3: Sample characteristics (n=202)

Variable	Mean or %	SD	Median	Min	Max
Farm type Specialised Crops	40.1 %				
Specialized-Orchard	3.5 %				
Specialized-Vineyard	0.5%				
Specialized-Horticulture Vegetables	11.9 %				
Specialized-Horticulture Other	6.9 %				
Specialized-Seeds	17.3 %				
Farm type Cereals, Oilseeds and Protein crops	19.8 %				
Farm type Livestock	0.5 %				
Farm type Mixed Crops & Livestock	21.3 %				
Farm type Mixed Crops	18.3 %				
UAA	112.11	92.75	101	1	600
Irrigated Surface	47.38	52.94	35	0.4	500
Ratio Irrigated/Total UAA	0.49	0.3	0.44	0.04	1
Average volume per hectare (2020-2022) (m3)	1423.42	1290.09	1152.63	37.11	10192.73
Under collective management (Authion Watershed)	81.6 %				
Certification including water management requirements (High Environmental Value, Global-gap)	20.83 %				
Organic certification (or transition)	20.3 %				
Score certif	0.391	0.655	0	0	3
Score DSS	0.5	0.633	0	0	3
Score contract	2.421	1.512	2	1	8

Note: Specialised crops includes Horticulture, Seeds, Vineyards and Orchards.

Score certif is the number of certifications including water management requirements (e.g. High Environmental Value, Global gap...)

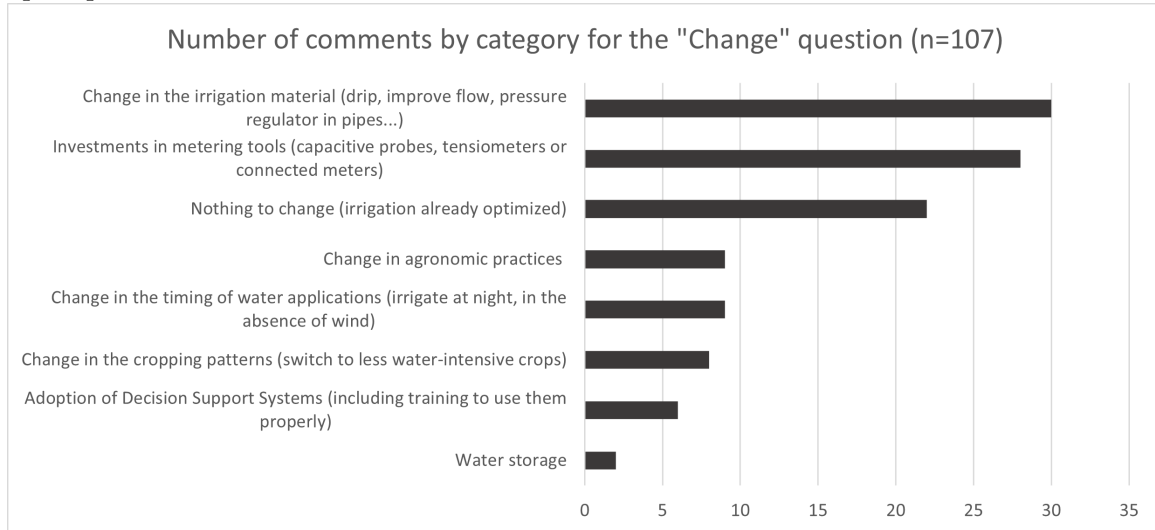
Score contracts is the number of buyers with which they have signed production contracts

Score DSS is the number of sensors or Decision Support Tools used for irrigation

* Statistics for n=199 (3 missing observations)

Prior to the choice experiments, we asked respondents to indicate what they could change to increase their irrigation efficiency. Interestingly because they are at the heart of the scheme, irrigation material and metering tools were most cited. However, change in cropping patterns (such as switch to less water-intensive crops) were also cited, while they cannot contribute to increase irrigation efficiency in this specific scheme. Indeed, the performance of deficit irrigation is assessed crop by crop, i.e. for a given cropping pattern.

Figure 3: What to change to increase irrigation efficiency ? Citation frequency in an open question



4.2 Adopters' profiles

We first analyse data with a random parameter logit model, with all parameters assumed to be normally distributed. On average, farmers have a preference for the status-quo (with no monitoring of physical irrigation efficiency and associated incentives): In Figure 4, the coefficient associated to the alternative-specific constant is positive. We can therefore not reject H_0 .

We observe preferences heterogeneity with significant standard deviation for all parameters. Moreover, Figure 4 highlights that the distribution of individual coefficients for the ASC is bimodal. This suggests that a share of our sample is interested by the scheme (negative coefficient for the alternative-specific constant ASC). To a lower extent, we observe that preferences towards the transmission of water consumption data are also splitted between positive and negative coefficients.

Further analysis of heterogeneity is performed through a latent class model. We select the number of classes based on the BIC and CAIC, as well as the interpretability of the parameter estimates. According to the values of the BIC and CAIC, the 4-class solution is preferred (Appendix A1). But two classes in the 4-class solution are small (12.3% and 15.9% of the sample). The 3-class solution offers a clear segmentation easier to interpret (Table 5). With a negative sign associated with ASC, farmers belonging to class 2 are on average interested by the scheme, but they reject the smart meter. On the contrary, respondents in class 1 show interest for the smart meter. On average, they prefer the status-quo but their preferences are more impacted by the size of the incentives (Vol). Respondents in class 3 (43.1%) are not significantly more interested by the scheme than

the status-quo, and they reject in particular the smart meter.

In order to test our hypotheses on the influence of farms' characteristics on scheme acceptability, we study their impact as potential determinants of class membership. We find no influence of the experience of restrictions in the past -rejecting H1a-, nor of higher dependence on irrigation (as proxied by the share of irrigated land in the total surface, being engaged in production contracts, being engaged into certifications including water management requirements -H1c is rejected-) or experience with irrigation decision support system -H1d is rejected-. On the contrary, beliefs with regard to the future shape preferences towards the scheme -we cannot reject H1b-. In particular pessimism with regard to the frequency of water restrictions in the future and confidence in the possibility to implement deficit irrigation and reach irrigation efficiency both increase the probability of belonging to classes 1 and 2. As a robustness check, we re-run the RPL model including these two variables and find that they both significantly reduce preferences for the status-quo (Figure 5), while other coefficients remain stable. This is consistent with the results of the theoretical model: farmer with optimistic beliefs concerning the probability to be granted derogatory water allocations in dry periods (δ_i) have more interest in participating to the scheme.

4.3 Preferences for contract features

If the scheme imposes smart meters, farmers are less likely to accept it (H3), but they are even more rejecting the manual transmission of their water consumption on a weekly basis. Concerning the information to be transmitted to the manager to measure the score, there is high heterogeneity in preferences, with no clear picture on average. Automatic transmission of cropping patterns data collected by the administration for distribution of agricultural subsidies or based on satellite observations is rather rejected, while providing information in order to get a more precise estimate of the score is rather positively perceived. We find no significant interaction between the automatic transmission of crops and automatic transmission of water consumption (smart meter), and can therefore reject H4.

The individual coefficients estimated from the RPL model provides complementary information on the share of the respondents with positive (and negative) preferences towards an attribute's level (Table 6). While a majority of the respondents prefer their status-quo than the smart meter, one third of them increases their utility if the scheme includes a smart meter.

We also calculate the adoption rate for different version of the schemes in terms of data requirement and size of the incentives. Scheme 1 with 0% incentives is similar to the status-quo under collective management (where cropping patterns data are shared with the manager), but farmers have access to more information through the app and sensors. We find that in this context 46.5% of the farmers accept to join the scheme. With access to 50% guaranteed volumes in restriction periods, the proportion of interested farmers can increase up to 58.4%. But this number drops to 40.6% when the scheme includes features less preferred by respondents such as scheme 3, where farmers have to provide detailed data (crops and soils at plot level and water consumption on a weekly basis). Less detailed declaration of cropping patterns and smart meters (Scheme 2) could constitute an in-between set-up which favors adoption. A scheme with fully automated data exchange (scheme 4) is less preferred.

Table 4: Random Parameter Logit

	Mean	SD
DeclaFarm	0.416 (0.39)	1.952*** (5.72)
DeclaPlotSoil	0.579 (0.53)	-0.236 (-0.36)
DeclaAuto	-0.625 (-0.59)	1.647*** (5.56)
ManualWeekly	-3.498*** (-3.33)	-1.748* (-1.94)
Smart	-1.042** (-2.03)	3.764*** (7.98)
Vol	0.0568*** (7.26)	0.0526*** (6.59)
ASC	1.256** (2.37)	6.212*** (8.46)
N	4848	

Figure 4: Distribution of individual parameters Kernel

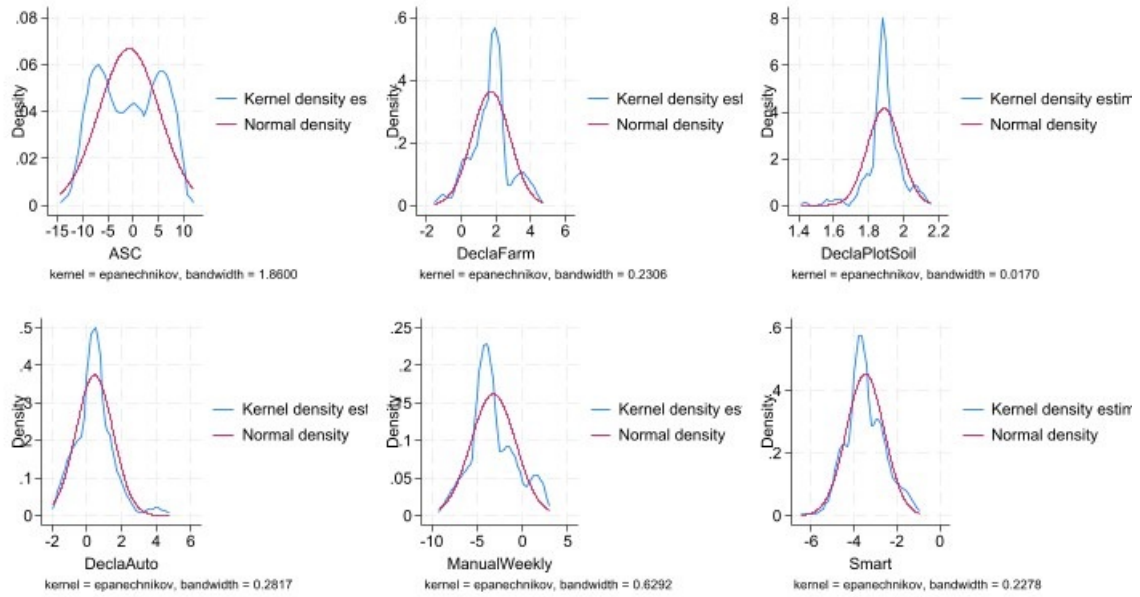


Table 5: Latent class: Probability to join the scheme

	Class 1 In favor of the smart meter only -28.20%	Class 2 In favor of the scheme but not the smart meter -28.60%	Class 3 Against the scheme -43.10%
ASC	1.239** -2.72	-2.102*** (-6.65)	2.895*** -7.82
DeclaFarm	-0.493+ (-1.71)	0.57 -1.39	0.929*** -3.48
DeclaPlotSoil	0.247 -0.8	0.187 -0.45	0.740* -2.28
DeclaAuto	-0.710* (-2.07)	0.18 -0.43	-0.287 (-0.76)
ManualWeekly	0.0349 -0.02	-1.725*** (-4.99)	-41.81 (-0.57)
Smart	1.604*** -5.94	-1.270*** (-7.29)	-1.479*** (-4.16)
Vol	0.0483*** -7.25	0.0292*** -3.58	0.0241** -2.77
	<i>Prob. to belong to class 1 rather than 3</i>	<i>Prob. to belong to class 2 rather than 3</i>	
Pessimism	0.21150 *** -2.78	0.27186*** -3.56	
Expected performance	0.13814** -2.08	0.12026* -1.82	
_cons	-2.851784 *** (-4.07)	-2.4597 (-4.37)	
N	4848		

t statistics in parentheses
* p<0.05, ** p<0.01, *** p<0.001

Figure 5: Random Parameter Logit, with interaction variables

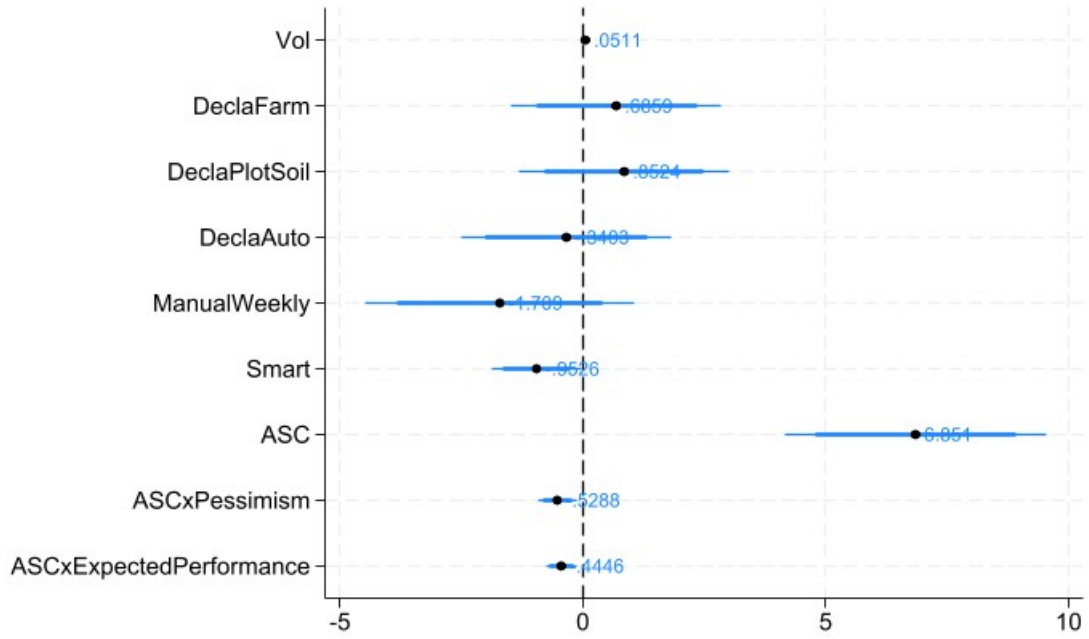


Table 6: Sign of individual coefficients: frequency among the 202 respondents based on RPL estimates in Table 4

Attribute	Frequency ≥ 0	Frequency < 0
DeclaFarm	74%	26%
DeclaPlotSoil	100%	0%
DeclaAuto	22%	78%
ManualWeekly	100%	0%
Smart	30%	70%
Vol	95%	5%
ASC	58%	42%

Table 7: Adoption rate by scheme type (in %)

Incentive size	Scheme 1	Scheme 2	Scheme 3	Scheme 4
0%	46.5	38.6	25.7	32.2
20%	50.0	43.6	31.2	42.6
30%	52.0	47.0	34.2	44.1
40%	57.4	50.5	38.6	48.0
50%	58.4	52.5	40.6	51.0

Note:

Scheme 1: Data sharing as the status-quo (only crops at farm level)

Scheme 2: Sharing cropping patterns at farm level with smart meter

Scheme 3: Sharing cropping patterns at plot level with manual weekly transmission of water consumption

Scheme 4: Automatic transmission of water and cropping patterns data

5 Discussion

Our results highlight preference for the status-quo for around half of the respondents (Table 6). While the attributes focus on the transmission of information to the manager, the scheme is also composed of elements providing information to farmers (e.g., sensors measuring the temperature of the soils or a phone app which provides information on the state of the resource in a water catchment). This suggests that farmers preferring the status-quo put limited value on this extra-information to pilot their irrigation. Among the limitations mentioned in an open question at the end (answered by 166/202 respondents), two third indicated the perceived high administrative burden associated with such a scheme implementation, or the fact that it was too far-fetched given their perception of the current water context. The fact that the scheme was unadapted to deal with farms' heterogeneity or even likely to generate inequalities was also mentioned. Lastly, several respondents questioned the fact that other means were more adequate to deal with water scarcity.

The need to go beyond water conservation technologies is also highlighted by Perrez-Blanco et (2020), who indicates that one cannot adapt to changing conditions by focusing primarily on increasing irrigation efficiency through WCTs. There is a need for more sweeping changes in water institutions, infrastructure, and management (Hanak et al. 2009). The original incentive we included to the scheme constitutes one step towards new water management. Rather than mobilizing the price mechanism to foster overall water use reduction, the scheme offers in-kind compensation to reduce water withdrawals from the beginning of the growing season. Doing so, it can contribute to reducing the frequency of irrigation restrictions, even if the compensation in the form of guaranteed volumes generates water extractions in the restriction periods.

We found that the size of the incentive (the % of weekly water needs guaranteed in restriction periods) has a significant positive impact on choices, but the effect size is low.² Other studies have found that some respondents ignore the price attribute (Zanten et al. 2016). Mariel et al. (2021, pages 27-29) indicated that a payment vehicle "has to be broadly accepted in the population and there has to be trust in the institutional setting". The exploratory preliminary research we conducted with the Q method has shown that most farmers find acceptable such an in-kind incentive. The respondents who have declared as likely or highly likely the scheme implementation in their watershed in

²While the volume attribute was assumed to be normally distributed, we found that only 3% of the respondents face a dis-utility when more volumes are guaranteed (negative coefficient).

the next years (56.4% of the sample) gave significantly (at the 5% level) more attention to the size of the incentives (as assessed by the individual parameters for the volume attribute estimated from the RPL model). The other respondents may have perceived the institutional constraints likely to deter the implementation of such original incentives, not yet permitted by French water regulation, and this translated by lower influence of the incentive size on their willingness to accept the scheme.

Concerning the influence of the data sharing attributes on preferences, we found that farmers' are rather keen of sharing cropping patterns and soil data, in order to benefit from a more precise score. This results highlights respondents on average well understood the efficiency score and the associated incentives. However, they are more reluctant to the set-up of smart meters to share automatically their water consumption data. Despite the time saving offered by smart meters, this result can easily be interpreted at the light of previous research reporting farmers' lack of trust in the privacy of data collected by smart farming technologies (Pfeiffer et al. 2021, Mohr and Kühl 2021, Jakku et al. 2019), or smart energy meters (Ram and Sheth 1989; Chamaret, Steyer, and Mayer 2020), and more generally farmers' aversion to control (Thomas et al. 2019). Indeed, several respondents reported they fear their data will be shared by the administration, even if the scheme focus on data exchange with the water manager.

A methodological contribution of this article relies on the selection of the attributes based on exploratory results of a Q-study. Furthermore, we check whether the profiles identified with the Q study ("the Q-profiles") match with the classes estimated with choices made in the DCE. The Q-profile of those who want to manage their production risk and receive compensation for participation to the scheme is more represented in class 3 (those against the scheme). Two Q-profiles are mostly represented in the class 2 (in favor of the smart meter): those who want to be actor of water preservation but first need to understand the scheme, and those who want a simple scheme with smart meters to save time. The fourth Q-profile of those who accept increased complexity in exchange of fairness are split across the 3 classes. Overall, there is a partial match between Q-profiles and DCE-classes.

Interestingly, being located in a watershed already under collective management has no impact on preferences. For those farmers located in the Aubance watershed, the change towards collective management is perceived as unavoidable, even if they are not yet concerned by the consequences in terms of data transmission (their water allocation does not yet depend on their cropping patterns). This can explain why they have not

shown more reluctance towards the scheme.

The robustness of our results relies on the complementary between the theoretical predictions and the empirical test with the DCE, particularly relevant when predictions are ambiguous or behavioral factors are coming into play. In particular, in the DCE, we found that the need to share data has a significant influence on the scheme acceptance. Moreover, we found that perceived probabilities of benefiting from the compensation influences the willingness to join the scheme. Previous research on preferences has shown the importance of beliefs variables. For example, subjective probabilities of hazards influence insurance decisions (Čop, Cerroni, and Njavro 2023). In environmental valuation, Dis-sanayake and Meyer (2021) found that stated beliefs about the status quo long-term land use influences willingness to pay for a new national park. Here the perceived probability to face restrictions (*Pessimism*) and the expected probability to be efficient (*Expected performance*) significantly explain the probability to fit in a class rather than another. Water institutions working on the design of new water allocation rules should account for behavioral factors such as beliefs towards the future and control aversion.

The adoption rates estimated here should be taken with a grain of salt given the hypothetical nature of choices in DCEs. Respondents may indeed underestimate the costs of participating in such a scheme. Moreover, while we analysed with the DCE individual adoption, collective adhesion is a pre-requisite for the scheme to work, in the framework of the "Single Unique Organisation for collective water management". Another main limitation of the study is the limited external validity of the results. The scheme has been developed for this particular case study area and consequentiality may seriously decrease if we would analyse preferences of farmers located in another area. Replication in other areas would allow to assess the role of past and future water flows and restriction background.

6 Conclusion

By providing an ex-ante robust evaluation of an innovative water allocation scheme coupled with water saving technologies, this article contribute to the literature on the use of digital technologies to improve the sustainability and resilience of agri-food systems, in particular irrigated agriculture. We find that half of the respondents are willing to join such a scheme, but we observe that automatized data sharing, for example through smart meters, can be an adoption barrier. The conditions of implementations of the scheme, and in particular the choices made in terms of data transmission, will influence

the acceptability and, most likely, the efficiency of the scheme on water preservation. Our results also suggest that raising awareness on the changes in water availability in the context of climate change can foster adoption. Development of extension services on deficit irrigation could also foster confidence in the probability to reach a sufficiently high efficiency score, and therefore increase the number of farmers willing to join.

References

- Armatas, Christopher A., Tyron J. Venn, and Alan E. Watson (2014). “Applying Q-methodology to select and define attributes for non-market valuation: A case study from Northwest Wyoming, United States”. en. In: *Ecological Economics* 107, pp. 447–456.
- Barton, David N. and Olvar Bergland (2010). “Valuing irrigation water using a choice experiment: an ‘individual status quo’ modelling of farm specific water scarcity”. In: *Environment and Development Economics* 15.3. Publisher: Cambridge University Press, pp. 321–340.
- Boxall, Peter C. and Wiktor L. Adamowicz (2002). “Understanding Heterogeneous Preferences in Random Utility Models: A Latent Class Approach”. en. In: *Environmental and Resource Economics* 23.4, pp. 421–446.
- Chabé-Ferret, Sylvain et al. (2019). “Can we nudge farmers into saving water? Evidence from a randomised experiment”. In: *European Review of Agricultural Economics* 46.3, pp. 393–416.
- Chai, Qiang et al. (2016). “Regulated deficit irrigation for crop production under drought stress. A review”. en. In: *Agronomy for Sustainable Development* 36.3.
- Chamaret, Cécile, Véronique Steyer, and Julie C. Mayer (2020). ““Hands off my meter!” when municipalities resist smart meters: Linking arguments and degrees of resistance”. In: *Energy Policy* 144, p. 111556.
- Čop, Tajana, Simone Cerroni, and Mario Njavro (2023). “Farmers’ acceptance of the income stabilisation tool: a discrete choice experiment application”. In: *European Review of Agricultural Economics* 50.4, pp. 1520–1546.
- Damania, Richard et al. (2017). *Uncharted Waters: The New Economics of Water Scarcity and Variability*. en. World Bank Publications.
- Dissanayake, Sahan T. M. and Andrew G. Meyer (2021). “Incorporating Beliefs and Experiences into Choice Experiment Analysis: Implications for Policy Recommendations”. en. In: *Applied Economic Perspectives and Policy* 43.2, pp. 823–848.
- FAO (2019). *FaoStat. Food and Agriculture Organization of the United Nations*. Tech. rep.
- Geerts, Sam and Dirk Raes (2009). “Deficit irrigation as an on-farm strategy to maximize crop water productivity in dry areas”. In: *Agricultural Water Management* 96.9, pp. 1275–1284.

- Giannoccaro, Giacomo et al. (2022). “Design of an incentive-based tool for effective water saving policy in agriculture”. In: *Agricultural Water Management* 272, p. 107866.
- Hampson, Danyel I., Silvia Ferrini, and R. Kerry Turner (2022). “Assessing subjective preferences for river quality improvements: combining Q-methodology and choice experiment data”. In: *Journal of Environmental Economics and Policy* 11.1. Publisher: Routledge .eprint: <https://doi.org/10.1080/21606544.2021.1879682>, pp. 56–74.
- Hanak, Ellen et al. (2009). *California water myths*. Report. San Francisco: Public Policy Institute of California.
- IPCC (2023). *IPCC sixth assessment report (AR6). WGII*. Tech. rep. Geneva, Switzerland: Intergovernmental Panel on Climate Change.
- Jakku, Emma et al. (2019). ““If they don’t tell us what they do with it, why would we trust them?” Trust, transparency and benefit-sharing in Smart Farming”. In: *NJAS - Wageningen Journal of Life Sciences* 90-91, p. 100285.
- Jensen, Anne Kejser (2019). “A Structured Approach to Attribute Selection in Economic Valuation Studies: Using Q-methodology”. en. In: *Ecological Economics* 166.106400.
- Koetse, Mark J. (2017). “Effects of payment vehicle non-attendance in choice experiments on value estimates and the WTA–WTP disparity”. In: *Journal of Environmental Economics and Policy* 6.3. Publisher: Routledge, pp. 225–245.
- Louviere, Jordan J., David A. Hensher, and Joffre D. Swait (2000). *Stated Choice Methods: Analysis and Applications*. en. Google-Books-ID: nk8bpTjutPQC. Cambridge University Press.
- Mariel, Petr et al. (2021). “Econometric Modelling: Basics”. en. In: *Environmental Valuation with Discrete Choice Experiments: Guidance on Design, Implementation and Data Analysis*. Ed. by Petr Mariel et al. SpringerBriefs in Economics. Cham: Springer International Publishing, pp. 61–81.
- McFadden, D. (1974). “Conditional logit analysis of quantitative choice behavior”. In: *Frontiers in econometrics*. P. Zarembka, pp. 105–142.
- Mohr, Svenja and Rainer Kühl (2021). “Acceptance of artificial intelligence in German agriculture: an application of the technology acceptance model and the theory of planned behavior”. en. In: *Precision Agriculture* 22.6, pp. 1816–1844.
- Ouvrard, B et al. (2023). “Nudging and subsidising farmers to foster smart water meter adoption”. In: *European Review of Agricultural Economics* 50.3, pp. 1178–1226.

- Pacifico, Daniele and Hong il Yoo (2013). “Lclogit: A Stata Command for Fitting Latent-Class Conditional Logit Models via the Expectation-Maximization Algorithm”. en. In: *The Stata Journal* 13.3. Publisher: SAGE Publications, pp. 625–639.
- Pérez-Blanco, C. Dionisio, Arthur Hrast-Essenfelder, and Chris Perry (2020). “Irrigation Technology and Water Conservation: A Review of the Theory and Evidence”. In: *Review of Environmental Economics and Policy* 14.2, pp. 216–239.
- Pfeiffer, Johanna, Andreas Gabriel, and Markus Gandorfer (2021). “Understanding the public attitudinal acceptance of digital farming technologies: a nationwide survey in Germany”. en. In: *Agriculture and Human Values* 38.1, pp. 107–128.
- Ram, S. and Jagdish N. Sheth (1989). “Consumer Resistance to Innovations: The Marketing Problem and its solutions”. In: *Journal of Consumer Marketing* 6.2. Publisher: MCB UP Ltd, pp. 5–14.
- Stephenson, William (1953). *The study of behavior; Q-technique and its methodology*. The study of behavior; Q-technique and its methodology. Pages: ix, 376. Chicago, IL, US: University of Chicago Press.
- Thomas, Fabian et al. (2019). “Greening the common agricultural policy: a behavioural perspective and lab-in-the-field experiment in Germany”. In: *European Review of Agricultural Economics* 46.3, pp. 367–392.
- Venus, Terese E. and Johannes Sauer (2022). “Certainty pays off: The public’s value of environmental monitoring”. In: *Ecological Economics* 191, p. 107220.
- Wang, Xiaowei et al. (2017). “Implementing the Prepaid Smart Meter System for Irrigated Groundwater Production in Northern China: Status and Problems”. en. In: *Water* 9.6, p. 379.
- Watts, Simon and Paul Stenner (2012). “Doing Q Methodological Research : Theory, Method & Interpretation”. en. In: Publisher: Sage, pp. 1–248.
- WEF (2019). *Global risks 2019. Report 14th Edition. Global Risks. World Economic Forum*. Tech. rep.
- Welling, Malte, Ewa Zawojcka, and Julian Sagebiel (2022). “Information, Consequentiality and Credibility in Stated Preference Surveys: A Choice Experiment on Climate Adaptation”. en. In: *Environmental and Resource Economics* 82.1, pp. 257–283.
- Zanten, Boris T. van, Mark J. Koetse, and Peter H. Verburg (2016). “Economic valuation at all cost? The role of the price attribute in a landscape preference study”. In: *Ecosystem Services*. Integrated valuation of ecosystem services: challenges and solutions 22, pp. 289–296.

Zekri, Slim et al. (2017). “Feasibility of adopting smart water meters in aquifer management: An integrated hydro-economic analysis”. In: *Agricultural Water Management* 181, pp. 85–93.

7 Appendix

A1: Robustness checks

We run the same RPL model than the one presented in the main text (Figure 4) to different subgroups. In column (1), we first exclude responses to the first choice card seen by respondents, to account for learning effects. In column (2), we exclude responses to the last choice card in order to check for a lassitude effect. In column (3), we exclude respondents who indicated no interest in the scheme before answering choice cards, since they are more likely to have provided random answers. In column (4), we exclude those who have always opted-out. Finally, in column (5), we exclude respondents who read the description of attributes, including the video presenting the scheme in less than 4’, which is considered as too short for a comprehensive overview. In column (6), we exclude the 36 respondents who were interviewed face to face in order to keep only self-completed responses.

Table 8: RPL estimates for subgroups

	1)Excl. first choice	(2)Excl. last choice	(3)Excl. Not in- terested	(4)Excl. Always opt-out	(5)Excl. Low time	(6)Excl. Face to face	(7) Excl. Low Un- derstand
Mean							
ASC	2.099 (1.43)	0.658 (0.77)	0.103 (0.11)	2.216** (2.28)	0.204 (0.21)	3.909*** (3.05)	1.481* (1.76)
DeclaFarm	1.996 (1.37)	0.625 (0.71)	0.177 (0.18)	2.022** (1.98)	0.387 (0.39)	4.105*** (3.07)	1.632* (1.81)
DeclaPlotSoil	0.759 (0.52)	-0.481 (-0.54)	-0.960 (-0.95)	1.113 (1.10)	-0.780 (-0.80)	2.677** (2.14)	0.235 (0.27)
DeclaAuto	-2.714** (-2.55)	- 3.101*** (-3.45)	-1.395 (-1.35)	- 3.290*** (-3.20)	-2.916* (-1.93)	- 39.83*** (-5.04)	-1.104 (-1.02)
ManualWeekly	-1.545*** (-2.90)	- 0.919*** (-2.64)	-0.979** (-2.23)	-0.724** (-2.00)	- 1.544*** (-2.75)	- 1.499*** (-2.68)	-0.405 (-1.19)
Smart	0.0586*** (6.07)	0.0537*** (6.82)	0.0603*** (6.19)	0.0671*** (7.16)	0.0517*** (6.15)	0.0825*** (5.68)	0.0691*** (7.22)
Vol	1.680*** (2.62)	1.464*** (2.74)	0.768 (1.26)	1.521*** (3.15)	1.312** (2.00)	0.915 (1.10)	3.074*** (4.32)
SD							
ASC	1.670*** (5.21)	1.561*** (3.48)	1.904*** (4.06)	1.572*** (5.20)	1.371*** (4.23)	1.856*** (4.33)	-0.451 (-0.76)
DeclaFarm	0.586 (1.33)	-0.856** (-2.03)	-1.029* (-1.94)	0.988** (2.44)	-0.541 (-0.44)	0.468 (1.00)	- 1.622*** (-4.44)
DeclaPlotSoil	1.611*** (4.50)	1.517*** (4.13)	1.650*** (4.94)	- 1.539*** (-5.25)	1.532*** (5.60)	2.774*** (5.88)	2.312*** (5.84)
DeclaAuto	-4.610*** (-3.84)	-1.596** (-2.26)	1.103 (1.27)	0.538 (0.47)	-0.293 (-0.26)	44.29*** (4.98)	1.577** (1.96)
ManualWeekly	4.007*** (6.23)	3.365*** (7.83)	3.790*** (7.73)	3.628*** (8.30)	3.495*** (7.42)	4.590*** (5.51)	3.736*** (8.54)
Smart	0.0773*** (5.92)	0.0502*** (5.67)	0.0545*** (5.25)	0.0504*** (6.33)	0.0551*** (5.73)	- 0.0918*** (-5.43)	- 0.0512*** (-5.46)
Vol	6.542*** (8.56)	6.163*** (8.09)	7.516*** (8.46)	8.788*** (7.02)	7.421*** (8.28)	5.476*** (6.00)	8.872*** (6.40)
N	4242	4242	4688	3864	4464	2736	3624

t statistics in parentheses : * $p \leq 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 9: Criteria for determining the optimal number of classes in the Latent Class model

Number of classes	Log-likelihood (LL)	AIC	BIC	Prediction accuracy: Average latent class posterior probability
2	-1154.205	2342.41	2398.65	99%
3	-1074.681	2203.362	2292.685	96%
4	-1019.046	2112.093	2234.499	96%

Notes: AIC (Akaike Information Criterion) is $-2(LL - j)$ where j is the number of parameters to be estimated in the model; BIC (Bayesian Information Criterion) is $-LL + (k/2) \ln(N)$ where N is the number of observations.