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TITOLO TESI

The digital irrigated agriculture: advances on decision modelling to accompany the sector in exploiting new opportunities

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Esame finale anno 2020

To my grandaunt Marisa,

Abstract

Irrigated agriculture is facing growing uncertainties under Climate Change (CC) due to the decreased predictability of weather events and increased variability of climate patterns. The farmers' and Water Authorities' (WAs) climate-related uncertainties can be lowered by Information and Communication Technologies (ICT) through the provision of weather and climate forecasts. Despite the growing interest for such platforms and their potential to favor CC adaptation, we see many ICT-development initiatives having less-than-expected diffusion and failing to solve informational issues in the short term. This PhD thesis deeply investigated the uncertainty settings around the decisions on ICT-information implementation to support irrigation management. Its ambition is to provide evidences on: (i) the circumstances in which ICT can be reliably used; (ii) the relative potential benefits; (iii) the barriers in the decision environment or in the Decision Maker's (DM) behavior which do not allow the achievement of such potential benefits. To do so, we defined an innovative uncertainty framing, distinguishing between elements of risk and ambiguity, and developed two separate decision models under uncertainty. One model allowed to estimate potential economic benefits from the ICT-informed decision process of irrigation management, while accounting for the restrictions to information usability. The other model represented subjective behavior in the decision on ICT-information implementation and highlighted how it can impact on ICT-benefits in irrigation districts. The capability of decision models was then tested in two separate empirical examples. Results confirmed the hypothesis on ICT potentials, but underlined that benefits are extremely variable and subjected to constraints. These are relative to the decision environment, to the form and quality of ICT-information and to the behavior of DMs. Conclusions provide policy suggestions to help irrigated agriculture unlocking ICT potentials, overcoming barriers to ICT-information implementation. Specifically, we highlight how ICT-development policies, uncertainty-management policies and water policies are respectively needed to: (i) favor ICT development with end users to answer their information needs; (ii) help DMs facing risks caused by the imperfect nature of ICT-information; and (iii) ensure that excess-use of water does not undermine ICT-benefits.

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Acronyms

AA	Ambiguity aversion
BDT	Bayesian Decision Theory
CC	Climate Change
CE	Certain Equivalent
CWD	Crop Water Demand
DM	Decision Maker
ICT	Information and Communication Technology
PDF	Probability Density Function
PP	Precautionary Plan
RA	Risk Aversion
RP	Risky Plan
SEU	Subjective Expected Utility
TF	Time Frame
WA	Water Authority
WP	Water Productivity
WU	Water Use

Chapter 1

1. Introduction

1.1 Background and motivations

Agriculture has always been affected by uncertainty. This is mainly due to the open-air characteristic of production processes carried out in complex agroecosystems with highly variable driving elements such as pests, climate and soil. To face uncertainty, the development of agriculture has been characterized by farmers' effort to control environmental variables (Hardaker et al. 2015). The result of this development process is in distributions of yields which have lower variability and higher averages. Water management and irrigation are a clear example of this. By collecting water in reservoirs before the cultivating season, water management allows to diminish the share of production processes subjected to the variability of unknown and upcoming rainfalls. By moving water from where it is abundant to the field, irrigation allows a more suitable environment for crops. Overall, the irrigation system lowers climate-vulnerability while it increases the average crop productivity (Galioto, Raggi and Viaggi 2017). Examples of this kind are available all along the development of agriculture from food gathering to hi-tech greenhouses. This is especially true during the *Green Revolution,* which is widely recognized as one of the periods where agriculture has been more effective in implementing innovations for the control of agroecosystem's processes (Gingrich and Krausmann 2018).

Nowadays, Climate Change (CC) is exacerbating uncertainty issues by making forecasts more difficult and by increasing the variability of weather events (Allen, Dube and Solecki 2018). At the same time, as in everyday life we have seen the proliferation of Information and Communication Technology (ICT) contributing to support many decisions, also agriculture is taking part to this digitalization process. Decision Support Systems, IoT, Climate Services and GIS are exponentially growing in the agricultural sector and offer Decision Makers (DMs) a wide variety of support (Cambra Baseca et al. 2019). Because of the great potential of such ICTs, many authors call this period *Digital agriculture revolution* and believe it is the answer to the challenges the sector is facing due to CC (Rotz et al. 2019). This title highlights how scholars consider important the stage of agricultural development we are living in.

While the *Digital agriculture revolution* can be expected to be comparable in magnitude with the *Green Revolution* (Rotz et al. 2019), the approach with which innovations contribute to the sector is radically different. During the *Green Revolution* technologies were aimed at altering the agroecosystem through fertilizers, pesticides and genetics, while the *Digital agriculture revolution* is altering the decision environment through information provision. Accordingly, all digital technologies in agriculture have one common element, which is in the use and generation of data. With it, the new platforms generate information aimed at supporting decisions by lowering uncertainty. Decision processes can now move from precautionary and inefficient choices forced by uncertainty, to decisions based on sound information. In this context, water management is one of the key sectors where ICT-information would have the most important applications with the highest benefits (Jeuland et al. 2018; Cambra Baseca et al. 2019).

In the industrial and utility sectors, the adoption of ICT to support decisions on water use and allocation is already widespread in what is defined by the International Water Association as *Digital water journey* (Ceo, Foundry and Webb 2019). In agriculture, the *Digital water journey* is more difficult due to the intrinsic characteristics of the sector. Here, dynamics for ICT implementation are extremely complex and infrastructures, technical issues and low profitability pose significant constraints (Cavazza et al. 2018). As a result, in some occasions WAs and farmers might decide to not implement an ICT because it cannot be used, or it is not profitable, given the current settings (Galioto et al. 2020). For example, low accuracy of available devices make many platforms useless to aid farmers' irrigation decisions (Galioto et al. 2017). At the level of Water Authorities (WAs) the prevalence of open-air canals does not always allow to precisely allocate water between farmers according to the ICT (Cavazza et al. 2018). Even when an ICT is profitable when used, behavioral barriers can hinder the digitalization process (Kirchhoff, Lemos and Engle 2013). Between these, aversion to the uncertainty involved in the implementation of a new ICT is the most relevant, with a key role played by the DM not knowing the ICT reliability. As a result, the digital transition for irrigation management cannot be self-accomplished by the sector. Constraints to digitalization will not only slow ICT implementation, but they also risk compromising ICT benefits in the long term, leaving the sector with few tools to face issues of CC-related scarcity and conflicting uses (Ceo et al. 2019).

In the literature, there are several studies addressing the topic of ICT implementation in agriculture and water management (Jeuland et al. 2018; Meza, Hansen and Osgood 2008); many of these highlight the key role of ICT for CC-adaptation. Nevertheless, results are contradictory, and none provides a comprehensive assessment addressing, with a holistic approach, the whole decision environment. The most important works, estimate the benefits of ICT implementation by defining the circumstances in which information has a value for a DM (Keisler et al. 2014). Although scholars agree on the theoretical settings in which ICT-information is valuable, empirical applications show discordances and ICT-benefits are still unclear. This highlights how results are extremely context-dependent and models must be adapted to the decision environment in which the ICT is introduced. Given the context-specificity of ICT-benefits, we carried out a review on ICT implementation for irrigation management both at the farm- and WA-level. Especially at the latter decision level, we found few or no work addressing the issue. In addition, there are gaps in the modelling of decisions to account for: (i) the specificities of the irrigation sector; (ii) the farmer's and WA's subjective behavior under the uncertainty affecting decisions for new ICT implementation. As briefly described in the previous paragraph, the irrigation sector is peculiar for its technical elements which constraint the range of applicability of ICT. Not accounting for these constraints brings to significant over-estimations of benefits, which, in the long term, might further increase uncertainty on the convenience of ICT implementation. Other than technical constraints, one of the major issues highlighted in both qualitative and quantitative studies is that new ICT platforms generate uncertainty on information reliability. However, the DM's behavior is often assumed as rational and aversion to uncertainty overlooked. Even in those applied studies which relax assumptions of rationality, different sources of uncertainty are treated indistinctly, and the issues generated by a lack of knowledge on ICT reliability are overlooked. This does not allow to model how perceptions on information reliability affect the farmer's or WA's behavior and, in turn, the decision on ICT implementation. Overall, uncertainty remains on the magnitude of benefits which can be achieved through ICT-aided decision processes in irrigated-agriculture and on what hinders the sector to such achievements.

In this research, we acknowledge that ICT-information is not always profitable when implemented in the target decision processes (Galioto et al. 2020). As highlighted before, ICTs are promising tools, but in many occasions their development is shown to be unproductive due to a wide variety of constraints. To help understanding the problem, we distinguish between two classes of constraints limiting ICT adoption and ICT-benefits in irrigated agriculture:

- Restrictions to information usability: these occur when the ICT provides information that cannot be implemented, or it is not profitable when implemented in real-life irrigation management decisions. Such restrictions cannot be overcome because they are intrinsic characteristics of the decision environment. For example, some decisions can be so risky that precautionary strategies are always more profitable. More simply, it can happen that in the current management system there are not information needs or the current infrastructures or management systems do not allow ICT-information implementation. In presence of restrictions to information usability there are no potential economic benefits from ICT-information implementation.
- Barriers to the achievement of ICT-benefits: these can be due to characteristics of: (i) the ICT, like its form, content or time provision which are not compatible with the local decision process; (ii) the decision environment, like technical barriers, for example, the water delivery system can be too imprecise if compared with ICT-information; (iii) the DM himself, like aversion to uncertainty which might cause low expected utility from information implementation from ICTs whose reliability is unknown. Such barriers can be overcome by modifying ICT-information's form or accuracy to meet DMs' needs or by adapting decision processes or the decision environment to implement information. Behavioral barriers too can be solved by educating end users or by providing them information on ICT reliability.

In this context, when approaching a new ICT, one must ask himself three questions: Are there any restriction undermining information usability? What are the potential benefits from the use of such information? Which are the barriers to the achievement of such benefits? At this end, the role of agricultural economists is key to fill the knowledge gaps and support policy makers to accompany irrigated agriculture in the *Digital water journey*. Specifically, there is a strong need to provide evidence on information usability, potential economic benefits from ICT and barriers to the achievement of such benefits. On the one hand, the assessment of information usability and ICT-benefits will provide the needed data to justify and encourage investments and policies for ICT development in those settings where ICTs can be profitable when implemented. On the other hand, by assessing the barriers which hinder the achievement of such ICT benefits, it will be possible to design policies tailored to overcome the problems. Overall, evidence would support policy makers in the design of new tools to guide irrigated agriculture in unlocking ICT potentials. To deliver this evidence, there must be advances in the modelling of decisions. The available literature should be improved by two kinds of model developments: (i) one is in designing a new decision model by adapting existing ones to the peculiarities of the sector; (ii) the other is in designing a new model capable of assessing the impacts that subjective behavior under uncertainty has in the process of new ICT implementation.

1.2 Objectives

This doctoral dissertation is positioned in the context above described, with the ambition of answering to the need of evidence on restrictions to ICT-information usability, ICT-benefits and barriers to ICT adoption in irrigation management. A holistic approach is used to analyze the decision processes and to account for the multiplicity of aspects which are peculiar in the sector's decisions. To do so, decision models are required to simulate the DMs' choices on ICT information implementation and their impacts on the irrigation activity. Therefore, behind the major objective of this dissertation, three sub-objectives can be identified, each contributing to design new methods which address specific issues of the bigger problem. In particular, the methodological sub-objectives can be described as follows, where to the fulfillment of each objective corresponds a specific chapter of this dissertation:

1. To build the theoretical foundations for new behavioral decision models of ICT adoption under uncertainties in irrigation management: in applied studies we did not find the basis to support models capable of accounting for the peculiarities of decisions, so, in the economic literature, we sought for theories on which to build the framework needed to address the specific problems.
2. To develop a new decision model to understand when ICT information is usable and to estimate potential economic benefits from the ICT-informed decision process of irrigation management while accounting for the barriers to information implementation. This model is applied to the water management decisions that occur at the WA-level and specifically accounts for technical barriers to the achievement of ICT benefits and restrictions for ICT-information implementation.

3. To design a new behavioral decision model capable of representing the decision processes of ICT information implementation, while assessing the impacts that subjective behavior under uncertainty have in undermining ICT potentials in settings where ICT can be profitable when implemented. In literature no model was found to address the issues caused by lack of knowledge on ICT-information reliability, this model filled the knowledge gab by modelling aversion to such uncertainties and the relative barriers this behavior poses.

The theoretical framework developed to fulfill objective 1, will define the specific aims and the background on which we will build the two models of objectives 2 and 3. Then, by developing such models we will provide a detailed representation of the major dynamics which condition the *Digital water journey* in agriculture. Finally, by testing and implementing the models to case studies we will provide the quantitative estimations of ICT impacts needed to support new policies to aid the sector.

1.3 Novelties

The research stands out of the current literature for its comprehensive approach with which decision processes are analyzed. In particular, the first novelty is in the theoretical framework developed to model the uncertainty settings around ICT adoption by distinguishing between the different sources of uncertainty involved in the implementation of a new ICT. Contrarily to most of applied studies where risk is considered to be the only element building uncertainty, we introduce the concept of ambiguity. This arises from a lack of knowledge on information reliability and expresses the degree of confidence the DM puts on the risk estimations provided by the ICT. The uncertainty framing proposed was made possible by the application of the theory of ambiguity developed by Ellsberg (1961) and it allows to model the process of familiarity which occurs as the DM gains experience on the ICT. Familiarity plays a key role in the ICT adoption decision as it favors uncertainty-averse DMs in ICT-information implementation.

The novelty of the first decision model developed is in being capable of addressing technical constraints characterizing irrigation management at the WA level. Between these, the main methodological advancement is in accounting for the timing issues in sequential and inter-correlated decision steps. Accordingly, one peculiarity of water allocation decisions is in the fact that they are repeated before and along the irrigating season, with one decision having impacts on the outcome of the subsequent one. Further, decision variables, technical constraints and information requirements vary depending on the time of the season. The model developed accounts for such elements by considering two decision steps, the first occurring before the irrigating season, while the second is repeated weekly along the season. Because the decisions made in the second step are also influenced by the accuracy of ICT-information provided before the irrigating season, we model a strict dominance of the accuracy of ICT-information provided in previous time steps on subsequent ones. This issue was not tackled in literature and allowed to develop a new decision model by adapting the existing ones to the context of the study. The empirical application of the model is also original: to the best of author' knowledge no economic research deals with ICT adoption by WA for the management of irrigation.

In the second model, novelties are twofold: (i) the first is in providing as output both the farmers' and WAs' water demand from ICT-aided irrigation plans; (ii) the second is in developing a new learning rule to describe how DMs get familiar with a new ICT as they gain new insights on its reliability. By considering water demand as function of DM's behavior and by accounting for the governance system, the model highlights how poor coordination in water use can undermine ICT benefits. Previously, this issue was never raised by scholars; it is caused by subjective attitudes and perceptions on ICT reliability. Because perceptions evolve in time as DMs become familiar with the ICT, choices on water use will evolve too. To model such process, we did not find any suitable model to represent the update of beliefs on ICT reliability, therefore we developed a new one. The learning rule is innovative because it accounts for two main peculiarities of ICTs providing weather-related information:

- differently from other technologies, the performance of ICT cannot be directly measured in terms of production;
- accuracy of information is difficult to estimate at the end-user level because quantitative comparisons between forecasts and observations need specific tools and knowledge.

Overall these modelling advancements allowed to assess the impact that subjective behavior on ICT implementation have in undermining the efficiency of ICT-aided irrigation plans in districts.

1.4 Overview

The thesis is a combination of three individual papers, each building a single chapter and contributing to the understanding of specific aspects of the decision problems at hand. Overall, the papers will provide the picture needed to represent the key elements of decision process of ICT implementation and will analyze the problem in its complex and wide aspects.

In the next chapter, we will analyze the economic literature to seek for theories of decision-making under uncertainty capable of better explaining the problems of ICT-information implementation. Results of this chapter will build the theoretical foundation for the decision models of ICT-information implementation which will be developed in the subsequent chapters.

In the third chapter, we will focus on ICT-information usability and benefits generated from ICT implementation. In particular, through a model based on Bayesian Decision Theory (BDT), we address ICT-information usability and estimate economic benefits from the ICT-informed decision process of water management in agriculture at the WA level. This is done by testing an applying the model to a case study represented by a WA which is implementing a new ICT platform developed to provide climate information to support irrigation.

In the fourth chapter, we focus on the fact that it is not only information usability which affects its implementation and related benefits, but also the farmers' and WA's subjective behavior. To assess the impact of such issue, we develop a behavioral model to represent the decision between inefficient but riskless irrigation plans or ICT-aided efficient irrigation plans with uncertain outcomes. The model will allow to assess the impact that subjective behavior on ICT implementation have on the efficiency of ICT aided irrigation plans in irrigation districts. Then, the model is implemented in a numerical example to underline, in a scenario analysis, how poor governance can further hinder the achievement of ICT-benefits

Finally, we provide the full descriptive analyses of the modelling results and the relative limitations and policy implications and draw the final conclusions in chapter five and six respectively.

Chapter 2

2. Towards a framework for comprehensive analysis of decision processes for ICT adoption in irrigation management

2.1 Introduction and objectives

In the previous chapter, we highlighted how uncertainty has always affected agriculture and how irrigation management is one of the areas mostly needing information to solve it. Information needs are further exacerbated under CC scenarios. Climate-related uncertainties could be lowered by weather and climate forecasts and disseminated to farmers and water authorities through ICT. Despite the growing interest for such technologies and their potential to favor adaptation, we see many ICT-development initiatives having less-than-expected diffusion and failing to solve informational issues in the short term. This is mainly due to technical barriers, which undermine information usability, and a lack of knowledge on ICT reliability, which undermines information implementation. The latter barrier is true even in settings where otherwise ICT would have allowed significant benefits.

Here we do not want to highlight the usefulness of ICT, contrarily, knowing their potential key role for CC adaptation (Allen et al. 2018), we see a strong need to understand decision processes in ICT-information implementation. To do so, we will analyze the economic literature to seek for theories of decision-making under uncertainty capable of better explaining the problem. Results will build the theoretical foundation for decision models of ICT-information implementation which will simulate decisions for irrigation management. This will help to understand how barriers to the achievement of potential economic benefits can be better overcame. Moreover, it will allow ICT developers in tailoring platforms to answer DMs' information needs and policy makers in defining uncertainty-management policies.

The remainder of this chapter is organized as follows: in the next section we will frame the problem and describe how uncertainty rise due to CC, the role of ICT in CC-adaptation and the gaps between expectation and real ICT implementation. Then, we will review the most relevant theories and applications of decision making under uncertainty. In Section 2.4, we will focus on the theory developed by Ellsberg (Ellsberg 1961) and apply it to the context of our research; finally in Section 2.5 and 2.6 we respectively discuss what we have learned from this review and draw conclusions and policy implications.

2.2 Climate Change and uncertainty

Due to the open-air characteristic of farming activities, agriculture has long been recognized to be one of the most weather sensitive sectors (Hardaker et al. 2015). Farmers have always faced their susceptibility to weather events, but recent CC trends are posing further obstacles in their activities prompting two main issues: (i) a raise in the frequency of extreme events and (ii) a raise in the variability of weather patterns. This results in an increased vulnerability of agriculture and rural areas (H. de Coninck et al. 2018).

The former issue of increased frequency of extreme events corresponds to a fattening in the tails of the climate-events' probability distributions. Tail-events generate losses despite the side of the climate distribution considered because large deviations from mean (or expected) values have often negative effects on yields (Hardaker et al. 2015). For example, both droughts and excessive rainfalls are negative for agricultural production and one does not compensate for the other. This results in an increased frequency of climate-related losses which can only be mitigated, if predicted, by implementing protective actions. Because these actions are costly and predictions are seldomly available at a sufficient level of accuracy to be reliably used (Cavazza et al. 2018), climate shocks are always welfare-reducing events.

With regards to the raise in weather patterns' variability, it is to be said that variability *per se* is not negative for agricultural production (Hallstrom 2004). For example, seasonal variability is taken as an advantage for agricultural systems in temperate areas and experience in seasonal fluctuations is used by farmers to predict upcoming trends and act consequently (Letson and Solı 2013). The problem arises when variability is unpredictable (Hansen 2002). This is typically the case of CC where the change in climate trends means that past records are less relevant in making future predictions and climate models propose different projections (H. de Coninck et al. 2018). As a result, unpredicted climate variability due to CC is systematically causing production losses in agriculture.

In this scenario, irrigation is an important tool which farmers can use to protect themselves from: (i) climate shocks, such as droughts, and (ii) climate variability, in the form of high variances in rainfall patterns. Accordingly, irrigation is recognized to be one of the most effective means to decrease climate-vulnerability of agricultural production (Skarbø and Vandermolen 2014; McCarl and Hertel 2018) and irrigation efficiency is fundamental to allow adaptation (H. de Coninck et al. 2018). Apparently, this is in contrast with the fact that, between agricultural systems, irrigated agriculture is one of the most vulnerable to climate-related uncertainties (Archibald and Marshall 2018). However, in semi-arid and Mediterranean areas, irrigation is already rooted in production systems, hence, no access to the resource can compromise the whole farming activity (Calzadilla et al. 2014). Here, climate shocks affect the short-term irrigation water activities and uncertain climate trends pose constraints in the long-term water supply and resource availability. This might result in yields of irrigated crops being lower on average and more variable (Galioto et al. 2017).

In this framework, the most relevant role is played by WAs, which see the need to solve climate uncertainty in their water allocation activities (Kirchhoff et al. 2013; Cavazza et al. 2018). Their objective is to maximize farm revenues in the basin they are managing, while minimizing water use and the related costs. The main issues WAs are facing are related with the availability and management of the resource (Li et al. 2016), inability to meet the target farmers' demand (Archibald and Marshall 2018) and missed water savings due to unpredicted rains (Archibald and Marshall 2018). As a result, WAs are extremely sensitive to uncertainty, needing to plan water allocation now to accomplish future and uncertain climate settings (Giupponi 2014).

2.2.1 Information provision and ICT adoption in Climate Change adaptation

The common element of both CC-related issues above described is linked with uncertainty on future climate events: if climate shocks could be better anticipated, farmers and WAs would protect themselves; if future climate trends could be known, farmers and WAs would tailor production systems to fit future settings. In this context, meteorological sciences can provide forecasts of climate fluctuations and decrease the level of climate-uncertainty (Hansen 2002). With such information DMs would be better equipped in CC adaptation (World Metereological Organization 2015). Accordingly, in presence of uncertainty regarding the occurrence of alternative climate states, forecasts have the potential of reducing variance in the upcoming events' probability distributions (Meza et al. 2008).

In parallel with the development of forecasts capability, ICTs are continuously growing and, by providing climate information, are potentially helpful in favoring adaptation. For this reason, ICTs are considered as strategic to aid decisions under climate uncertainty in agriculture (Crean et al. 2015) and in water management (Kirchhoff et al. 2013). The integration of ICT-information in decision processes can help irrigating farmers achieving water savings and higher yields with lower variances (Galioto et al. 2017). Further, if also used by WAs, ICT can provide the information needed to implement efficient irrigation management plans capable of delivering farmers the right amount of water at the right time (O'Mahony et al. 2016). A specific potential is then identified at the WA level where such tools would help mitigating agricultural losses from climate shocks and climate variability (Cavazza et al. 2018). This is why there is a strong need for policies to favor the development and uptake of ICT for water management in agriculture (Irrigants d'Europe 2018; Giupponi 2014).

2.2.2 State of the art in ICT adoption

The topic of ICT adoption in agriculture is of growing relevance and numerous ICT development initiatives have been carried out to aid the sector (Aker et al. 2016). Despite being a niche in this field, the use of such technologies for water/irrigation management is considered one of the most promising applications (Jeuland et al. 2018). This is confirmed by the growing body of articles published on the topic (Figure 1) and by the interest in the applied economic literature (Jeuland et al. 2018; Martin 2016; Giupponi 2014).

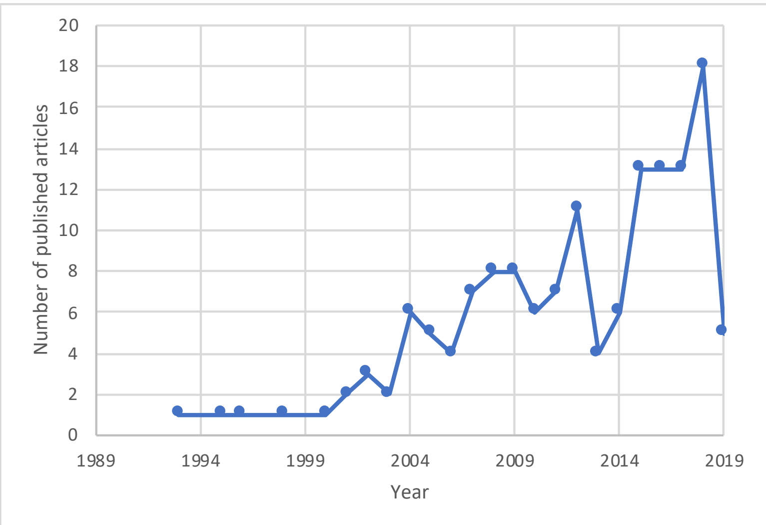

Figure 1: N. of articles on ICT adoption in agriculture water management

Source: own elaboration from data obtained with the search in Scopus (dated 04/04/2019) having the following parameters: TITLE-ABS-KEY ((ICT OR DSS OR "climate services") AND agriculture AND ("water management" OR irrigation))

Regardless the great interest for ICT, in many cases their impact is not well-defined and results of applied economic studies are extremely variable (Aker et al. 2016). ICT can provide benefits only if information delivered is eventually implemented by DMs to improve decisions (Vogel, Letson and Herrick 2017). As evident, this occurs only when information content answers DMs' needs (Furman et al. 2011) and its form is compatible with technical restrictions, such as timeliness of information provision or spatial scale (Vogel et al. 2017). It is not only information usability which conditions ICT-benefits; DM's behavior can strongly affect ICT-information implementation. Tumbo et al. (Tumbo et al. 2018) in their analyses found that farmers in Tanzania are seeking ICT-information to adapt to CC, especially in their irrigation activities. Though, they highlight that uncertainty on ICT reliability can limit information uptake. Nesheim et al. (Nesheim, Barkved and Bharti 2017) found that the use of ICT in India has not reached its potential and many farmers do not implement the forecast received. This is mainly due to farmers not understanding information received or having doubts on ICT reliability (Nesheim et al. 2017). Kirchoff et al. (Kirchhoff et al. 2013) carried out qualitative and quantitative analyses on ICT adoption for water management in the U. S. and Brazil. They found that, when DMs perceived information reliable, this helped information uptake and efficient water management; while, in case of skepticism, information was not implemented (Kirchhoff et al. 2013). Hawoth et al. (Haworth et al. 2018) underline that, between all the 27 ICT reviewed, only a few were actually used to improve decisions. They identify restrictions for ICT-information implementation, between which the most relevant ones are associated with information quality and perceived reliability. Lack of knowledge on the technology's reliability is an issue highlighted also by O'Mahony et al. (O'Mahony et al. 2016) who show that it can prevent achieving sustainable water management practices in Australian agriculture. Accordingly, if the ICT or the information itself are considered unreliable or are mis-interpreted, DMs do not implement the message received and gain no benefit from the technology (Aker et al. 2016).

Such findings are confirmed by several quantitative studies, out of which a selection of empirical application for ICT benefits estimations is reported in Table 1. As can be seen from the table, benefits can get null and every paper highlight elements of the decision environment or the information itself which prevent ICT-information implementation. Although the table is not comprehensive of all the work done in the field, it allows to understand how the impact of ICT-information implementation is still mixed. To gain better insights from this topic, please refer to the works of Jeuland et al. and Meza et al. (Jeuland et al. 2018; Meza et al. 2008) which provide respectively reviews of studies for ICT-information benefits estimation in water management (predominantly irrigation) and in the broader agricultural sector.

This situation in which not all the DMs who receive information actually implement it, and both technical, but most of all, behavioral barriers undermine information implementation, brings to unclear settings. Further, even when ICT information is implemented and put into actions, quantitative studies highlight that in many occasions there is a lack of benefits from ICT-aided decision processes. This poses constraints for ICT development and growth because investments are not easily justifiable and returns doubtful (Jeuland et al. 2018).

Table 1: Examples of estimation of benefits from information implementation

Authors	Journal	Field of application	Case study	Type of information	Benefits	Constraints
Bouma, van der Woerd and Kuik 2009	Journal of Environmental Management	Water quality	Netherlands	Earth observations	0-0.4mln€	Quality of information; uncertainty on reliability; DM's prior expectations; lack of confidence on informed actions; political barriers
Letson and Solı 2013	Regional Environmental Change	Agriculture	U.S.A.	Climate information	0-3.4mln$	Agricultural sector; region; use of discrete-type forecasts
Crean et al. 2015	Australian Journal of Agricultural and Resource Economics	Agriculture	Australia	Seasonal forecasts	0-55$/ha	Quality of information; crop-planting time; poor timeliness of information provision
Kusunose and Mahmood 2016	Agricultural Systems	Crop plan	U.S.A.	Weather forecasts	0-12$/ha	Quality of information; management strategies; uncertainty on reliability; crops revenues
Fernandez et al. 2016	Climatic Change	Agriculture	U.S.A.	Decadal climate variability	0-1.7$/ha	Quality of information; cropmix; irrigation
Galioto et al. 2017	Water	Irrigation	Denmark, Portugal, Spain, Greece Italy	Crop water requirement	0-250€/ha	Quality of information; irrigation water cost; output price; risk aversion
Cavazza et al. 2018	Water	Water management in agriculture	Italy	Long- and short-term crop water requirement	0-26.2€/ha	Quality of information; the stake in the decision process; time of information provision; land use; water delivery system
An-Vo et al. 2019	European Journal of Agronomy	Sugarcane irrigation	Australia	Seasonal forecasts	0-200$/ha	Quality of information; uncertainty on reliability; type of forecast

2.3 Behavioral approaches to uncertainty

In the words of Machina and Siniscalchi *"Almost by its very nature, the phenomenon of uncertainty is ill-defined"* (Machina and Siniscalchi 2014). This is clear after considering the number of theories developed to frame the problem; often one theory is in discordance with the other. In this chapter we aim at providing a short review of the major theories explaining decision making under uncertainty to build the context in which we will develop the modelling foundations to achieve our objectives.

2.3.1 Perceptions and attitudes

Decisions are affected by the DM's behavioral perspective with a relevant role played by attitudes toward uncertainty (Letson et al. 2009). In every decision under uncertainty, risk is involved and aversion to it might cause DMs to sacrifice part of their revenues to lower the variability of uncertain outcomes (Meza et al. 2008). This is confirmed by An-Vo et al (An-Vo et al. 2019) for the irrigating sector, where uncertainty leads to the implementation of inefficient precautionary actions. Information provision could lower the unpredicted climate variability and allow uncertainty averse DMs to relax protective actions and increase their expected utility. But this is not always true and, depending on the source, a new piece of information could even raise outcomes variability under the DM's perspective (Yokota and Thompson 2004). The topic of information implementation and aversion to uncertainty is widely debated in literature. Abbas et al. (Abbas et al. 2013) found that more uncertainty averse DMs will gain higher benefits in terms of utility from information, but this monotonous relation fails if the assumption of perfect information is released. A relevant contribution to the topic is given by Smith and Ulu (Smith and Ulu 2017) who showed a series of scenarios where uncertainty averse DMs did or did not seek for a new piece of information. He concludes that the relation between benefits from receiving a new piece of information and the degree of aversion to uncertainty is very situation dependent.

Besides attitudes toward uncertainty, the perception of uncertainty in itself is extremely important in affecting decisions for ICT adoption (Nesheim et al. 2017) and perceived uncertainty over forecasts reliability is found to be limiting information uptake (An-Vo et al. 2019). One strategy proposed to solve this uncertainty is in the estimation of the forecast reliability and in the incorporation of this information in the message itself (Kusunose and Mahmood 2016). This is commonly done with probabilistic climate forecasts, but still DMs could doubt on the probability estimation in itself. This explains one of the reasons why DM's beliefs are needed to be accounted for in decision analyses (Hardaker and Lien 2010). Nevertheless, in literature important challenges remain in understanding the role of perceptions and attitudes (Jeuland et al. 2018) and most of the studies in applied economics make relevant behavioral assumptions to overcome the issue (Bobojonov et al. 2016). This gap in applied economics motivated us to seek for theories in the broader economic literature to understand the problem.

2.3.2 Toward a framework for uncertainty modelling

To solve the relation between uncertainty aversion, perceptions and information implementation, a better picture of what uncertainty is built of is needed. Useful insights can be gained from decision theories developed in the economic literature and describing decision making under uncertainty.

The representation of preferences over uncertain actions meaning actions whose payoff is dependent on the emergence of uncertain states, is firstly addressed by von Neumann and Morgenstern (von Neumann and Morgenstern 1947). They developed the Bernoullian (Bernoulli 1954) concept of expected utility and outlined the dominant theory to describe attitudes toward uncertainty (Hardaker and Lien 2010). The theory is defined on the basis of the following four axioms:

- A1 – *Completeness*: every state of the world involved in a decision can be completely ranked.
- A2 – *Transitivity*: the property of transitivity holds for preferences for alternative states.
- A3 – *Independence*: preferences for alternative states are context independent.
- A4 – *Continuity*: preferences for alternative states are expressed on a nominal scale.

By holding these four axioms, a wide variety of utility functions have been developed in literature to represent DM's preferences under uncertainty (Hardaker et al. 2015). The common characteristic of all von Neuman-Morgenstern's utility functions is that concave functions represent an uncertainty aversion behavior, while if linear or convex, neutrality or love for uncertainty are modelled respectively.

With regards to the representation of perceptions over uncertainty, the first theory considered in this research is the one proposed by Knight (Knight 1921). He was the earliest who gave a complete picture of uncertainty. His main contribution was in distinguishing between: (i) measurable uncertainty, occurring when the statistical frequencies of events are known to the DM and (ii) un-measurable uncertainty when they are not. The former uncertainty was defined as pure risk, while the concept of un-measurable uncertainty remained unclear (Machina and Siniscalchi 2014). Even Knight in his work considered the fact that under un-measurable uncertainty DMs formed subjective "*probability estimates*" and treated them as risk. Accordingly, he postulated that "*there is no difference for conduct between a measurable risk and an unmeasurable uncertainty*".

The idea of subjective probabilities was further developed by Keynes (Keynes 1921) and Ramsey (Ramsey 1926) who both contributed to the formulation of the concept of *"degrees of belief"* representing the DMs' rational probabilistic estimation in condition of un-measurable uncertainties. Because they, and the vast literature following, recognized that most of the decisions were characterized by the absence of measurable frequencies; the concept of subjective probabilities had a large success. This is especially true after Savage (Savage 1954) built on it the theory of Subjective Expected Utility (SEU). Savage defined a theory of decision making under uncertainty characterized by preferences over acts with uncertain outcomes being compliant of 7 axioms, out of which the most studied ones are described as follows:

- A1 – *Complete ordering*: there is a preference relation over uncertain actions which is complete, reflexive and transitive.
- A2 – *Sure-Thing principle*: the preference relation over two uncertain actions is not affected by their payoffs in states where both actions have the same payoff.
- A3 – *State-wise monotonicity*: in a given state, one action is preferred to another if and only if their payoff is equally ordered.
- A4 – *Independence between payoffs and probabilities*: given preferences between payoffs, the choice between two uncertain actions is not affected by the value of the payoffs.

When representing choices under uncertainty, the SEU model developed by Savage allowed to distinguish between subjective probability and preferences. Often, these take the form of a von Neumann-Morgernstern's (von Neumann and Morgenstern 1947) utility function. The SEU generated from an action whose state-dependent payoff is $f(s)$, takes the following expectational form (Machina and Siniscalchi 2014) (Eq. 1):

$$V(f(s)) = \int_S u\big(f(s)\big) d\pi(s) \equiv \mathbb{E}_{\pi(s)} u \circ f(s)$$

Eq. 1

Where *S* describes the state space and elements of *S* (state of the world, $s \in S$) represent all the possible realizations of uncertainty; $u(\bullet)$ is a von Neumann-Morgenstern utility function and $\pi(s)$ is the subjective probability on *S*. The practical implication of the theory is that the DM builds probabilistic representations of states and uses these linearly by weighting uncertain payoffs. With the application of the theory, observed decisions under uncertainty can be used to assess DM's beliefs (Machina and Siniscalchi 2014). This is true even in presence of measured frequencies where the DM might doubt their reliability and assuming that they will represent future likelihoods is a subjective judgment per se (Hardaker and Lien 2010).

Despite the great success of SEU, there have been applications that showed some of its limitations. Between these, Allais (Allais 1953) highlighted that, even with objective lotteries, preferences are context-dependent and, in some cases, the von Neuman-Morgernstern's independence axiom did not hold. In turn, Ellsberg (Ellsberg 1961) showed exceptions of Savage postulates in describing perceptions. Finally, Kanemann (Kahneman et al. 1979), by developing prospect theory, presented that often both preferences and perceptions did not follow von Neuman-Morgernstern's and Savage's axioms respectively. Other theories describing perceptions and preferences have been developed in literature, but here are cited just the most significant for clear space limits.

2.4 Ambiguity and ICT-information implementation

Because every exception to the SEU theory tend to be specific to the uncertain prospect considered, in this work we believe that the settings described by Ellsberg (Ellsberg 1961) are the ones most powerful in representing the uncertainty environment affecting decision processes for ICT-information implementation. In the following sections we will briefly describe the theory of ambiguity developed by Ellsberg and the ample literature following him as well as the motivations which prompted us to argue that this theory can provide the foundations for developing a model to fill the knowledge gap around the drivers for ICT-information implementation.

2.4.1 The theory of ambiguity and ambiguity aversion

In 1961, during his PhD studies, Daniel Ellsberg reconsidered Knight's distinction of uncertainty. In his work he focused on un-measurable uncertainties to show important exceptions to the Savage axioms which impaired the capability of SEU to represent decisions. He considered a series of thought experiments, out of which, the most famous is the one involving two urns. There is a transparent urn with observable content of 50 red and 50 black balls and another opaque urn with the same amount of balls, but with unknown ratio between the two colors. While in the transparent urn the DM faces a situation of pure risk, because probabilities are observable and measurable; the bet in the opaque urn is different because such measurement is not possible. To describe the opaque urn's content (hence the probability of a specific ball's color) hundred combinations between red and black balls are possible. This raises uncertainty over which combination is the one really describing the urn's content.

In such settings, Ellsberg considered that most of the DMs would have preferred to place a bet on the ball's color from a draw in the transparent urn, instead of a draw from the urn with unknown balls' ratio. For a given prize in the bet, he proved that this choice cannot only be driven by a mere difference in subjective probabilities. Rather, the preference to bet on the transparent urn and, in general, the preference for gambles with known probabilities, is driven by a behavioral phenomenon called AA. The concept of AA is similar to RA, where ambiguity is identified as:

"*the nature of one's information concerning the relative likelihood of events... a quality depending on the amount, type, reliability and 'unanimity' of information, and giving rise to one's degree of 'confidence' in an estimation of relative likelihoods*." (Ellsberg 1961).

Or, in the words of Camerer and Weber (Camerer and Weber 1992), ambiguity is more clearly defined as "*uncertainty about probability, created by missing information that is relevant and could be known*". Overall, similarly to what Knight did, uncertainty is then characterized by two elements: (i) risk, represented by the share of measurable uncertainty or estimated trough subjective probabilities, and (ii) ambiguity, expressing the degree of confidence over these probability estimations.

Because ambiguity affects a large share of decisions under uncertainty, there have been several experimental studies showing its relevance in decision making. Results highlight that AA impacts are comparable with, if not higher than, RA (Cubitt, van de Kuilen and Mukerji 2018). Further, these studies showed that AA is the major preference behavior of DMs under ambiguity, because DMs dislike situations where more than one probability estimation is possible (Etner, Jeleva and Tallon 2012). The presence of ambiguity in probability estimations, even if subjective, is in itself an exception to the Savage's postulates. Moreover, AA implies that decisions do not only reveal subjective probabilities, but also relative preferences for expected outcomes. There are situations, such as in the urns' examples (and, as described later, in ICT-information implementation), in which we need to distinguish between the two elements of uncertainty to understand DM's behavior. In these situations, SEU models cannot be applied straightforwardly but ambiguity sensitive preferences have to be accounted for.

2.4.2 Ambiguity and ICT-information

The capability of the theory developed by Ellsberg to provide a complete picture of the elements building uncertainty explains its large adoption in different decision problems (Machina and Siniscalchi 2014). In the majority of decisions, DMs have to cope with a certain level of risk and ambiguity. The latter expresses the degree of confidence the DM puts on the former (Visschers 2017). This situation is typical with decisions under CC (Koundouri et al. 2017). Here, probabilistic distributions built with past records are doubted to be representing future climate trends and different models propose different projections. Ambiguity can be found in climate forecasts too. Uncertainty in forecasts is characterized by two elements: (i) the intrinsic variability of climate events, represented by probability distributions and (ii) the uncertainty about the forecast itself (World Metereological Organization 2015). The first uncertainty can be expressed as risk, over which, the second uncertainty emerges because the DM does not know whether the forecast is reliable. This lack of knowledge raise ambiguity because several forecasts could be delivered and the DM is not sure whether the one received is really representing future states. One common way to deal with such complex uncertainty settings in forecasts is through *uncertainty folding* (Allen and Eckel 2012). It consists in *folding* ambiguity with risk to obtain a single probability estimate used as input in SEU models. Though the method is quite simple, it has been shown by Allen (Allen and Eckel 2012) to fail in representing real decision making with important informational losses.

As with forecasts information, ambiguity rises even with the adoption of new technologies (Engle-Warnick and Laszlo 2017). When a DM is faced with a new technology, he is uncertain on the probability of such technology to be good performing. In this context, even if the DM has expectations or information from the developer, neither of the two probability estimations can be reliably assessed. As a result, in the first stages of a new technology, AA has the potential to strongly limit its diffusion. Only after having gained enough experience with the new technology, prior expectations can be confirmed or rejected and ambiguity solved in a learning process (Barham et al. 2015). Most of the applied economic literature consider ambiguity generated by new technologies to be risk, thereby losing precious DM's behavioral insights (Ross, Santos and Capon

2012). If risk and ambiguity are treated as one, risk-averse and ambiguity-averse DMs would behave equally. Both would be less prone in experimenting new technologies or implementing new forecast information, but this does not always happen. A new technology could be risk-reducing but ambiguous, or the opposite, it is possible to gain information reducing ambiguity but not risk (Nocetti 2018). In this complex framework, Snow (Snow 2010) defined the relation between information value and AA, where information reducing ambiguity is always sought by AA individuals, and the benefits from its implementation rise with the degree of aversion. The same applies with information reducing risk and RA. But while information solving ambiguity is valued only by AA DMs, if information solving risk completely disclose states of the world, its benefits rise with both AA and RA (Snow 2010). These phenomena are extremely important in the context of new technology adoption. If a new technology reduces the variability of outcomes, it is risk-decreasing but, as said before, it might raise ambiguity. Here, RA plays in favor of the technology, while AA might limit its implementation.

2.5 Discussion: lessons learned from literature and implications for further research

The complex nature of uncertainty has been widely analyzed in the economic literature's history. In the previous sections we have considered just a small share of theories developed to better understand the various behavioral aspects of decision making under uncertainty. Between these, the one of AA is considered the most useful to understand the behavior of forecast implementation (Allen and Eckel 2012) or new technology adoption (Barham et al. 2014). Innovative technologies are frequently raising ambiguity either because the probability of a good performance is uncertain or, as in the case of ICT-climate-information, because they provide probabilistic information whose reliability is unknown. A new platform developed to deliver climate forecasts to DMs can be considered risk reducing because it lowers the variance in the upcoming climate states' distribution. If so, it is always positively valued and implemented by RA DMs, given technical barriers are overcame. All the same, the DM does not know if the platform (hence the piece of information received) is reliable. This might raise ambiguity and is discouraging AA individuals to implement ICT-information until they do not gain enough information, or even better experience, on the technology's reliability. Accordingly, with experience the DM would learn if the technology is reliable and solve ambiguity (Gars and Ward 2019). The phenomenon is identified as familiarity with a technology and might allow AA individuals to implement information received. While risk is often intrinsic to the technology and can hardly be modified, by providing ambiguity-reducing information or allowing DMs experience with the ICT, even AA individuals might find benefits from information.

The approach proposed to deal with uncertainty in ICT adoption is expected to be capable of providing the required framing for applied models aiming at further deepening the issue of low ICT-information implementation. The main limitation of the results of this review is in the absence of a practical example with which to test the framework developed. Further research is suggested on the topic, especially focusing on modelling application of ambiguity sensitive preferences. In this field, theoretical alternatives are proposed (Machina and Siniscalchi 2014). Between these, the smooth ambiguity model developed by Klibanoff, Marinacci and Mukerji (Klibanoff, Marinacci and Mukerji 2005) is considered the best performing in accounting for AA and RA behavior (Machina and Siniscalchi 2014). It allows the separation between perceptions and attitudes, both with reference to risk and ambiguity. This would permit comparing the condition of ICT-information implementation when the DM is uncertain on its reliability and after he has gained enough experience on the technology's reliability. In such settings, uncertainty will be firstly made by risk and ambiguity, then, with experience, ambiguity vanishes, and risk remains unaltered.

2.6 Conclusions and policy implications

In this chapter we started underlining the need for climate information to favor irrigated agriculture in CC adaptation. At this end ICTs are recognized to be one of the most promising tool to aid the sector (H. de Coninck et al. 2018). Through a brief review of applied economic studies, we highlighted a lack of success of many ICT-development initiatives (Vogel et al. 2017). Technical barriers undermine information implementation and benefits from ICT-aided decision processes are unclear and extremely variable. This poses constraints for ICT development and growth because investments are not easily justifiable and returns doubtful (Jeuland et al. 2018).

Other than technical barriers, one of the major issues highlighted in both qualitative and quantitative studies is that new ICT platforms generate uncertainty on information reliability. Because of this, DMs' behavior appears to be strongly limiting ICT-information implementation, but the topic remains to be deepened. Accordingly, we found no study in the applied economic literature to be addressing this issue and providing the needed theoretical support to model behavior in ICT-aided decisions. To face this problem, we sought for support in the wider economic literature. Here, many theories have been developed, but the one considered to best fit with our uncertainty settings is the one of AA developed by Ellsberg (Ellsberg, 1961). With it, we framed uncertainty and explained why ambiguity and AA are key elements in describing the issue of low rates in new ICT-information implementation. Our approach is different from most of applied studies where RA is considered to be the only behavioral driver for technology adoption and different sources of uncertainty are treated indistinctly. Because ICT are peculiar technologies providing information capable of reducing risk but raising ambiguity, AA need to be analyzed to better explain the process of ICT-information implementation. Accordingly, since the reliability of new platforms is uncertain, an AA behavior can impede DMs in implementing ICT-information. Key role is played by a DM experiencing with the new technology without necessarily need to buy information received or put information into actions at his own risk. This would help WAs or farmers to learn whether the ICT provided is reliable or not, therefore reducing or solving ambiguity.

What we have learned on how ambiguity enters into ICT-information uptake in irrigated agriculture is of strong policy relevance too. Accordingly, to be able to implement optimal strategies for ICT development and adoption, it is important to understand how DMs perceive new pieces of information (Visschers 2017). ICT developers should favor the involvement of end users and offer long trials or demonstrative events rather than a plug and play approach. Having hands on the platform, without necessarily implementing its information at DM's own expenses, allows users to gain experience on ICT reliability. This would lower ambiguity and potentially foster the diffusion of ICT-information implementation. If applied studies will find that ambiguity affects decisions, policy should aim at ensuring DMs have access to ambiguity-reducing information on the technology's performance (Ross et al. 2012). Further, better knowledge on the impacts that behavior has on ICT adoption would support uncertainty-management policies. If ambiguity is prevailing over risk, demonstrative initiatives and extension services addressed to show ICT reliability will better help DMs than ex-post risk management tools.

The above described policies call for two kinds of model applications: one is related with the estimation of potential ICT-benefits; the other with the assessment of impacts of AA in the process of ICT implementation. If research will be developed in these ways, it will provide the evidences needed by policy makers for effective support to the sector. On the one hand, assessments of potential ICT-benefits would allow DMs being less doubtful on the economic performances of ICT tools for irrigated agriculture. These would help investments for ICT development and adoption, overall facilitating the transition from precautionary decisions based on experience to ICT-supported irrigation plans. Further, empirical assessments would allow to highlight restrictions for information usability which undermine ICT-benefits. This would support ICT-developers in targeting technologies to fit end users' informational needs. On the other hand, because in this transition AA has the potential to undermine information implementation, the impacts of DM's behavior must be assessed. Here, better insights on the behavioral perspective affecting ICT adoption would highlight the critical issues in the decision system to be targeted with ambiguity-management policies. On these two modelling developments will focus the following Chapter 3 and 4, where, respectively, we will develop a model to assess ICT benefits at the WA-level and a model to estimate the impacts of AA in the process of ICT implementation in irrigation districts.

Chapter 3

3. The role of ICT in improving sequential decisions for water management in agriculture[1]

3.1 Introduction and objectives

For the management of water resources, WAs have to take decisions before knowing the weather conditions they are going to face. The high variability of weather patterns increases the level of uncertainty regarding future weather conditions causing a moving-target problem. In it, every year, due to CC, WAs are less and less able to take decisions consistent with the weather pattern of the following season due to the decreased predictability of events and to the less and less relevant use of past records to take future decisions. As a consequence, current water management decisions are often a compromise between the outcome determined by all the weather states that could emerge. Such compromise is balanced to the selection of less risky decisions instead of the decision that is best suited for the state that will emerge (Meza et al. 2008). As a consequence, WAs' take sub-optimal decisions, with negative impacts on profits and water uses (Hallstrom 2004). In this respect the availability of ICTs might contribute on mitigating the moving target problem by providing timely information on future climate and weather conditions, thereby reducing uncertainty before and during the irrigating season (Fernandez et al. 2016). Overall, the ICT-informed decision process of water management could help irrigated agriculture by reducing losses from climate shocks and taking advantage of favorable years (Deichmann, Goyal and Mishra 2016; Guerra et al. 2017).

These potentialities of ICTs for irrigation management together with the uncertainties on ICT benefits highlighted in 0 motivated our study. The objective is to address the issues of restrictions to information usability and quantitatively estimate economic benefits from the ICT-informed decision process of water management in agriculture at the WA-level. In this respect, a theoretical

[1] Published paper

model is designed based on insights from the BDT. It assesses the economic benefits brought by new pieces of information, influencing WA's perception of uncertain events with direct consequences on its strategic decisions. Specifically, the model investigates the role played by information in supporting WAs to rationalize the management of water resources and the prevention of extreme weather events impacts. Because decisions on land and water allocation are sequential across the season and influenced one by the other, the methodology accounts for the passing of time in the decision process to assess how the time of information provision affects its usability. An empirical application is also provided to test the model by comparing current information tools with a new information technology developed in the MOSES H2020 European project.

Developing and applying a method to assess the economic value of ICT seems to be an interesting topic for agricultural and resources economists (Tyrychtr et al. 2016). Moreover, considering the growing societal demand for climate services together with the limited budget availability (Vogel et al. 2017), this topic is of high policy relevance. The novelty of the present paper is twofold, both in the theoretical model and in its empirical application. To the best of author' knowledge, the former stands out from the existing literature for considering the timing variable in sequential and inter-correlated decision steps. The empirical application of the model is also original: to the best of author' knowledge no economic research deals with ICT adoption by WA for the management of irrigation.

The remainder of the chapter is organized as follows: in Section 3.2 we review the recent literature on the assessment of ICT; in Section 3.3 we describe the case study; in Section 3.4 we define the methodology and the empirical implementation; in Section 3.5 we show our main results; in Section 3.6 we discuss the main findings and in Section 3.7 we draw final remarks.

3.2 State of the art

In agriculture, numerous ICTs have been developed and disseminated (Aker et al. 2016). Great potential is found for such technologies in contributing to food security and climate change adaptation in the agricultural sector (Vogel et al. 2017; Nakasone and Torero 2016). Qualitative studies showed their potential benefits for both developed and developing countries (Martin 2016). Among these, Deichmann, Goyal, and Mishra (Deichmann et al. 2016) identified the following: (i) promoting economic performance, (ii) raising efficiency, and (iii) fostering innovation. Nevertheless, Aker et al. (Aker et al. 2016) suggested that ICTs impacts on decisions outcomes are highly variable. One reason of this variability lies in the findings of Nakasone and Torero (Nakasone and Torero 2016); according to them, ICTs are successful only when key information needs are addressed. In addition, many ICT projects do not reach the expected success because developers take for granted information to be useful (Vogel et al. 2017). As a consequence, ICT developers tend to poorly consult end users on their information requirements and the resulting ICT may turn out to be inapplicable in their decision process. Quantitative analyses bring to similar conclusions. Accordingly, Macauley (Macauley 2006) finds that information services are useless if the WA do not need the information provided. To measure ICT benefits, Macauley treats information like other production factors, with both a value and a cost (Macauley 2006). According to him, Keisler et al. (Keisler et al. 2014) defined the Value of Information (VOI) as an increase in the Expected Value (EV) of the decision outcome arising from the introduction of a new piece of information in the decision process. Quantitative analysis determined the VOI not only by accounting for the characteristics of the information provided, but also for the environment in which decisions take place (Meza et al. 2008). The elements characterizing information and determining its value are:

a) content of information: the WA must be able to implement the additional information in the decision process; if the WA is not able to act upon information, it has no value for it;
b) accuracy of information: the more accurate information is, the smaller will be the risk of failures and the higher the VOI; imprecise information is not capable of inducing any change in WA beliefs;
c) timing of information provision: information must be provided at the right time in the decision process; late messages have no value.

The timing factor (point c) plays a key role in influencing the accuracy of information (point b). Usually, information provided well in advance to the occurrence of an event might condition strategic decisions, but it will not be so accurate. If information is provided with a short advance, the decisions influenced by information will not be so strategic, but the information will be likely more accurate. This is typically the case of emerging information, as weather forecasts. Waiting to get more precise information about the occurrence of events has a cost (Smith and Ulu 2017). The cost of waiting is often identified with losses due to sub-optimal decision performances (Bikhchandani, Hirshleifer and Riley 2013). Taking into account such timing element adds complexity to models. Nevertheless, it leads to results more reliable than those coming out from analyses that ignore this important factor (Hardaker et al. 2015).

Some parameters of the decision environment are capable of affecting the VOI too; among these, the following can be identified as the most important (Bikhchandani et al. 2013):

a) uncertainty in the decision process: the higher climate variability is, the higher will be the benefits brought by information;
b) the stake in the decision: the higher is the variance of decision outcome the more the WA will be willing to use information for reducing uncertainty.

As a result, each element characterizing information or the decision environment have the potential to set the VOI to zero (Crean et al. 2015). For these reasons, the evaluation of investments in ICT must go beyond the traditional analysis of costs and revenues by accounting for the peculiarities of the VOI. To do so Bouma (Bouma et al. 2009) applied BDT to model the VOI from imperfect satellite-based technologies. According to them, Hardaker and Lien (Hardaker and Lien 2010) in their literature analyses found BDT a suitable tool to model decision making under uncertainty. Finally, Galioto et al. (Galioto et al. 2017) measured the VOI deriving from sensors adopted in precise irrigation technologies through a model based on the framework of BDT.

3.3 Case Study

3.3.1 Description of the case study area

The WA selected as case study is a reclamation and irrigation board named Consorzio di Bonifica della Romagna (CBR) and located in northern Italy. It covers 352,456 hectares out of which around 165,000 hectares are cultivated (1.2% of the Italian cultivated land). Although the basin includes plain, hilly and mountain areas the case study region is centered on irrigation districts situated in plain areas (Figure 2). Here the landscape is characterized by a dense irrigation network, where the majority of water delivery infrastructures is made by open-air canals. In the basin 4.8% and 1.4% of the Italian fruits and vegetables are respectively produced, generating an estimated revenue of around 700 million euros per year. The climate of the region is continental (summer maximum temperatures above 30 °C), mitigated by the sea influence in the North-Eastern part. Drought events are frequent in summer with a variable intensity. Although the total amount of rainfall appears to be stable (750-850 mm), in the last few years it was recorded a change of the rainfall distribution. Specifically, it was noticed an increased frequency of heavy rainfall events alternated with longer periods of severe droughts characterizing a dry irrigating season.

The case study region is selected because its decision process for water management is representative for other WAs located in Mediterranean countries where climate uncertainty strongly affects decisions for land and water allocation before and during the irrigating season. Further, the prevalence of open-air canals in the water delivery network enhances both the challenges and the potentialities of ICT adoption at the WA level. Accordingly, with canals technical barriers require the WA to anticipate decisions, making forecasts more needed compared to similar conditions with pressurized pipe networks. Finally, the CBR's management board is considering adopting a new information service named MOSES and developed in the framework of the MOSES H2020 European project, recently introduced to fulfil WA's requirements.

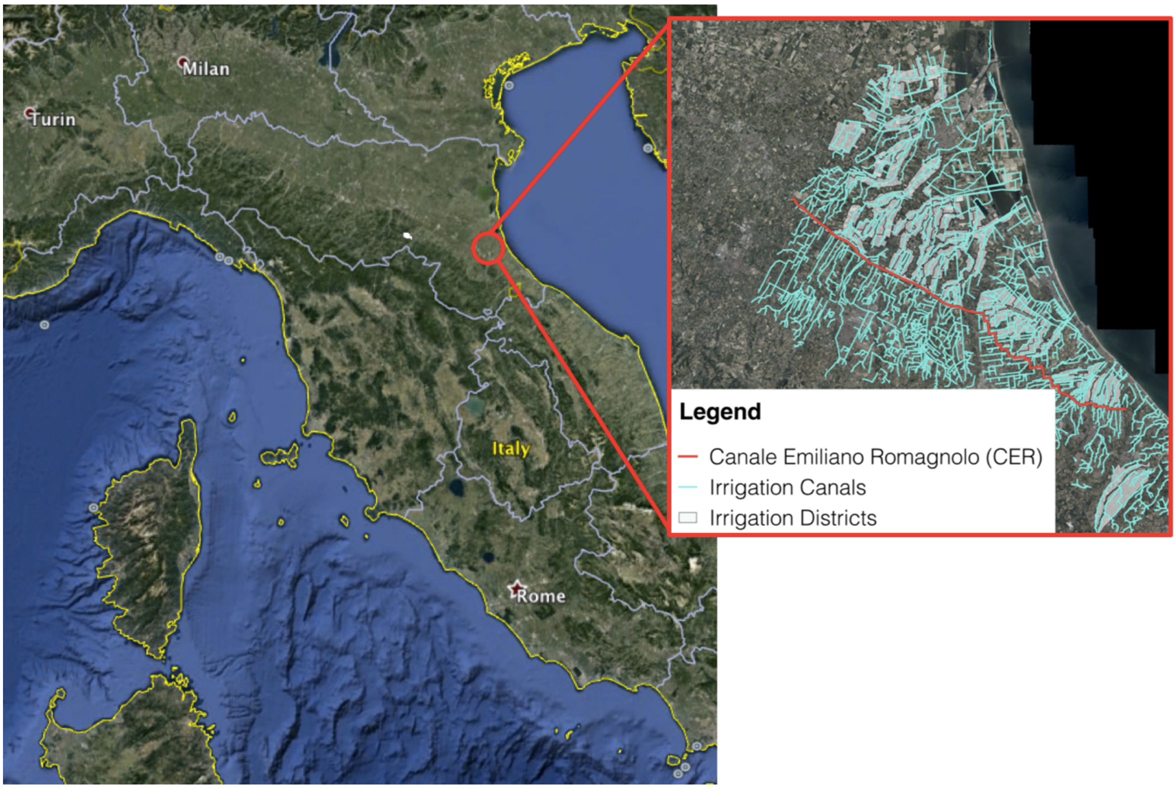

Figure 2: Case study region

The predominant water source for irrigation is the Canale Emiliano Romagnolo (CER). The CER is an open-air canal which diverts part of the water from the Po river to several irrigation boards. The irrigating season generally takes place from May to September. However due to yearly variability it can be anticipated or delayed. Peaks in water delivery are in June and July, when crop water demand is higher. The operational unit at which decisions on water management are taken is the irrigation district. The basin of the CBR counts 81 irrigation districts located in a plain area. The average irrigated area is 68 hectares per district and the average length of the water delivery network is 6Km per district. To verify the usability MOSES services, the WA decided to narrow down the scope of investigation to a sub-group of its districts. Specifically, the WA selected only 32 of the 81 districts covering an area of 18,845 hectares out of which 6,012 hectares are cultivated. Such districts have the common characteristics of a unique water source (represented by the CER) that is managed on demand, and of an irrigation network characterized by open-air canals. On average the irrigated land is around 2,878 hectares, 48% of the cultivated land (Figure 3). This area corresponds to the land that can be irrigated in conditions of average operational capacity of the water supply network. However, in regular seasons the network reaches its maximum operational capacity being able to satisfy the demand from irrigated crops for around 3,741hectares (130% of the average operational capacity). On the other hand, in dry seasons, the water supply network reaches its minimum operational capacity and the WA is able to satisfy the demand for irrigation for 2,014 hectares (70% of the average operational capacity). Despite the fluctuations in rainfall patterns, the land use tends to be constant, where winter crops are prevailing (wheat, barley and meadow), followed by perennial crops (alfalfa, orchard, vineyard) and summer crops (maize and sorghum). The irrigation activity is centered around maize, orchard, vineyard and horticulture; winter crops are generally not irrigated, while other crops such as sugar beet and alfalfa are occasionally irrigated.

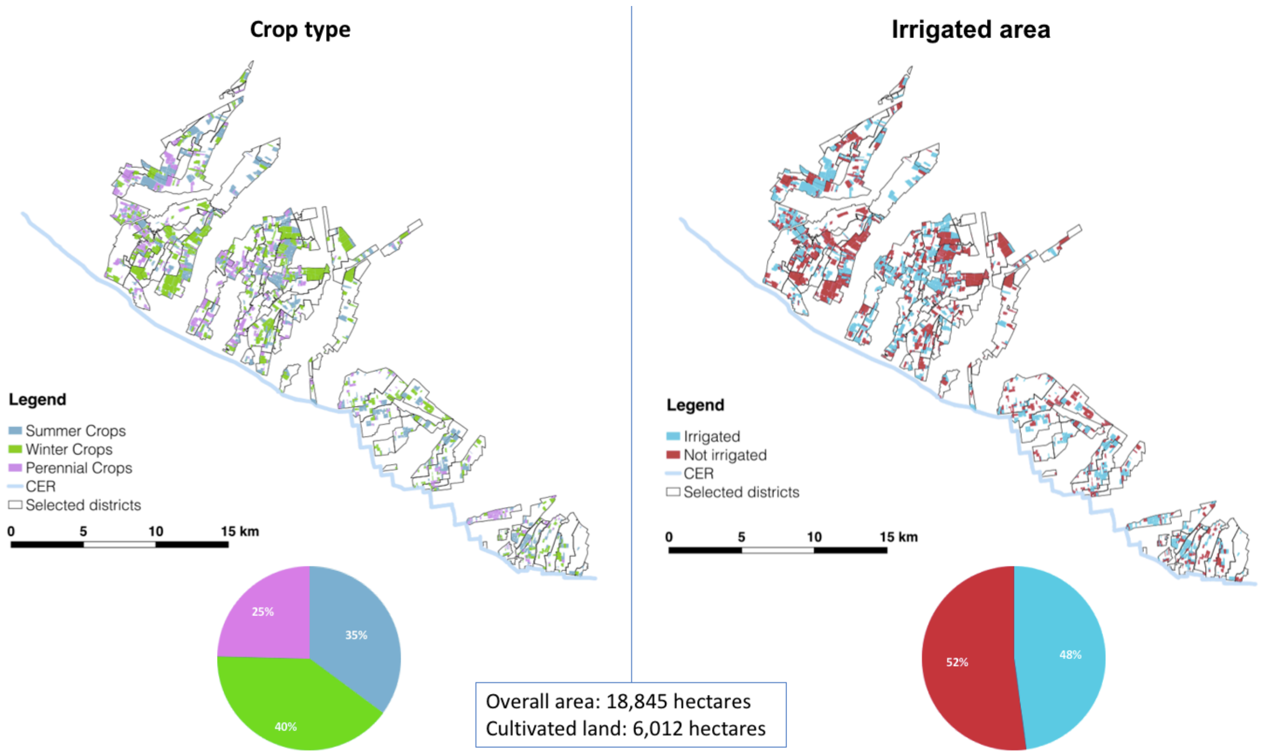

Figure 3: Land use in the case study region

3.3.2 Management systems and information requirements

Before the irrigating season, the WA decides about the amount and allocation of yearly concessions to cultivate annual irrigated crops. Concessions to irrigate permanent crops are granted for the whole lifespan of the plantation. The decision on the amount of yearly concessions to irrigate is taken at the time of seedling/transplanting annual irrigated crops, usually in April. Typically, the WA forbids concessions to latest applicants if the demand for concessions exceeds the average operational capacity of the supply network (6,012 hectares). Under conditions of uncertainty regarding the rainfall pattern of the upcoming season, this decision is the best compromise between releasing concessions to the maximum or to the minimum operational capacity of the supply network. During the irrigating season and in each sector of the agricultural region supplied, the WA has to plan with some advance (let's say one week) whether to deliver water to a sector or not. This is typically the case of surface irrigation networks supplying water to an extended agricultural region. In such conditions, variations in the flow of water downstream the network occurs with some delay with respect to upstream variations in water flows. Thereby, under uncertain weather conditions, usually, WAs decide to supply water on the basis of fixed flow rates varying with the season and consistently with the average climatic condition of the region and with the amount of concessions provided.

Under this framework, the WA is considering the possibility of using MOSES service to improve its capacity to condition and to satisfy the demand for water to irrigate. Specifically, the WA is interested in knowing the average weather conditions for the upcoming season at the time of seedling/transplanting and short-term forecasts about irrigation requirements in each sector of the region served by the WA during the irrigating season. The first piece of information might influence the WA's decision on providing concessions to cultivate irrigated crops, reducing the risk of making wrong choices. If a dry season is forecasted, the WA might decide to limit the number of concessions to the minimum operational capacity of the supply network. Otherwise, if a regular season is forecasted, the WA could set the limit of concessions to the maximum capacity of the network. The second piece of information would allow the WA to know whether to deliver water in each sector of the network enough in advance to take timely actions, adjusting water flows with the demand. Thus, this additional piece of information might influence the WA decisions on changing the management of the supply, improving the efficiency of the supply network. However, because of technical barriers the WA must guarantee a threshold of minimum flow in the main canal for each district to allow an even water distribution. This condition does not allow the WA to effectively manage water supply volumes and limits its capacity to save water when the demand for water is low.

3.3.3 Usability of the MOSES information service

MOSES provides spatial-detailed information to WAs both before and during the irrigating season. In the first case, information is a seasonal forecast of weather conditions and crop water requirements. In the second case, MOSES delivers every day a seven-day forecast of crop water requirements and weather forecast. To produce such information, MOSES combines, as input, crop maps determined with satellite images, crop transpiration models, climate data and weather forecast information. Specifically, with crop maps, crop water requirements are estimated and forecasted in each plot using crop models with input from climate data and weather forecasts.

As seen in the previous section, MOSES predictions before the irrigating season are likely to be used to manage yearly concessions to irrigate. In the current condition, the WA fixes concessions to irrigate to the average operational capacity of the supply network. With MOSES services, if a dry season is forecasted, the WA would limit the number of concessions to the minimum operational capacity. Otherwise, in view of a regular season it will release more concessions, up to the maximum operational capacity. Hence, the decision due is binary: to limit concessions to the maximum operational capacity or to the minimum operational capacity of the water supply network. The benefits generated are of avoided drought losses if the dry season occurs or of higher agricultural revenues in case of regular season. Nevertheless, information is not perfect, and two types of errors can emerge:

1. the wrong prediction of a regular season: the WA receives a message specifying a regular season will emerge, but eventually the season will be dry;
2. the wrong prediction of a dry season: the WA receives a message specifying a dry season will emerge, but eventually the season will be regular.

The above errors lead to higher or lower concessions than the ones actually possible causing a sub-optimal use of land. If the number of concessions exceeds the contingent capacity of the WA, as a consequence of error 1, farmers would experience a loss given by the difference between the average income of rain-fed crops and irrigated crops with no irrigation water availability. It can be expected that rain-fed crops have a higher comparative performance in terms of income in case of low or no irrigation water availability. If the number of concessions is below the capacity of the WA as in the case of error 2, farmers would experience a loss that is given by the difference between the average income of irrigated crops with fully available water and rain-fed crops.

MOSES forecasts during the irrigation season are likely to be used to support decisions on water allocation. Because of the fixed water flows and technical thresholds, water allocation decisions are binary: to deliver water to a district or not. Such decision is repeated daily during the irrigating season and for each irrigation district. Compared to the current condition where the WA delivers water to districts disregarding the demand, predictions of crop water requirements could support decisions on water allocation during the irrigating season. The potential benefits generated by this piece of information are: save water, lowering supply costs, allocate water efficiently and softening damages in dry periods. Here again, the provided information is not perfect, and two type of errors can emerge:

1. the wrong prediction that water requirements are above 0: the WA receives a message specifying that water is needed for irrigation in a specific sector of the network, but eventually water for irrigation is not needed;
2. the wrong prediction that water requirements equal 0: the WA receives a message specifying no water demand for irrigation in a specific sector of the network, but eventually water for irrigation is needed.

The above errors lead, respectively, to water flows or no water flows in sectors where respectively no water is needed, and water is needed. This causes a sub-optimal use of water, where the first error leads to water waste (measured by the amount of water actually distributed in the sector) with unnecessary supply costs. The second error leads to damage irrigated crops because of missing to deliver water when water for irrigation is actually needed (difference between the average income of irrigated crops with irrigation and irrigated crops with no irrigation).

The whole decision process is represented in the decision tree of Figure 4. Decision alternatives branch form square nodes; the probabilities of uncertain events branch form round nodes and consequences of actions in states of the world are expressed in terminal nodes with prisms. In the two decision time steps (before and during the irrigating season) information is provided through a message. This might cause a revision of WA's beliefs depending on the expected consequences associated to each message content and on the accuracy of the ICT. The decision process is made by two sequential binary decisions: to release concessions to the maximum operational capacity or to the minimum operational capacity of the water supply network and to deliver water to a district or not. The decision made in the second step is influenced by the expected consequences of that decision during the irrigating season and by the accuracy of the messages provided before the irrigating season. That implies a strict dominance of the accuracy of the messages provided in previous time steps on subsequent ones.

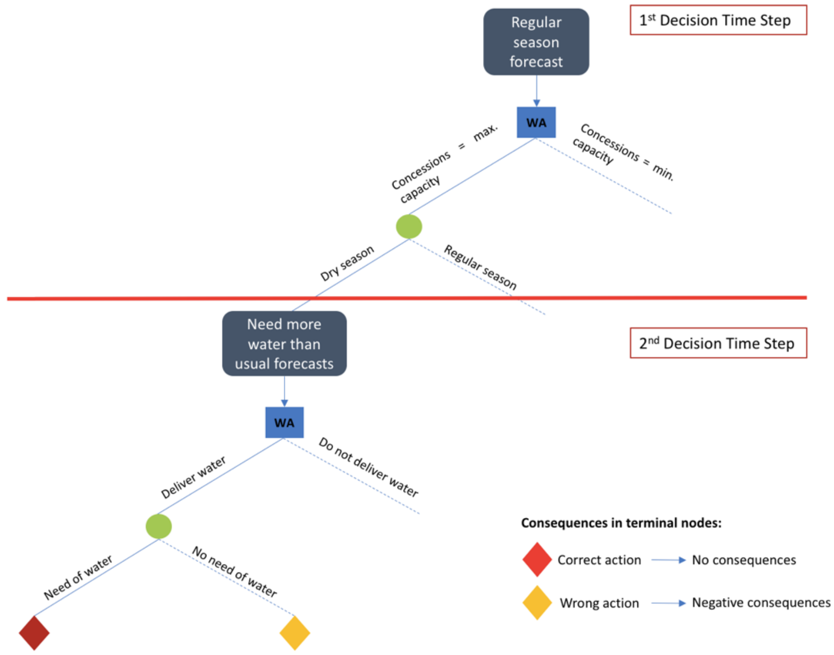

Figure 4: Decision process of MOSES adoption by the CBR (source: own elaboration)

3.4 Methodology and empirical application

3.4.1 Definition of the model

The methodology adopts a simplified decision model to represent the decision-making process of the case study WA to select the best alternative among a set of actions upon receiving new information. The model assumes that a WA is managing water procurement and supply for a given agricultural region and that the WA must plan in advance some actions during two different inter-correlated decision time steps. The first decision step is supposed to be at the time of seedling transplanting, far in advance to the irrigating season, and involves the decision (action): release concessions to the minimum / maximum operational capacity of the supply network. Such decision is conditioned by the WA's expectation about the occurrence of the states of the world (states, from now on): dry / regular season. The second decision step is supposed to be at the time of supplying water for irrigation and involves the decision: deliver / do not deliver water to irrigation districts. Such decision is conditioned by the WA's expectation about the occurrence of the states: need / no need water for irrigation. In a chronological order the first decision influences the second. Thus, the usability of such information is then depending on the accuracy of the messages provided by the information service in both decision steps and on the stakes in the decisions, contributing in determining the expected consequences of using the information. In the following we provide an analytical representation of the decision process both in case of un-informed decisions and ICT-informed decisions. In the latter case, in each decision time step, a new piece of information is provided by a message.

The decision model described above represents a decision process taking place in conditions of uncertainty. In the first place, we assume that the decision process involves a set of actions, X, and a set of states, S. The combination of the possible actions with the possible states determines the associated consequences, $c_{x,s}$ measured in terms of economic payoff of the decision, $v(c_{x,s})$. The subscript x denotes a specific action among the set of possible actions and the subscript s denotes a specific state among the set of possible states, where $x \in X$ and $s \in S$. For example, the consequence of not limiting yearly concessions for irrigable areas in a regular season is of drought losses and the associated payoff is the economic estimation of such losses. Thus, the actions taken by the WA have uncertain consequences determined by probability of occurrence of upcoming states, π_s. In our case, the probability coincides with the climate-relative frequency of the event. Assuming the WA is acting rationally, it will base the choice of an action on the concept of EV maximization. EV of an action depends on the probability of the different states and on the payoff of the set of possible actions under the different states of the world (Bouma et al. 2009). With no information service, the maximization of the EV is obtained by the following equation (Eq. 2):

$$\underset{(x)}{max} EV(x, \pi_s) = \sum_s \pi_s v(c_{x,s})$$

Eq. 2

In case of ICT adoption, the WA can receive a message, μ, among a set of messages, M ($\mu \in M$) The probability of receiving message μ is identified as π_{μ}, which is measured as the frequency of that message relative to all messages delivered by the ICT. Messages provide information regarding the emerging states of the world. For example, a message can specify that a dry season will occur. Messages might modify the WA's information environment altering the expectations associated to the upcoming states of the world. The extent to which the WA reviews his prior expectations follows the Bayes Theorem and is measured by the probability of state occurrence conditional to the message received, $\pi_{s|\mu}$, also known as posterior probability (Eq. 3):

$$\begin{cases} \pi_{\mu|s} \equiv \dfrac{j_{s\mu}}{\pi_s} \\ \pi_{s|\mu} \equiv \dfrac{j_{s\mu}}{\pi_\mu} \end{cases} \qquad \Rightarrow \qquad \pi_{s|\mu} \equiv \pi_s \frac{\pi_{\mu|s}}{\pi_\mu}$$

Eq. 3

Where $\pi_{\mu|s}$ is the probability of receiving message μ, conditional to the emergence of state s, and $j_{s\mu}$ is the joint probability of state s and message μ, also known as hit rate (Kusunose and Mahmood 2016). This is measured in a likelihood matrix by the frequency of correct messages on all messages delivered by the ICT. As can be noticed, the higher is the hit rate of the ICT, the higher will be the extent to which the WA will revise is prior expectations. This implies that, by means of the accuracy of the ICT, the WA revises its beliefs about states occurrence after receiving a message. This in turn will have an effect on expectations about decision outcomes with direct consequences on the choice of actions, allowing the WA to identify a new optimal action. The EV of this action after receiving a message is determined by the sum of payoffs weighted by the unconditional probability of the message and the respective conditional probability of the states. Considering an ICT delivering multiple messages, the maximization of the EV will be as follows (Eq. 4):

$$\underset{(x)}{max} EV\left(x, \pi_{s|\mu}\right) = \sum_{\mu} \pi_\mu \sum_{s} \pi_{s|\mu} v(c_{x,s})$$

Eq. 4

Now, consider a simplified version of the model described above, with only two alternative states ($s_1$and s_2), two alternative actions (x_1 and x_2) and one decision time step. This model can be represented through the diagram of Figure 5. In it, payoffs in each state are measured vertically and probability horizontally, ranging from zero to one in a bi-directional segment. Since states are alternative, meaning that one excludes the other, probabilities of state occurrence are complementary ($\pi_1 + \pi_2 = 1$). Hence, a point along the segment represents both probabilities. In the diagram, the blue line joining $v(c_{s1x1})$ and $v(c_{s2x1})$ is the probability weighed average of payoffs for action x_1. This line expresses the EV for that action as a function of probabilities. Similarly, the pink line, which joins $v(c_{s2x2})$ and $v(c_{s1x2})$ represents the EV of action x_1 for any probability distribution. For a given probability, the EV of the optimal action is displayed by the vertical distance from a point in the horizontal segment of probabilities to the higher EV function between x_1 and x_2. Taking into examination an information service that can generate two alternative messages (μ_1 and μ_2), either message will lead to a vector of posterior probability, $\pi_{|\mu} = (\pi_{s1|\mu},\ \pi_{s2|\mu})$. The line joining the EV of the optimal action if μ_1 is received and if μ_2 is received, defines the EV of the message service. This is mathematically represented by the probability weighted average of payoffs. So, following Eq. 4, the VOI is graphically represented by the vertical distance from the line of the EV of the message service to the EV of the best un-informed action (green segment in Figure 5).

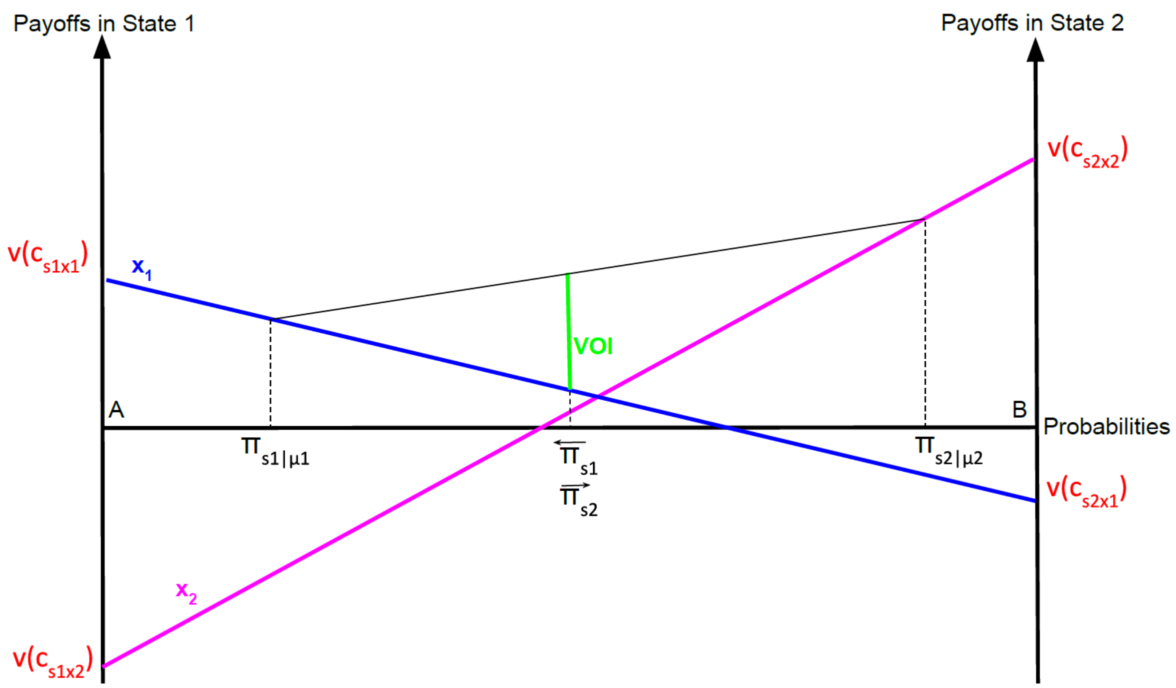

Figure 5: Graphic representation of the decision model after receiving a new message

Source: own elaboration from Bikhchandani et al. (Bikhchandani et al., 2013)

Finally, we take in exam a decision problem involving T decision time steps. Decision steps are identified as sequential decisions occurring during time (before and during the irrigating season). For each decision step, t, there are independent actions, x_t, messages, μ_t, and states, s_t The set of possible consequences is obtained with the combination of actions and states in each time step, t, for the subsequent combination till the final decision step. In other words, the combination of actions, states and decision steps allows to identify the range of final outcomes of the decision process. Since decision steps, states and messages are independent, the expected value maximization problem can be reformulated as it follows (Eq. 5):

$$\underset{(x_{\mu t})}{max} EV\left(x_{\mu t}, \pi_{st|\mu t}\right) = \prod_{t} \left[\sum_{\mu t} \pi_{\mu t} \sum_{st} \pi_{st|\mu t}\right] v(c_{x_{\mu t},st})$$

Eq. 5

Hence, during time in the decision process, the final choice of actions made by the WA depends on the accuracy of the messages received until the final decision step. This way, a lack of accuracy in the first messages has a multiplier effect in determining the expected consequences of sub-sequential actions. Finally, in each decision step and for each message received the WA seeks the optimal choice of actions among the available. This is done through the identification of the optimal informed action ($x_{\mu t}^{*}$) achieving the highest EV given the states that can emerge and their relative posterior probabilities. The same happens in un-informed conditions, where, given the prior probabilities of states, the WA identifies the optimal un-informed action in each decision step (x_{0t}^{*}). After optimizing action choices, the VOI can be estimated as the difference between the EV from the sequence of optimal informed actions given the messages received and the EV of the optimal un-informed actions given the prior information environment (Eq. 6):

$$VOI = EV\left(x_{\mu t}^{*}, \pi_{st|\mu t}\right) - EV(x_{0t}^{*}, \pi_{st})$$

Eq. 6

As can be seen, the VOI of the ICT is positive only when the expected value of the best informed-decision is higher than the EV of the best un-informed decision. That is when posterior probabilities of the states given messages are higher than a threshold value that is at some point up to their prior. Otherwise messages would be uninformative, not conditioning any appreciable change in the behavior of the WA.

3.4.2 Data collection and assessment procedure

The usability of the information service is depending on the accuracy of the messages provided by the information service itself and on what is at stake in the decisions. These elements contribute in determining the expected consequences of using the information. The sources of information needed to carry out the economic analysis are mainly based on: (i) information obtained by interviewing the WA; (ii) information provided by MOSES service; (iii) additional ancillary information.

The first type of information is about the collection of primary data through an ad-hoc questionnaire. The questionnaire includes sections on: (i) WA information requirements; (ii) irrigation infrastructures (including details on water supply costs, efficiency of the supply system and on the amount of water delivered in each sector/district of the network); (iii) land use and cropping patterns (rain-fed and irrigated crop yields) and (iiii) damages caused by extreme weather conditions (probability of a drought, expected damages per crop categories). The questionnaire helped building the ICT informed decision model and to identify consequences of actions in states. Then with the joint use of secondary economic data on prices and yields from public databases (RICA – Rete di Informazione Contabile Agricola, 2017: http://rica.crea.gov.it/public/it/index.php) and information on land use, damages, crop prices and costs and on water price and use, it was estimated the economic payoff associated to consequences of actions in states. To simplify the assessment procedure, impacts of the decisions where estimated with the spatial limitation of the case study area.

The second type of information is about the new pieces of information provided by MOSES before and during the 2017 irrigating season. These are mainly, crop water demand seasonal and in-season forecasts. Such data were provided with different spatial resolutions, then aggregated in functional management units (sectors of the irrigation network). The collection of such information allowed us to build a complete picture of the information environment which would have characterized the ICT-informed decision process of the WA in 2017.

The third type of information collected was needed to assess the accuracy of MOSES services. These are observed data in the form of: (i) aerial photos (provided by the WA); (ii) weather observation (available from MOSES meteorologists) and (iii) observed crop water requirements. The collection of such information is justified by the fact that the accuracy of the service is mainly depending on three sources of uncertainty, contributing conditioning the accuracy of the messages provided by MOSES: (i) crop maps; (ii) water demand estimates; and, (iii) forecasts. The accuracy of information was estimated from the hit rate of the service, coming from the ratio between the number of correct messages on the overall messages received by the WA. This ratio is a rough estimate of the probability of correctly predicting current and upcoming states. Specifically: (i) by comparing MOSES crop maps with aerial photos (provided by the WA) we calculated the probability that an irrigated crop mapped with MOSES satellite images match with an irrigated crop mapped with aerial photos; (ii) by comparing MOSES rainfall forecasts with rainfall observation we calculated the probability that a forecasted rainfall above the estimated crop water requirements match with observed rainfall above the estimated crop water requirements. In addition, due to missing information, we assumed that, by comparing MOSES estimates of irrigation requirements with measured irrigation requirements, the probability that a positive irrigation requirement estimates (greater than zero) match with a positive irrigation requirement measured with soil moisture sensors is close to 1. Each of the above comparisons and assumptions contributed to the calculation of the probability to predict a dry or a regular season before the irrigating season and the probability to predict water requirements above or below a threshold value of 10mm. This value is assumed to be the critical level influencing the amount of water to be supplied for each sector of the irrigation network during the irrigating season.

3.5 Results

The estimation of the accuracy of MOSES information was carried out by comparing MOSES output with observed data, as described in the previous section. Results about the accuracy of the messages provided through MOSES are displayed in the probability matrix of Table 2 and Table 3. The overall accuracy of each message is expressed by the probability to correctly detect the land use multiplied by the probability to correctly predict if water requirements are above the 10mm threshold. As can be seen from the tables, the accuracy of the messages is not evenly distributed between states and the crop classification appears to be less reliable than the forecast of water requirements.

		MOSES crop classification	
		Irrigated	Not irrigated
Observed data on land use	Irrigated	0,66	0,41
	Not irrigated	0,34	0,59

Table 2: Probabilities to detect the land use

		MOSES irrigation forecast	
		Water requirements above the threshold	Water requirements below the threshold
Observed data on water requirements	Above the threshold	0,80	0,06
	Below the threshold	0,20	0,94

Table 3: Probabilities to predict water requirements

Water saving brought by the use of the forecast information are determined both in regular and dry season. Water saving variability is measured during time and it is calculated by comparing water requirement estimates with the water actually supplied to districts in 2017 (Figure 6). Water savings and water use tend to show a parallel trend. This highlights the fact that higher water savings are better achievable in periods with higher water use. In the first weeks of the irrigating season higher variability of water use can be found, with two peaks at week three and six. Such phenomenon is mainly due to the rain distribution in late spring which is particularly variable in the case study area. Further, at the beginning of the season peaks in water demand are caused by early concessions to irrigate. These are released to allow the seedling/transplanting of summer crops, extremely sensitive to droughts in the first phenological stages. Finally, in dry season, with water scarcity, lower water savings are achievable because water demand tends to be equal to the water available.

Table 3 represents the payoff matrix expressing payoffs in each state action combination for both decision steps. In the assessment, the impact of optimal decisions is estimated to be zero, since they stand for the most suited management strategy given the emerged climate conditions. Then, with reference to the optimal decisions, losses are estimated for each sub-optimal state-action combination. Great variability in decision outcomes can be found because the same action has extreme consequences with the emerging of a dry season or a regular season. For example, with wrong water allocation decisions, great drought losses can emerge, or wrong land allocation causes sub-optimal use of resources with negative impacts on farmers' income.

By applying the model of Section 3.4.1, the accuracy of the ICT-information is used to compute the EV of each action whose payoffs are represented in Table 4. Then, the VOI is assessed as the difference in expected decision outcome between the best decision process with information and without information. Summing over the VOI assessed in each district, potential benefits of the ICT-informed decision model are estimated to be 156,426€ for the irrigating season of 2017 and for all the 32 districts taken in examination (26.02 €/cultivated hectare/year). The spatial distribution of the VOI (Figure 7) is highly variable. Some districts have a null benefit from the implementation of such technologies, other very high.

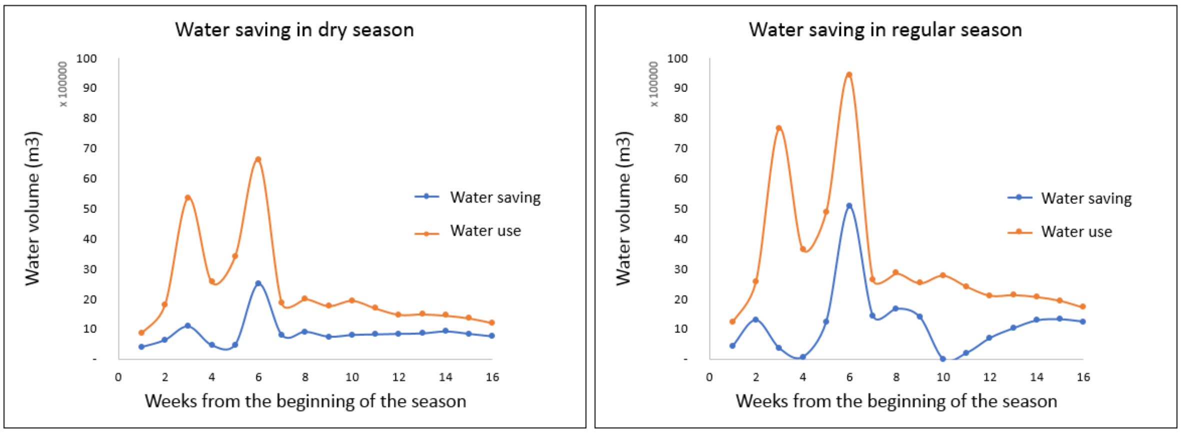

Figure 6: Estimated water savings during the irrigating season

			States			
			s'_1		s'_2	
			s''_1	s''_2	s''_1	s''_2
Actions	x'_1	x''_1	-	- 608,181	- 252,155	- 1,112,491
		x''_2	- 464,777	-	- 366,491	- 252,155
	x'_2	x''_1	- 252,155	- 1,112,491	-	- 860,336
		x''_2	- 366,491	- 252,155	- 728,569	-

Table 4: Payoffs of the decision model in the case study region (€)

Because the accuracy of information is estimated using inputs from only one irrigating season, it was considered useful to run a sensitivity analysis. This method is frequently adopted in literature for the estimation of ICTs (Hardaker et al. 2015). By varying the accuracy of information in both decision steps, we determined the VOI in each condition of the information environment. In other words, we built an index named Quality of Information (QI), ranging from 0 to 1 and expressing the probability to correctly predict events. It is determined by the average accuracy of the messages provided to the WA before and during the irrigating season. QI will equal 0 when the posterior probability to correctly predict events equals its prior. The opposite, in case of perfect information QI will equal 1. In the graph of Figure 8 it is shown how the VOI is related to the QI by rising the accuracy of information of every message in the two subsequent decision time steps. As expected, by raising QI for both decision steps, we see a non-decreasing linear trend of the VOI. It reaches its minimum in un-informed conditions (QI=0) and its maximum with perfect information (QI=1), where the WA is sure to make optimal decisions. The trend is linear because of the linear equation used to model the VOI, which is determined as the difference in EV between informed and un-informed decisions. Kinks can be noticed in the trend of the VOI, these take place when a new piece of information is introduced with the required accuracy to cause a belief revision. Accordingly, for each decision there will be a threshold in the accuracy of the message provided, under which the WA does not revise its expectations about states occurrence. Above such threshold the WA revises its beliefs and perceives benefits of the improved decision. In the second decision step (T2) we determined the VOI both in case of perfect information at T1 (before the season) and no information provision at T1. This choice is motivated by the fact that the overall decision outcome is affected by the accuracy of information at both decision steps. In other words, water allocation decisions are influenced by the expected consequences of that decision during the irrigating season and by the decisions on land allocation made before the irrigating season. This implies that the accuracy of information provided in the first decision step has an effect on the minimum accuracy for information to be usable in the second decision step.

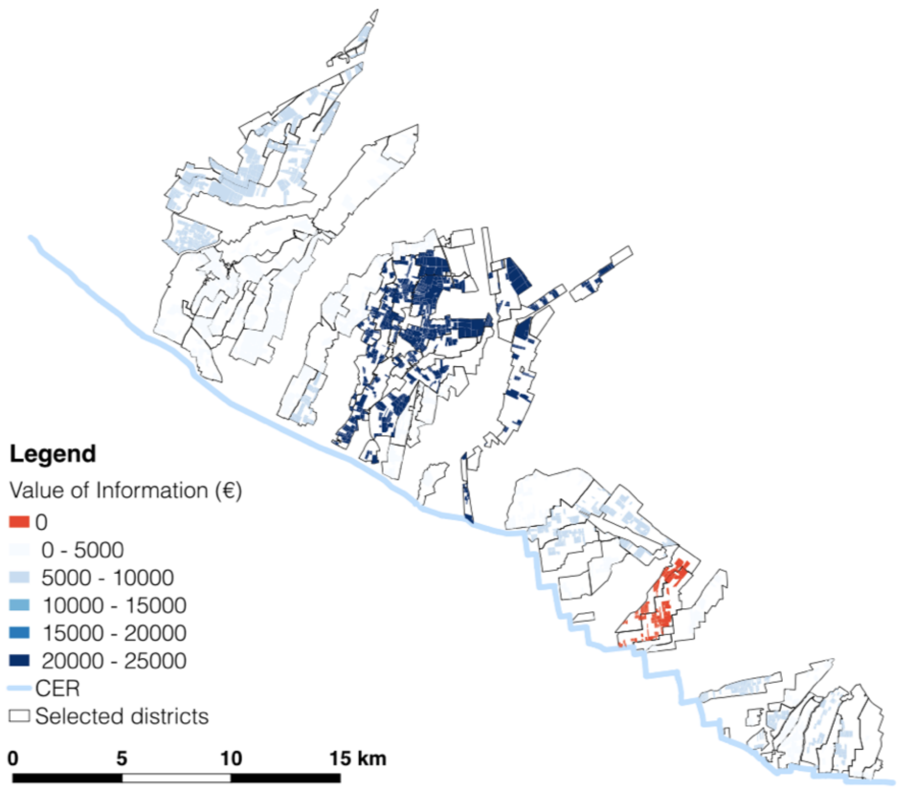

Figure 7: Distribution of the VOI between irrigation districts

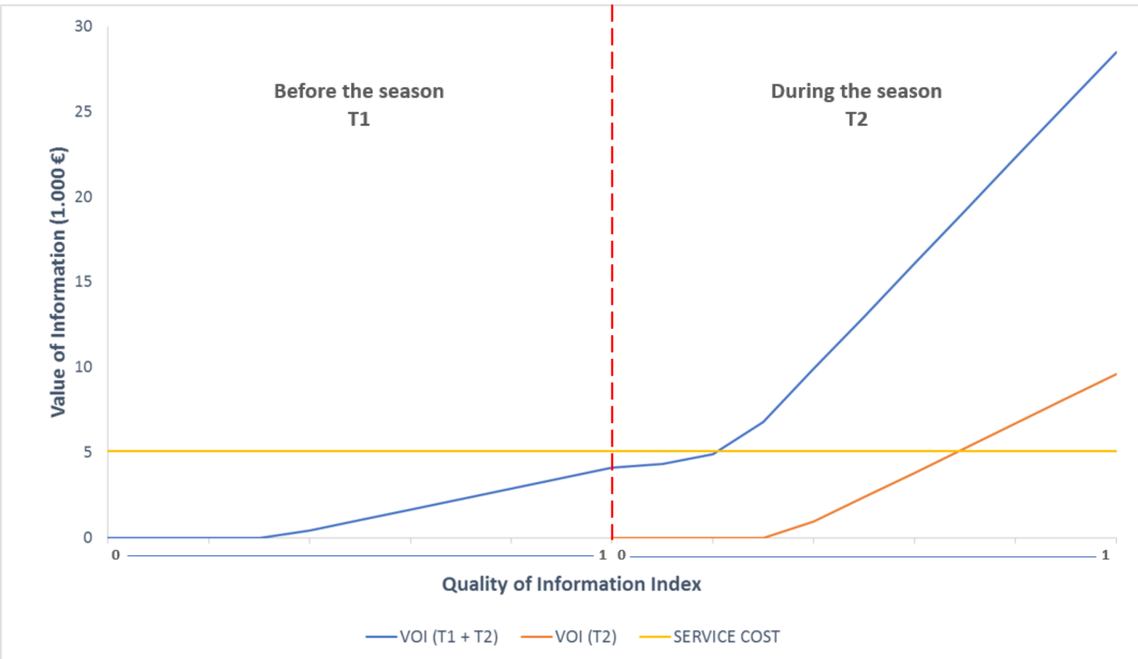

Figure 8: Sensitivity analysis for the VOI

3.6 Discussion

Results from the model show positive impacts form ICT adoption but with a high variability in its spatial and temporal distribution. The former variability is caused by different cropping patterns between districts. Specifically, in districts with high added value crops, the accuracy of information might be too low to cause a change in WA's belief. Accordingly, stakes are higher with added value crops in respect to other crops. Thereby, losses caused by wrong information are relatively higher, diminishing the net benefit from following MOSES advices. The latter variability is caused by the fluctuation of water savings during time all along the irrigating season. Peaks are mainly due to the combined effect of rainfall patterns and crop water requirements. Considerable water savings can be achieved if a consistent rain or no water demand are correctly predicted. When crop water demand is lower than some specific technical threshold in water delivery, no water saving is attainable.

The analyses of the case study showed that in some districts permanent crops are prevailing, here the VOI is low. This is due to the decision power of the WA which is not enough to influence land allocation of permanent crops in the medium term. Thereby, the WA cannot act upon the information received. This factor limits the efficiency of land allocation schemes informed by seasonal forecasts and enhances the spatial variability of the VOI. Moreover, due to the characteristics of the supply network, the WA is not able to precisely allocate water according to needs. At this end, decisions are simply on whether to deliver water to a district or not. This, together with the limited decision power of the WA, limits the potential of MOSES services and highlights how local barriers might have a strong impact on benefits from ICT adoption.

The complex nature of the decision-making process studied posed limits in the model capabilities to represent the decision problem. The WA selected as case study has a complex decision environment, with multiple sources of information, stakeholders, and complex decisions. This caused the first modelling limitation which is rooted in the simplification of the decision process of the WA. Further, the model overlooks transaction costs in information processing and implementation. The estimation of which was unfeasible due to lacking data and over-complexity of the model. Transaction costs can be expected to be relevant due to the often-lacking skilled human-resources needed for information processing. Their impact will cause ICT-benefits to get lower in the short term.

The analyses showed a decision process that involves high risky prospects with decisions having extreme consequences at stake. As seen in the matrix of payoffs, decision outcomes are extremely variable and wrong decisions bring great losses. Because of this, the model finds its main limitation in neglecting the choice of risky actions by the WA. Accordingly, other behavioral aspects not reflected in the maximization of EV might drive WA's decisions. By addressing the risk behavior in perceiving the quality of information, a more reliable estimation of ICT economic benefits would be achieved. In addition, deepening the knowledge regarding the relation between uncertainty and risk aversion seems a promising topic in the decision analytic literature (Keisler et al. 2014). Other than risk aversion, more emotional factors may influence ICT adoption, such as fascination with new technologies or aversion to adapt the decision making process to the same technologies (Plant 2001). Nonetheless, we considered the impact of such emotional factors negligible in the medium/long term. In light of the risky elements in the decisions, the model should be developed to account for more long-term strategies in the decision process. Here, the information implementation choice might not only be driven by the contingent accuracy of information, but also by the perspective of service improvements. Finally, this work, as well as the recent literature on the topic (Aker et al. 2016), do not consider the potential external benefits of improving WA's knowledge. For example, the WA could disseminate the received forecasts between farmers to help them in planning their activities.

A limitation of the exercise carried out in this paper is the data used. Data used as input in the model are just from the 2017 irrigating season. Given the variability of weather data, it would be preferable having a higher number of years observed. In addition, 2017 was a season particularly dry in compared to the climate average, which implies a likely overestimation of benefits. Even though results are not representative of the climate average or trends, they can show the VOI in a future climate scenario where drought events are expected to increase in frequency and length. Because the VOI is found to be dependent on agricultural revenues too, agricultural prices play a key role in determining ICT adoption. Furthermore, in future scenarios where high price volatility can be expected, this will reflect in an increase in the level of uncertainty in the decision environment. This will have a strong effect on the VOI, whose extent is not tackled by the present paper. The sensitivity analysis not only overcame the problem of estimating the accuracy of information with data from only the 2017 irrigating season. It showed the accuracy threshold levels over which decisions are influenced by a new piece of information. More importantly, it proved that despite the above limitations, the model is able to capture the VOI as a function of the accuracy of the messages provided. Finally, as decision problems are very much local-specific, also in relation with existing infrastructures and decision-making flexibility, the results cannot be generalized and would rather benefit of a wider testing exercise in areas with radically different decision-making conditions.

Despite the limitations described above, the estimation of the VOI is comparable with and confirmed by results of other studies found in literature. In their review, Meza, Hansen, and Osgood (Meza et al. 2008) found the value of seasonal forecast for agricultural decision making ranging from 0 to 700 $/ha. Such values are strongly affected by crop types. Lower bounds can be found in areas predominantly cultivated with cereals and extensive crops, with estimations that are in line with the findings of the present paper. Galioto et al. (Galioto et al. 2017) found higher VOI ranging from 40€/ha to 200€/ha depending on water cost, crop price, farmer's risk attitudes, quality of information and land quality. Particularly, their characterization of the VOI with the quality of information brings to similar conclusions to the sensitivity analysis carried out in this study. Results are confirmed by the work of Fernandez et al. (Fernandez et al. 2016) too. They estimate and characterize a VOI comparable to our findings. Crean et al. (Crean et al. 2015) identify a comparable VOI too, ranging from 0.20 to 23.18 $/ha. Further they carry out a sensitivity analysis on the VOI by varying the accuracy of information, which results are of a non-decreasing trend of the VOI.

3.7 Conclusions

The paper quantitatively estimated the potential economic benefits from the ICT-informed decision process of water management in agriculture at the WA's level. To do so, a theoretical model was designed, simulating the decision process of a case study WA. The proposed methodology accounted for the combined effect given by: (i) the accuracy of information in a multiple decision step process and (ii) what is at stake in the decision process. This paper has shown that a combination of BDT and EV maximization can offer a suitable approach to deal with complex VOI modelling such as the ones of WAs. This approach seems promising as it links information with the time it is provided in a sequential decision process made by several decision steps. The implementation of such methodology showed that ICTs can provide useful climate information for improved decision support. Economic benefits are then recognizable, especially if considering adaptation strategies to extreme drought events related with CC. The magnitude of such benefits is conditioned by barriers due to local characteristics of the decision process: (i) site specific condition (land use and water delivery system); (ii) the decision power of the WA in affecting land allocation and, most of all, (iii) the quality of information required to take decisions. Notwithstanding the great potential of ICTs for WAs, these barriers strongly affect actual applications. Moreover, since many ICTs offer discrete technology components without providing any support to adapt the technology itself to each specific reality, this undermines their usability. VOI is strongly affected by the information environment and ICT should aim at delivering information tailored to WA's specific needs (Furman et al. 2011). In other words, requirements in terms of accuracy of information; timing of information provision and restrictions in the application of the information have to be considered. This highlights the necessity to develop ICT jointly with end users. The simple provision of forecast information, even though high-quality, follows the "loading dock approach" (Cash, Borck and Patt 2006). This is described as the production of relevant climate information which has no use in reality because its form or time provision is incompatible with actual decision making (Vogel et al. 2017). Hence, future ICT development in irrigated agriculture should aim at better answering to WAs' specific needs of information. An approach based this way will foster WA's adaptation capacity. Because public institutions have the potential to guide decision making processes through a better use of existing knowledge (Cash et al. 2006), policy intervention is advised. The suggestion is to implement policy tools to help private initiative facing high transaction costs in ICT implementation jointly with end users. This is especially necessary in the case of ICT for WA, given their growing demand for detailed climate information (Vogel et al. 2017).

Chapter 4

4. Ambiguity, familiarity and information provision: implications for irrigation management

4.1 Introduction and objectives

Under the perspective of farmers and WAs, one of the major issues of CC is in the increased uncertainty brought about by unpredicted variability in weather patterns. In irrigated agriculture, this translates in two main sources of uncertainty: (i) uncertainty on the availability of water resources and (ii) uncertainty on water demand from crops. In general, the former uncertainty occurs before the irrigation season and affects land allocation, while the latter uncertainty occurs during the irrigation season and affects water allocation (Cavazza et al. 2018).

Land allocation decisions are taken when seedling/transplanting irrigated crops and could be key to face dry seasons. In particular, if water scarcity was anticipated, arable land would be allocated to drought resistant crops, limiting climate losses. Nevertheless, in this time of the year it is too early to assess the availability of water resources. Accordingly, reservoirs are mostly filled up by rainfalls occurring between the land allocation decision and the start of the irrigating season. Then, during the irrigating season the available water in the reservoir is known. At the same time, CWD is uncertain due to the unpredicted variability in upcoming temperatures and lack of tools to determine transpiration. This limits the decisions on how to allocate water both in case of scarcity and with resource availability. In case of water scarcity, not knowing Crop Water Demand (CWD) does not allow to set priorities in the use of the available resources to minimize losses. In regular years, not knowing CWD can cause excess uses which can induce scarcity, other than unnecessary environmental and energy costs. Because of such uncertainty settings, farmers and WAs are forced to implement precautionary irrigation plans which are inefficient, but their outcome is not subjected to risks with average climate conditions. However, the increased frequency of extreme events located at the tails of the climate distributions is posing new challenges for irrigation management. Here, inefficiency can further increase susceptibility to CC even in those years when reservoirs are full, because un-expected and prolonged droughts might determine scarcity afterward.

The present chapter focuses on these issues in water allocation. Here there is a strong need for new irrigation governance paradigms where resource-efficient irrigation plans must be implemented by all actors managing irrigation to save water and to favor adaptation in the sector. At this end, climate-information is key to lower uncertainty and to support efficient decisions. ICT can be powerful tools to this purpose and numerous platforms have been developed to aid decisions at the farm and at the WA- level (Cavazza et al. 2018). These ICT are capable of providing information on CWD, overall allowing reductions in the use of water, granting at the same time to achieve optimal production levels.

However, the simple information provision is not sufficient to achieve the expected benefits from ICT-development initiatives (Vogel et al. 2017). If DMs receive an ICT but do not implement it, putting ICT-information into action, there are no economic benefits from ICT development. This is true even with high quality information (Cash et al. 2006) and is testified by numerous examples in literature that show behavioral barriers in ICT implementation (O'Mahony et al. 2016). This is often caused by a lack of knowledge on information reliability: if on the one hand technologies providing relevant information are extremely useful in lowering climate uncertainty, on the other hand they raise uncertainty on their reliability. The latter uncertainty can be identified as ambiguity over information reliability. Ambiguity is common with the adoption of a new technology and rises from a lack of knowledge on its performance (Barham et al. 2014; Ward and Singh 2015). In the case of ICT, DMs frequently perceive a certain degree of ambiguity because they have never experienced information reliability. Thus, to foster ICT uptake, it is not sufficient to understand if the new technology can be reliably used to support strategic decisions. Because ambiguity can limit information implementation, we also need to understand if DMs have enough knowledge on ICT reliability. This rarely occurs with new ICTs, on which DMs are likely to have no direct or indirect experience. Anyhow, they might be able to try the ICT and test information, without necessarely implementing it. If so, with the passing of time, DMs would gain experience with the technology and might solve their ambiguous perceptions in the, so called, process of familiarity. This favors technology adoption (Gars and Ward 2019), but it can take a fairly amount of time (Barham et al. 2015) which might cause inefficiencies and further discourage information implementation.

The problem is exacerbated in the management of common pool resources, where efficiency is conditioned by the choices of all actors involved in the exploitation of the resource itself. Here, when actors are not coordinated, virtuous choices of some can be undermined by others who might not implement information received (Alpizar, Carlsson and Naranjo 2011). This is the case of irrigation districts, where decisions on water use are taken at the farm- and at the WA-level: farmers have to decide the amount of water to deliver to crops, the WA, in turn, has to decide the amount of water to deliver to farmers. Here, a new ICT could help at both levels, but its benefits will be appreciable only if information is reliable and all actors implement it. Namely, when the WA puts information into actions to save water, but farmers in the irrigation network do not, there will be losses or inefficient allocation even if the ICT proves to be reliable. Between farmers, when information is not implemented by some who excess-use the resource, the others might experience water un-availability. Because each actor (farmers and WA) have different attitudes toward ambiguity on ICT reliability, this problem will frequently affect ICT implementation.

These settings prompted us to assess the impacts that subjective behavior under ambiguity has in undermining ICT potentials for efficient water management in irrigation districts. To do so, we developed a behavioral model representing the decision between inefficient but riskless irrigation plans or ICT-aided efficient irrigation plans with uncertain outcomes. At this end, ambiguity perception plays a key role, but it evolves with familiarity. Therefore, we addressed the issue of learning on ICT reliability and developed a new learning rule representing the update of ambiguous beliefs. Finally, we consider an empirical example of a simplified irrigation district located in Northern Italy. Here, we implemented the model to quantitatively estimate how Water Use (WU) and Water Productivity (WP) vary after the introduction of a new ICT. These indicators are used to estimate ICT-impacts on the district's efficiency and its evolving in time. The empirical implementation helped to highlight issues in the governance system which lower the district's efficiency in the time lag between the first time DMs receive the ICT until when they are familiar with it. Findings will support irrigation districts in the implementation of efficient ICT-aided management plans as well as uncertainty-management policies in fostering ICT diffusion.

The remainder of this chapter is organized as follows: in the next section (Section 4.2) we will briefly consider the literature of uncertainty on technology's reliability and its dynamics as DMs gain experience on it. Then, we will describe the theoretical model developed (Section 4.3); in Section 4.4, we implement the model to highlight the impacts that ambiguity has on WU and WP. In Section

4.5, we provide an empirical example of a simplified irrigation district to highlight the relative governance issues. In Section 4.6 we present results. Finally, in Section 4.7 and 4.8 we discuss the main findings and draw conclusions and policy implications.

4.2 State of the art

In this section we will analyze the most relevant literature which is considered helpful in understanding the uncertainty settings around decisions for ICT-information implementation. In the following subsection we will frame uncertainty affecting the adoption of a new technology, underlining the role of lack of knowledge on its reliability. Then, we will analyze how perceptions on ICT reliability might evolve in time as the DM gains new insights and how this learning behavior is modelled.

4.2.1 Ambiguity and new technologies adoption

The literature on technology adoption in agriculture is widely tackled and sees the major contribution from one of the most cited paper of Caswell and Zilberman (Caswell and Zilberman 1985). These authors carried out a literature review on determinants of technology adoption and found that risk and uncertainty had frequently a significant role. Specifically, they highlighted the importance of a *subjective risk* caused by farmers being unfamiliar with the new technology. However, they do not deepen the issue and, given the time, do not consider those technologies providing information such as ICT.

To assess the potential impact that a lack of knowledge on technology reliability has on the adoption of the same new technology, the framework of ambiguity can be a powerful tool (Engle-Warnick and Laszlo 2017). The role of ambiguity in agricultural decision problems was firstly addressed by Engle Warnick, Escobal and Laszlo (Engle Warnick, Escobal and Laszlo 2008), who highlighted that both RA and AA affect farmers' choice between the technological *status quo* and a new technology. Specifically, they consider that AA might limit the adoption of new crop varieties because their performance is unknown. Later, Ross et al. (Ross et al. 2012) confirmed these findings and underlined that more than RA, it is AA to reduce the probability of technology adoption. Further, they expressed the need to have policies ensuring farmers having access to information on the technology's performance to lower their perceptions of ambiguity. Contrarily to these findings, Barham et al. (Barham et al. 2014) showed a case where AA increases the likelihood of farmers to implement new technologies. However, in their analyses they considered a technology which helps reducing crops exposure to pests whose occurrence is ambiguous. Similarly, Alpizar et al. (Alpizar et al. 2011) found AA favoring the adoption of technologies against extreme CC-related events. Here again, the technology protects DMs against events whose occurrence is ambiguous because of the un-measurability of CC (Alpizar et al. 2011). Finally, Ward and Singh (Ward and Singh 2015) considered a new technology which does not alter ambiguity distributions. As expected, they found that AA did not favor the technological *status quo* nor the adoption of the new technology.

Even if the above studies take into consideration different technologies and none address the issue of ICT-information implementation, their findings are extremely useful to our context. Specifically, by comparing results, it is evident that the impact of AA in determining technology adoption is specific to the effect the technology has on un-measurable uncertainty. If a new technology is expected to lower variance in the distribution of ambiguous events, its adoption will be favored by AA as found by Alpizar et al. (Alpizar et al. 2011) and Barham et al. (Barham et al. 2014). Otherwise, if it will raise ambiguity due to lack of knowledge on its reliability, ambiguity-averse individuals will be reluctant in implementation. The latter case is found by Engle-Warnick et al. (Engle Warnick et al. 2008) and Ross et al. (Ross et al. 2012) and is expected to be more frequent because the technological *status quo* is known to the DM, as opposed to a new technology whose performance is uncertain (Alpizar et al. 2011).

If we take into consideration those type of technologies providing information, such as ICT, no paper is found by the authors to be addressing the role of AA. However, Nocetti (Nocetti 2018) and Snow et al. (Snow 2010) analyze the relation between AA and the value of new pieces of information. Again, the relation depends on the type of information considered. Risk-reducing information is positively valued by risk-averse DMs, while ambiguity-reducing information is positively valued by ambiguity-averse DMs (Snow 2010). If we apply this concept to the case of an ICT delivering climate information, we ascertain that it will lower the share of climate uncertainty which is risk. Here the new piece of information will narrow variability in the risk distribution of climate events. Therefore, the ICT will deliver risk-reducing information and will be positively valued by risk-averse DMs. These will find higher expected utility from ICT-informed decisions than in the un-informed settings. However, if we consider that the same ICT is a new technology, another share of uncertainty will rise in the form of ambiguity which is due to a lack of knowledge on ICT reliability.

This issue will cost an ambiguity-averse individual to lower his expected utility from the same ICT-informed decision. Nocetti (Nocetti 2018) further deepened this phenomenon and highlighted that it is the share of ambiguity remaining after information is received that mostly affects its value. This does not depend on the message itself, but it is due to a lack of knowledge on the reliability of the message-service (Nocetti 2018). Overall, risk-reducing information provided by an ambiguous ICT will have a positive value for a risk- and ambiguity-averse DM only in case of a positive tradeoff between risk reduction and ambiguity rise.

As a result, ICT implementation will only occur when risk reduction is prevailing over ambiguity rise and the DM puts into actions the ICT-information received. This occurs only in some situations, but the tradeoff evolves in time as ambiguity lowers thanks to the process of familiarity described in the following section.

4.2.2 Familiarity and learning patterns in technology adoption

In the previous subsection we highlighted how, when approaching a new ICT, DMs have personal beliefs on the technology's reliability expressing ambiguity over information received. Ambiguity is then updated as the DM gains experience helping him to assess whether information can be trusted or not (Epstein and Schneider 2007). This phenomenon is described as familiarity which takes place as a learning process where the DM updates ambiguous beliefs on the basis of new insights.

In literature, the topic of DM's learning behavior in technology adoption is deeply analyzed. Here, learning is defined as "*the evolution of assessed subjective probabilities, as new information becomes available over time*" (Barham et al. 2015) and allows DMs becoming familiar with the new technology. One of the first to analyze learning under ambiguity was Marinacci (Marinacci 2002) which modelled how ambiguity disappears as the number of draws from an Ellsberg's urn coincides with the number of balls in the urn. Later, Epstein and Schneider (Epstein and Schneider 2007) considered more complex settings and proposed a learning rule which is one of the most relevant to model decisions under ambiguity (Machina and Siniscalchi 2014). He modelled ambiguity as variability in a set of risk distributions over future states of the world. This set is then updated during the learning process and variability shrinks as the DM becomes familiar with the new environment (Epstein and Schneider 2007). Because he found Bayesian update to be too extreme under ambiguous settings, he developed a model to account for more intuitive choices. Despite being reliable, the model proposed by Epstein and Schneider (Epstein and Schneider 2007) is referred to data-generating problems where the only repetition of draws allows to solve ambiguity (Etner et al. 2012). However, such kinds of problems are not directly applicable to the learning behavior occurring with new technologies. Accordingly, while betting in an urn, the number of alternatives building risk can be objectively measured and objectively updated with the repetition of draws, with new technologies this is not always possible. This is mainly due to the fact that new insights on the technology's performance are often available in the form of noisy parameters (Engle-Warnick and Laszlo 2017) which are subjected to the DM's own perceptions.

Barham et al. (Barham et al. 2015) tested three learning rules applied to new technology adoption in agriculture: (i) Bayesian learning; (ii) First-1 and (iii) Last-1. In all alternatives, prior ambiguity perceptions are assumed to be un-informative. Bayesian learning is identified when a rational DM observes the performance of the technology over time and weights each observation equally. While in the First-1 and Last-1 learning rules the DM considers respectively only the first or the last observation. Between these three, the only Bayesian rule is the least representative and farmers tend to follow a mixt of this rule with First-1 or Last-1 rules (Barham et al. 2015). These results highlight the need to develop and test new learning rules for technology adoption. These should include elements of rationality from the Bayesian update, but allow at the same time some degree of intuitive choice as suggested by Epstein and Schneider (Epstein and Schneider 2007). Moreover, when considering the specific case of a new technology providing weather-related information, as the one analyzed in the paper, there are further obstacles in the application of existing models. While the performance of other technologies can be generally measured in terms of production, with weather-related ICT, the DM is not able to quantitatively assess the extent to which information received was reliable. Many climate parameters are hard to measure and quantitative comparisons between forecasts and observations are frequently impossible at the end-user level. This underlines the need to model an updating behavior having the qualitative approach with which the DM might judge ex-post the performance of the ICT and update his beliefs.

4.3 Methodology

4.3.1 Overview of the theoretical model

In the previous section, we have showed that the introduction of ICT in decision problems raises ambiguity due to a lack of knowledge on information reliability. This is generated by a DM being unfamiliar with the ICT and will limit him to implement information if he behaves as ambiguity-averse. The behavioral model developed in this section aims at representing the decision between implementing a riskless and inefficient Precautionary Plan (PP) and an efficient ICT-informed Risky Plan (RP) for irrigation. Further, we consider how such decision evolves with time, in the period between the first time the DM approaches the new ICT until when he is familiar with it. To do so, the model accounts separately for the effects that risk and ambiguity have on the adoption of a new ICT for water management. While the share of risk involved in the implementation decision is considered constant, ambiguity is updated in the process of familiarity. Because no learning rule for the update of ambiguous perceptions is found to be fitting to the context, we developed a new one. This allows to model how the decision evolves as the DM gains experience on information reliability.

In the following Section 4.3.2, we will define the decision environment. Here, two farmers and a WA are the actors managing water allocation in an irrigation district. In the business as usual settings, uncertainty forces all actors to manage irrigation by implementing an inefficient but riskless PP. Then, in Section 4.3.3, we consider how irrigation management can gain efficiency thanks to information provision by the ICT. Here, both ambiguity and risk occur, because, respectively, the ICT is a new technology and provides probabilistic information. The impacts of AA and RA on the information implementation decision is analyzed in Section 4.3.4. Finally, in Section 4.3.5, we assess how things change with time as the DM gains familiarity. Although the model assumes simplified settings, it is capable of describing how uncertainty affects the ICT-information implementation decision and, in turn, water demand (in Section 4.4). Finally, the model will be applied to the case study to assess how ICT-informed water demand translates into WU and WP to estimate the districts' efficiency (in Section 4.5).

4.3.2 Context: three actor districts

Suppose there is a WA managing water allocation for an irrigation district with two farms: farm 1 and farm 2. The two farms are comparable in size and cultivated crops; both have to make decisions on the right amount of water to irrigate. The main difference is in their location: farm 1 is upstream the irrigation network and farm 2 is downstream. This way, farm 1 is the first to access the resource and farm 2 gets the remaining water. No external regulation exists to avoid excess-use of water by farm 1. As a consequence, farm 2 is less favored and farm 1 owns a position rent at the expenses of farm 2. This condition is a frequent issue with common resources where differences in accessibility can cause uneven distribution of benefits (Cremer and Laffont 2003).

The model considers ordinary settings when reservoirs are full but excess-use cause environmental issues, unnecessary costs and might increase susceptibility to droughts occurring later in the season. Here, the WA has to decide how much water to pump in the irrigation network but does not know farmers' water demand. To avoid water un-availability at the farm level (especially at farm 2), the WA implements a PP for water management. In this plan, the irrigation network is filled up to its operational capacity, with flows being higher than the sum of what each farm can irrigate at the maximum. So, possible excess-use of the resource by farm 1 would not affect water availability in farm 2. Nonetheless, the plan comes at a cost being the water used overly high, up to a level defined by X_{WA}.

A similar decision is made by farmers, because: (i) they are unsure about CWD and, (ii) if they do not satisfy CWD, there will be production losses. To avoid letting part of their income being exposed to uncertainty, they implement a PP and irrigate at the field capacity, at a level that guarantees no water stresses (X_{farm_i}). Both PPs are riskless (at the cost of excessive water used) and their payoff function ($g(\cdot)$) is state independent, coinciding with the following value (Eq. 7; Eq. 8**Error! Reference source not found.**):

$$g(X_{WA}) = V(X_{WA}) - c_{WA}X_{WA}$$

Eq. 7

$$g(X_{farm_i}) = V\left(X_{farm_i}\right) - c_{farm_i}\, X_{farm_i}$$

Eq. 8

Where $V(X_{farm_i})$ represents the optimal revenues achieved when water demand is fully satisfied. Because the WA is not producing crops but its aim is to maximize farms' profits at the cost of water used, we represent its revenues as follows (Eq. 9):

$$V(X_{WA}) = V(X_{farm_1}) + V(X_{farm_2})$$

Eq. 9

In Eq. 7 and Eq. 8 we have two positive coefficients, c_{farm_i} and c_{WA}; these represent the volumetric cost of water under the actor's perspective. Here, c_{farm_i} is the volumetric cost needed to irrigate the field such as energy costs, resource costs and labor; it includes only those costs which are proportional to the quantity of water used. This simplification is driven by the fact that costs for machineries and in-farm delivery systems are fixed in the short term and cannot be reduced by efficient ICT-aided irrigation plans. Therefore, we assume that they will not be taken into account by the farmer during the implementation decision. On the other hand, c_{WA} represents the volumetric cost of water under the WA perspective. It includes costs for energy, water and external costs attributed by the WA to the resource (opportunity costs and environmental costs). Although costs which are disproportionate to the quantity of water used prevail in WAs' budget, they cannot be affected by efficient ICT-aided decisions. For this reason, we will focus just on the volumetric costs of water, overlooking infrastructure maintenance and other costs which are assumed to be fixed in the short term.

4.3.3 Information provision

Now, suppose a new ICT provides information: (i) to farmers, on the average water demand from crops cultivated in their field ($x_{farm_i}^{ICT}$) and (ii) to the WA, on the average water demand from crops cultivated in whole district ($x^{ICT}{}_{WA} = x_{farm_1}^{ICT} + x^{ICT}{}_{farm_2}$). Thanks to the new piece of information, farmers can now irrigate so as to distribute the exact amount of water needed by crops and the WA can pump into the network the water volumes really needed by farmers.

Although being resource-efficient ($x_{farm_i}^{ICT} < X_{farm_i}$), this plan is risky if compared to irrigating at the maximum level. This is due to the fact that the ICT is not capable of providing perfect information; therefore, errors in water requirement estimations are possible. Several states of water demand can occur, where water requirements from crops could potentially differ from the one estimated by the ICT. Each state ($x^{s}_{farm_i}$) identifies a specific event within the state-space defined by S and identifying the set of feasible states of water demand from crops ($x^{s}_{farm_i} = x^{s1}_{farm_i}, x^{s2}_{farm_i}, \dots x^{s3}_{farm_i}; x^{s}_{farm_i} \epsilon\, S$).

To help DMs facing this issue, attached to the estimation of water demand ($x^{ICT}_{farm_i}$), the ICT delivers the Probability Density Function (PDF) of revenues in states ($\pi(x^{s}_{farm_i})$). With the message, the DM knows the water volume needed by crops and the PDF of revenues achievable if he irrigates as specified in the message. The probabilistic nature of such kind of ICT-message helps DMs to account for uncertainty in states variability and to plan their actions consistently with it (Arnal et al. 2016). In this paper we assume that the PDF of states is normally distributed, where the average or expected payoff coincides with the optimal revenue achieved in the PP ($V\left(X_{farm_i}\right)$), minus the costs of water used (Eq. 10).

$$\mathbb{E}_{\boldsymbol{\pi}(\boldsymbol{x}^{s})}(f\left(x^{s}_{farm_i} \middle| x^{ICT}_{farm_i}\right)) = V\left(X_{farm_i}\right) - c x^{ICT}_{farm_i}$$

Eq. 10

This equation highlights how information allows to implement an irrigation plan in which the farmer can produce the same quantity of output as with the PP, with less water. However, the payoff of this output is subjected to the uncertainty estimated in $\pi(x^{s}_{farm_i})$. Therefore, we label this irrigation plan as RP and its uncertainty elements will be treated in depth in the next section.

An example of the PDF received by the DM is provided in Figure 9: PDF of states of water requirements. Since the two farms are different, each will receive a different distribution with a different average. The two distributions will have the same standard deviation because errors are unrelated with the value estimated and depend only on the technology generating information.

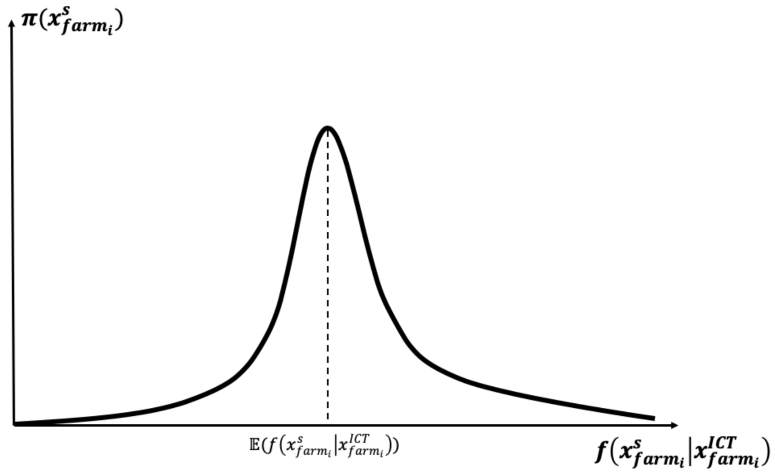

Figure 9: PDF of states of water requirements

4.3.4 Risk and ambiguity

In the previous subsection we highlighted how information provision by the ICT allows to save water. This comes with a cost of putting at risk the decision payoff. If the DM is risk-averse, he will find lower Expected Utility (EU) from the RP than a risk neutral DM. To understand the DM's choice, it will be necessary to estimate his EU for the uncertain payoff $f\left(x^s_{farm_i}\middle|x^{ICT}_{farm_i}\right)$. If we consider only the probability estimation ($\pi(x^s)$) provided by the ICT, EU for the RP (EU^r) is defined with the following formulation (Eq. 11**Error! Reference source not found.**) developed on the basis of Savage's postulates (Savage 1954):

$$EU^r\big(f(x^s|x^{ICT})\big) = u\left(\mathbb{E}_{\boldsymbol{\pi}(\boldsymbol{x}^s)} f(x^s|x^{ICT})\right) = \int_{\boldsymbol{S}} u\big(f(x^s|x^{ICT})\big)\pi(x^s)dx^s$$

Eq. 11

where $u(\cdot)$ is a von Neumann-Morgenstern utility function and $\mathbb{E}_{\pi(x^s)}$ is the expectation operator for the risky environment. Because the expected payoff coincides with the optimal revenue at the costs of water used (Eq. 10), Eq. 11 simplifies as follows (Eq. 12):

$$EU^r\big(f(x^s|x^{ICT})\big) = \int_{\boldsymbol{S}} u(V(X) - c\mathrm{x}^{\mathrm{ICT}})\pi(x^s)dx^s$$

Eq. 12

Despite the ICT providing a full probabilistic picture of risk, another share of uncertainty is un-measurable and generates ambiguity. This is due to the fact that the ICT is new to DMs and they do not know if the probabilistic estimations received are reliable. Apart from the PDF specified by the ICT, other probability functions are feasible. We now identify with $\pi^{ICT}(x^s)$ the PDF provided by the ICT to distinguish it from all other feasible I Order PDFs. As a result we have a set, Δ, describing the set of feasible first order probability estimations ($\pi^j(s) = \pi^1(s); \pi^2(s); \pi^{ICT}(x^s); \dots; \pi(s)$). To describe variability in Δ, DMs have personal beliefs identifying a distribution of first order probabilities ($\mu(\pi(x^s))$). This is a II Order PDF assigning a weight to each I Order distribution in Δ. The II Order PDF is assumed to be normally distributed and its average coincides with the probability estimation provided by the ICT ($\widehat{\pi(x^s)} = \pi^{ICT}(x^s)$) (Figure 10). In practice, by assuming such a II Order PDF, we consider that the DM builds his ambiguous perceptions in the form of a normal probabilistic distribution and believes that $\pi^{ICT}(x^s)$ is the most likely to be correct.

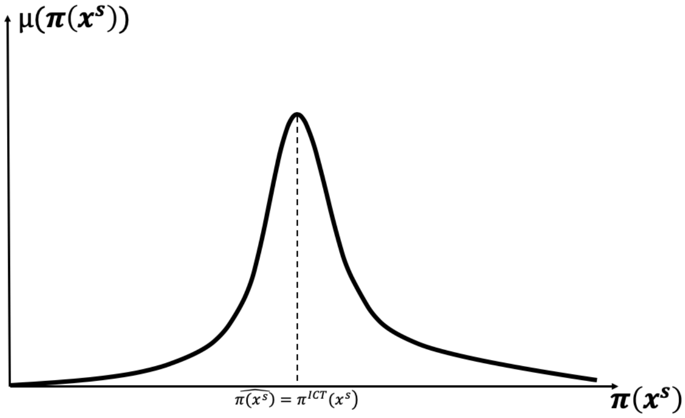

Figure 10: PDF of first order probabilities

If DMs are ambiguity-averse they perceive disutility from this variability in first order probabilities. Therefore, to reliably assess their EU it is necessary to account for ambiguity and ambiguity aversion too. The formulation adopted in this paper follows the smooth model of ambiguity sensitive preferences developed by Klibanoff et al. (Klibanoff et al. 2005) (Eq. 13):

$$EU^{r,a}\big(f(x^s|x^{ICT})\big) = \mathbb{E}_\Delta \phi\left(u\big(\mathbb{E}_{\boldsymbol{S}} f(x^s|x^{ICT})\big)\right)$$

$$= \int_\Delta \phi\left(\int_{\boldsymbol{S}} u(V(X) - cx^{ICT})\pi(x^s)dx^s\right)\mu\big(\pi(x^s)\big)d\pi(x^s)$$

Eq. 13

Similar to Eq. 12, $\phi(\cdot)$ is a von Neumann-Morgenstern second order utility function expressing preferences over first order probabilities. The model has a double expectational form which allows the separation between ambiguity, which is a belief of the DM, and ambiguity aversion which expresses his attitudes. Thanks to this feature, beliefs and attitudes are then treated separately, where to the first class belongs risk perception and ambiguity perception, while attitudes are RA and AA.

To aid the understanding of the problem, it is often useful to consider the Certain Equivalent (CE) of an uncertain payoff rather than its EU. This is defined for a DM as the "…*sum of money 'for sure' that would make that person indifferent between facing the risk or accepting the sure sum.*" (Hardaker et al. 2015). It is obtained by the inverse utility function of the EU of an uncertain payoff. Its practicality will be helpful to compare the sure payoff of the PP with the uncertain payoff of the RP. To assess the CE of the RP, we considered negative exponential utility functions for payoffs and probabilities (Eq. 14, Eq. 15):

$$u\,(\cdot) = -e^{-r(\cdot)}$$

Eq. 14

$$\phi\,(\cdot) = -e^{-a(\cdot)}$$

Eq. 15

where r and a are respectively the risk aversion coefficient and the ambiguity aversion coefficient, both are positive and range from 0 to 1 with higher aversion. The KMM model of **Error! Reference source not found.** is used to assess the CE of the risky plan, which simplifies as follows, given the assumptions of normality in both first and II Order PDFs (Eq. 16):

$$CE(f(x^s|x^{ICT})) = \mathbb{E}_\Delta\left[\mathbb{E}_S(f(x^s|x^{ICT})) - \frac{1}{2}r\sigma^2_{\pi^{ICT}(x^s)}\right] - \frac{1}{2}a\sigma^2_{\mu(\pi(x^s))}$$

Eq. 16

The proof is given in Appendix 1: Simplification for the CE computation**Error! Reference source not found.**.

4.3.5 Update of ambiguous beliefs

While ambiguity-attitudes can be assumed as constant in time (Hanany et al. 2009), the perception of ambiguity decreases as the DM gains experience on ICT reliability. This phenomenon frequently results in a slow and progressive implementation of new technologies to support decision making. In Section 4.2 we found no learning pattern to be capable of fully representing the update of ambiguous beliefs on ICT's reliability. Therefore, we propose a new learning rule developed to account for the peculiarities of the context

Until now we considered a single decision event, but decisions for water allocation are repeated periodically along the irrigating season and in every season. We identify with Time Frame (TF: $t \in T$) every period beginning with the choice of the irrigation plan and ending when the decision pays off. In the first TF ($t = 1$), when receiving for the first time ICT-information, DMs have no experience on its reliability. However, they build their own beliefs expressed in the form of a normal distribution of averages of I Order PDFs. The resulting distribution (II Order PDF: $\mu\left(\pi\left(x^{\hat{s}}\right)\right)$), is updated with time as the DM gains new insights on the ICT reliability, helping him to refine his beliefs.

To describe the updating process, we assume that, at the end of each TF, states are manifested and DMs can assess if ICT-information has proven to be correct. This phenomenon allows DMs to learn on the ICT reliability as they become more familiar with it. The learning process is modelled with the DM getting a binary signal from the environment ($h_t = h_{\mathrm{t}}^{+}; h_{\mathrm{t}}^{-}$), describing whether information has been correct (h_{t}^{+}) or not (h_{t}^{-}). Both the sum of the positive signals ($\sum_{\mathrm{t}} h_t^{+}$) and the sum negative signals ($\sum_{\mathrm{t}} h_t^{+}$) are weighted by a positive coefficient, named updating rate (w). This is included between 0 and 1 and reflects DM's subjective inclination to revise his prior beliefs in light of new evidences; the higher the coefficient the faster the learning will be. The updating model is described by the following step function (Eq. 17):

$$\mu(\pi(\mathrm{x}^{s})|\mathrm{t}) = \begin{cases} \dfrac{\mu\left(\pi(\mathrm{x}^{s})\right)^{\frac{1+w\sum_{\mathrm{t}} h_{\mathrm{t}}^{+}}{1+w\sum_{\mathrm{t}} h_{\mathrm{t}}^{-}}}}{\mu\left(\pi(\mathrm{x}^{s})\right)} \; if \displaystyle\sum_{\mathrm{t}} h_{\mathrm{t}}^{+} > \sum_{\mathrm{t}} h_{\mathrm{t}}^{-} \\ 1 \; if \displaystyle\sum_{\mathrm{t}} h_{\mathrm{t}}^{+} \leq \sum_{\mathrm{t}} h_{\mathrm{t}}^{-} \end{cases}$$

Eq. 17

The first time the DM is approaching the new ICT (t_0), the only element helping him to build his ambiguity distribution will be his prior belief ($\mu\left(\pi(x^{s})\right)$). Then, from the second TF on, ambiguity will be described by a posterior PDF, where the prior is updated on the basis of the signals received, as described in the equation above. Even after the third TF, the prior distribution to be updated remains the one built by the DM the first time he approached the ICT (t_0). For example, at t_5 if the DM has received 5 positive signals, the updated ambiguity distribution will be: $\frac{\mu(\pi(x^s))^{1+5w}}{\mu(\pi(x^s))}$. This behavior is similar to the First-1 learning rule described by Barham et al. (Barham et al. 2015). However, while with the First-1 rule the prior remains constant in time and is never updated, here it is constant in time, but it is updated every TF. This is also different from the Bayesian update, in which the posterior in a TF becomes the prior in the TF following. The developed rule highlights that, in every TF, the DM's choice takes always into account also the prior beliefs he had at t_0.

Because the updating process consists of scaling the prior PDF, all posteriors remain normally distributed. The only exception occurs if $\sum_t h_t^+ \leq \sum_t h_t^-$, where the prior transforms into a uniform distribution. If so, we reach the highest level of ambiguity, where variance is equal to infinite and all the I Order distributions are feasible and equally probable. In such settings, ambiguity is at its maximum and will likely cause the DM to not implement information received. Instead, if $\sum_t h_t^+ > \sum_t h_t^-$, as new positive signals are received and they outnumber negative signals, variability in $\mu(\pi(x^s)|t)$ lowers, while means remain unchanged. This mean-preserving contraction is represented in Figure 11 and is made possible by the shift in the updating process. To explain this phenomenon, as the DM receives new positive signals, we can consider that the probability of I Order distributions which are in the tails exponentially lowers. Therefore, the set of feasible distributions in first order probabilities shrinks ($\Delta_1 > \Delta_2 > \Delta_T$) as the DM observes that some distributions are unfeasible. This process of familiarity favors information implementation because it raises EU for an ambiguity-averse DM. The process continues as the ratio between positive and negative signals rises, up until the point when the only distribution remaining in the set is the one provided by the ICT. At this point, ambiguity is solved, and the DM recognizes that $\pi^{ICT}(x^s)$ always estimates uncertainty correctly.

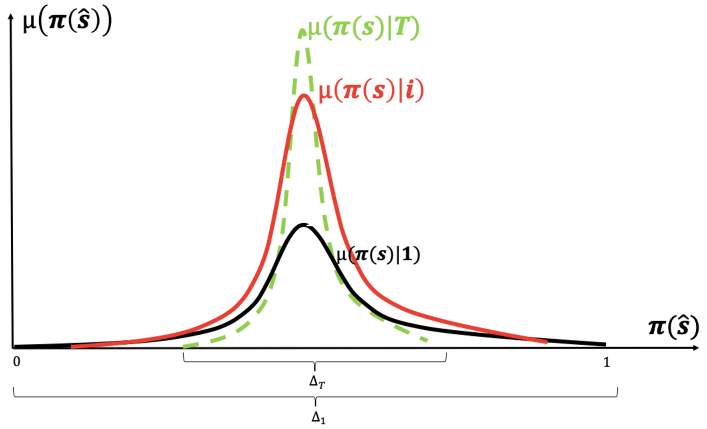

Figure 11: Mean-preserving contraction in second-order probabilities

As a result of the familiarity process, EU from the RP evolves, because perceptions are altered; the updated CE is computed as follows (Eq. 18):

$$CE(f(x^s|x^{ICT})|t) = \mathbb{E}_{\Delta_t}\left[\mathbb{E}_S(f(x^s|x^{ICT})) - \frac{1}{2}r\sigma^2_{\pi^{ICT}(x^s)}\right] - \frac{1}{2}a\sigma^2_{\mu(\pi(x^s)|t)}$$

Eq. 18

If we consider an ICT capable of estimating all errors in the I Order PDF, meaning that $\pi^{ICT}(x^s)$ is always the correct distribution, a DM familiar with the ICT ($t \to \infty$) will have the following CE (Eq. 19):

$$\lim_{t\to\infty} CE(f(x^s|x^{ICT})) = \mathbb{E}_S(f(x^s|\mathrm{x}^{\mathrm{ICT}})) - \frac{1}{2}r\sigma^2_{\pi^{ICT}(x^s)}$$

Eq. 19

This simplification is made possible because variance in II Order PDF is null and it results in a CE which is equal to the one of an ambiguity neutral DM ($a = 0$). Otherwise, if ambiguity remains because of errors in probability estimations, it will still affect expectations as shown in Eq. 18.

4.4 Identification of water demand

In the previous section we modelled how ambiguity affects expected utility from ICT-informed decisions and how this phenomenon evolves at the end of a TF, when the DM gains new insights on ICT reliability. Still, in each of these TF, it is to be defined the impact that ambiguity has on WU. Specifically, we saw each actor having to choose between a PP which is riskless but inefficient and an ICT-informed efficient RP, subjected to risk and ambiguity. Here, the DM will switch from the PP to the RP only when expected utility of the first plan is lower than expected utility of the second. Only in such condition the DM will implement the ICT and put information into action to save water, otherwise information provision will be useless. However, it is to be underlined that the decision variable is the volume of water used, which is a continuous quantity. Therefore, we will further develop the model to help identifying not only the switching point between the PP and the RP, but also the optimal water volume to be used under the DM's behavioral perspective. This will build the actor's water demand and will be key to understand issues in governance which undermine ICT potential benefits.

4.4.1 The cost-loss model in presence of ambiguity

To help understanding when the DM will switch from the PP to the RP, we will develop the widely adopted cost-loss model proposed by Thompson and Brier (Thompson and Brier 1955). The model helps to define when to take a PP and face a sure cost (C) instead of implementing a RP and risk a loss (L) with a probability (p) defined by a forecast. The model ignores ambiguity and assumes risk-neutral behavior. It suggests to DMs to take protective actions when the expected value of the RP is lower than the PP ($\frac{C}{L} > p$). As shown in the representation of Figure 12, the issue complicates in presence of ambiguity: even if $\frac{C}{L} > p$ it is not clear which action to take if the ratio falls within the II Order PDF (Allen and Eckel 2012)

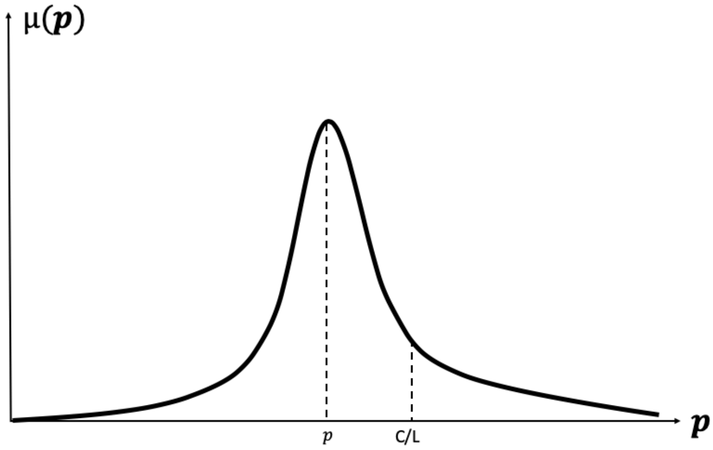

Figure 12: Cost-Loss model in presence of ambiguity

Source: own elaboration from Allen and Eckel (Allen and Eckel, 2012)

To answer to this issue, we follow the same principle of the cost-loss model and extend it to the DM's behavior. We consider that the DM will move from the PP to the RP when the CE of the

RP will be greater than the CE of the PP. In our example, this translates into the CE of the RP being greater than the sure payoff of the PP, given that the latter plan is riskless (Eq. 20):

$$g(X_{farm_i}) \leq CE(f(x^s | x_{farm_i}^{ICT}))$$

Eq. 20

When the two elements in Eq. 20 are equivalent, we reach an equilibrium where the DM is indifferent between being exposed to uncertainty and take the RP or avoid risk and ambiguity and implement the PP. Other things equal, information will only be implemented when ambiguity is as low as to let the DM being indifferent between being exposed to uncertainty in the RP or receive a sure payoff from the PP. This is likely to occur only when the DM has gained enough familiarity with the ICT to lower his doubts on its reliability.

4.4.2 Management of the input variable: from a discrete choice to a continuous decision

The model described until now represents a situation in which the DM is faced with a discrete choice among two different management plans. However, the DM has to decide the continuous quantity of water to use (X_{farm_i}; X_{WA}) in order to maximize his EU. Even if not applying the volume specified by the ICT, DMs could implement information and decide to rise $x_{farm_i}^{ICT}$ or x_{WA}^{ICT} to get rid of part of uncertainty, if not all. Therefore, we consider the DM will rise the water volume specified by the ICT until it will grant to reach the equilibrium in Eq. 20. The result of this problem will define the optimal water quantity, building water demand for farmers ($x_{farm_i}^{d}$; Eq. 21) or the WA ($x_{farm_i}^{d}$; Eq. 22):

$$x_{farm_i}^{d} = x_{farm_i}^{ICT} + \frac{\frac{1}{2} r \sigma_{\pi^{ICT}(\mathrm{x}^s)}^{2} + \frac{1}{2} a \sigma_{\mu(\pi(\mathrm{x}^s)|t)}^{2}}{c_{farm_i}}$$

Eq. 21

$$x_{WA}^{d} = x_{WA}^{ICT} + \frac{\frac{1}{2} r \sigma_{\pi^{ICT}(\mathrm{x}^s)}^{2} + \frac{1}{2} a \sigma_{\mu(\pi(\mathrm{x}^s)|t)}^{2}}{c_{WA}}$$

Eq. 22

where the proof can be found in Appendix 2: Simplification for the computation of the optimal water volume.

If considering neutrality to uncertainty, the equation is simplified and the optimal water quantity is the one specified by the ICT ($x^{d}_{farm_i} = x^{ICT}_{farm_i}$). Accordingly, the element $\frac{\frac{1}{2} r \sigma^2_{\pi^{ICT}(\mathrm{x}^S)} + \frac{1}{2} a \sigma^2_{\mu(\pi(\mathrm{x}^S)|t)}}{c_{farm_i}}$ can be interpreted as the cost of water, additional to the requirements, that is employed by the DM to get rid of part of uncertainty. Or $x^{ICT}_{farm_i}$ is the optimal water volume for an uncertainty neutral DM. As evident, an uncertainty-averse DM will rise the water volume specified by the ICT to account for his dis-utility coming from being exposed to risk and ambiguity. This will heavily impact on water allocation efficiency, as described in the following chapter.

4.5 Empirical Example

In the previous section we identified the water volume each actor wishes to use under his behavioral perspective. In this section we provide a numerical application of the model described until now. This example is aimed at highlighting issues in irrigation governance which contribute to undermine ICT benefits due to differential behavior among actors in the district. Accordingly, because perceptions and attitudes are subjective, there will be differences in the extent to which actors will implement information to save water. As a result, virtuous choices of some who decide to implement ICT-information to use less water can be undermined by others who do not (yet) rely on the same piece of information. For example, if farmers rely on information received and try to save water, but the WA does not, there will be water waste because of excessive volumes pumped in the network. Even worse, it can happen that the WA pumps in the network lower water volumes than with the PP, but farmers might not rely on the ICT and wish to implement the PP. This results in no water availability and drought losses in those farms located at the bottom of the irrigation network. These two are the main issues which can cause strong inefficiencies after the introduction of a new ICT for irrigation management. To analyze and estimate their impact singularly, we will carry out two scenario analyses, each corresponding to one of the issues highlighted above.

In this empirical application and in both scenarios, we consider a situation in which all actors in the irrigation district are given a new ICT. Then, they can decide whether to implement information received and put into action efficient and risky irrigation plans or not. Anyhow, they observe ICT-performance and, after each TF, they gain experience on information reliability. To simplify the model implementation, we analyze the specific situation in which all uncertainty around the ICT-message is included in the PDF received by each DM. This means that $\pi^{ICT}(x^s)$ is always capable of correctly estimating the likelihood of states. Therefore, when all DMs will be familiar with the technology, they will solve their ambiguity and act consistently. However, the process of familiarity can be long, this will cause very heterogeneous timing in information implementation. In this time lag, there will be inefficient water management.

In the following subsections we provide a general overview of the case study, describing the context in which we fit the model and how we collected data. Then, we will take into consideration each scenario singularly and highlight its implications and issues for water governance. Finally, we will analyze the role familiarity plays in this context and highlight how, apart from governance regulations, it is the only element capable of granting efficient ICT-informed water management.

4.5.1 Data collection

The data used for the empirical application described in this section is collected with the help of the Consorzio di Bonifica di Secondo Grado per il Canale Emiliano Romagnolo and of the Operational Group "*Reti di Consegna Intelligenti - Automazione della rete di consegna delle acque irrigue mediante calcolo dei fabbisogni delle aziende agricole aderenti a IrriNet*" financed by the Rural Development Programme 2014-2020 of the Emilia-Romagna Region (Italy). This Operational Group is aimed at assessing the viability of new ICT-based irrigation allocation models which require the automatization of hydraulic nodes in the irrigation network. The area considered for the case study is represented by the reclamation and irrigation board of Consorzio di Bonifica di Piacenza which is located in the Po valley, province of Piacenza, northern Italy. Here, several irrigation districts can be identified, each having independent water sources managed by a single WA. The district selected to implement the model is the one named Basso Piacentino. It covers a flat area of around 3,000 hectares and was selected for its representativeness of the irrigation context. The main crops cultivated in the district are corn, tomato for industrial processing, alfalfa and forage. All crops are irrigated, but corn and tomato are the most water demanding crops. The irrigating season starts from March-April and ends in September-October. The only water source in the district is the Po river, which is the major water source for irrigation in the whole Po Valley. To favor irrigation management, the district is divided in two separate sub-districts: Basso Piacentino Monte and Basso Piacentino Valle (Figure 13: Overview of the two sub-districts.

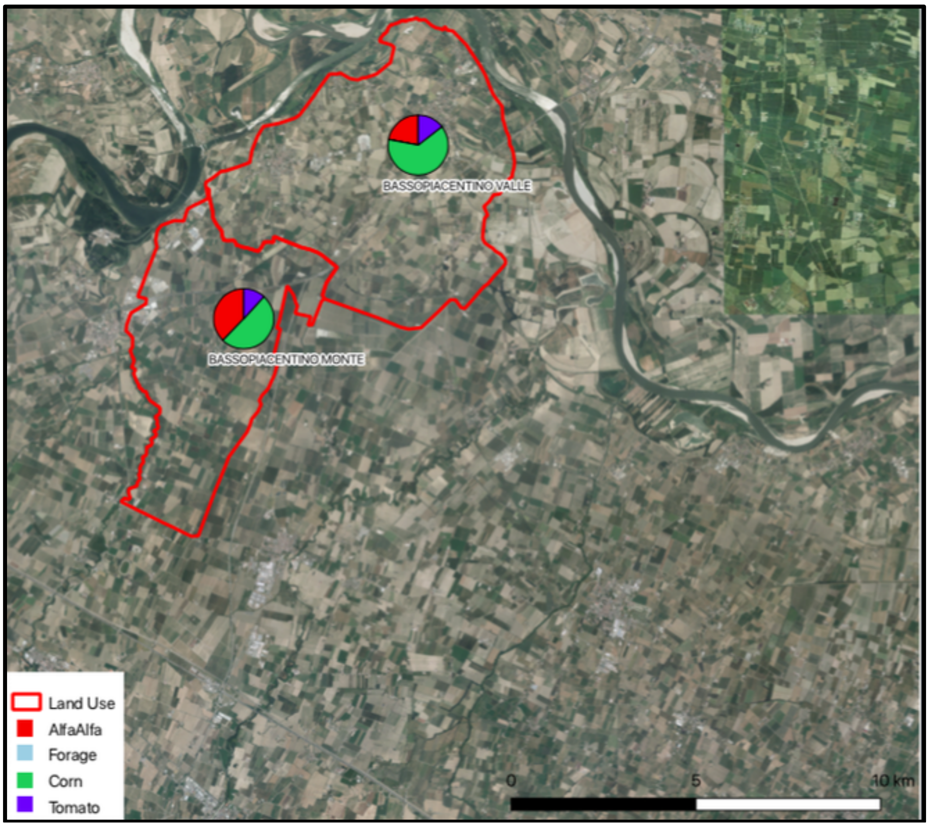

Figure 13: Overview of the two sub-districts

The two sub-districts are comparable in size and cultivated crops as shown in Figure 14: Land use. They include different farms, however, for the purpose of this paper, we consider each sub-district to be managed by a single DM, as if it was a single farm. Because Basso Piacentino Valle is located at the top of the irrigating network, it corresponds to Farm 1 in our model; Basso Piacentino Monte instead corresponds to Farm 2. Accordingly, the only water source in the district is an inlet from the Po River which is located at the border of Basso Piacentino Valle and is managed by the WA. Through the inlet, water is pumped from the river to the irrigation network which distributes water first in Basso Piacentino Valle, then in Basso Piacentino Monte. The WA can manage water volumes to be pumped from the river to the district but has no tool to manage water use within Basso Piacentino Valle, therefore Basso Piacentino Monte gets the remaining water.

	Forage (ha)	Alfalfa (ha)	Corn (ha)	Tomato (ha)	Total (ha)
BASSOPIACENTINO MONTE	0	514	687	160	1361
BASSOPIACENTINO VALLE	3	366	1060	242	1671
				Total	3032

Figure 14: Land use

4.5.2 Assessment procedure

To gather inputs for the assessment of WU and WP, we implemented a web-based platform, named IRRINET. This is an Italian ICT which provides farmers and WAs daily information on irrigation requirements (Munaretto and Battilani 2014). To run its agrometeorological models, IRRINET needs inputs on soil; precipitation; crop productivity and irrigation systems. This information was made available by the WA and helped to assess the daily evapotranspiration and CWD for each of the major crops cultivated in the district. Then, with the use of a modified version of the equation presented in the FAO Irrigation and Drainage Paper N°33 (Doorenbos and Kassam 1979) (detailed description is reported in Appendix 3: Relation between irrigation and crop production), we estimated crop productivity as function of the share of CWD satisfied by irrigation.

The WA provided also the volumetric cost of irrigation at the farm level (c_{farm_i}) and outputs prices. With regards to the volumetric cost of water at the WA-level (c_{WA}), this should include resource and external costs, as assumed in the model. Such costs are difficult to be estimated and the only available information was relative to the bill the WA has to pay to the provider per each volume of water pumped from the reservoir. Therefore, we made hypothesis considering c_{WA} as a function of the costs at the farm level. Specifically, we hypothesized c_{WA} being 50% higher than the weighted average volumetric cost of irrigation in the two sub-districts. To assume external costs of water being proportional to the in-farm water cost is a significant simplification. Opportunity costs might be somehow related to the in-farm water costs, but environmental costs are likely to be not. Following the purpose of this paper, we want to highlight how, if the WA considered higher water costs other than the private ones, this would affect water management. At this end, precise estimations of the total cost of water would be helpful, but at the same time, these would not change the decision dynamics which are the focus of this research. In addition, we will run a separate simulation to highlight the differences in decision dynamics between a situation where the cost of water is made only by the water bill and a situation with the assumed total cost of water.

Thanks to the use of economic data, together with crop productivity, we were able to assess net revenues as function of water used ($V(X_{farm_i})$). Finally, to estimate the dynamics of the district's performance in the time lag when actors' actions are not coordinated in information implementation, we analyze the evolving of WP (Eq. 23**Error! Reference source not found.**):

$$WP = \frac{V(X_{BM}) + V(X_{BV}) - c_{WA}X_{WA}}{X_{WA}}$$

Eq. 23

This is an indicator expressing the farm revenues per volume of water pumped in the network by the WA. Its use allowed to analyze the evolving of the district's performance from the time when the ICT is firstly introduced until when all actors are familiar with it.

In the district, choices for the irrigation plan are not made on a daily basis due to technical restrictions in water delivery and in-farm irrigation systems. To account for this issue and to simplify the analyses, results are considered on a two-months basis. The two-months periods in which the irrigating season is divided are: March-April; May-June; July-August; September-October. All the results derive from data of the 2018 irrigation season.

Because IRRINET provides deterministic information, to account for the probabilistic nature of the ICT-messages hypothesized in this paper, we applied Monte Carlo Simulation. This technique is used to generate normal distributions having as input the average and standard deviation of the samples. For each period and for each sub-district, we run one simulation with 500 iterations, using the software Palisade @Risk. Averages and standard deviations for the simulations are determined from the range of variability in revenues derived from the input data provided by the WA. The resulting distribution represents the variability in payoffs from the ICT-aided irrigation decisions in the period considered.

As an example of the simulated I Order distributions, Figure 15: I Order PDF of revenues in denotes the share of risk affecting seasonal revenues in the period March-April. This uncertainty is estimated by the ICT in the form of a normal PDF and describes how seasonal revenues in the whole district are distributed if irrigation follows the advice of the ICT in the period considered. Results are determined in absolute terms and on a per-hectare basis. In the district, the seasonal average revenue (7,769,648€ - 2,563€/ha) is constant between periods, while standard deviations vary, depending on the impacts that irrigation in one period has on the revenues of the whole season. In other words, the expected seasonal revenue is one, but its variability is conditioned by the time of the season the decision is taken. This is evident from Table 5 reporting standard deviations in the simulated PDFs of revenues at the district level. Here, in the periods May-June and July-August, variability is higher because of the key role irrigation has in these periods when crops are most sensitive to droughts. Accordingly, missing irrigation requirements in May-June and July-August has higher impacts than in other periods where the share of crop production subjected to uncertainty is lower.

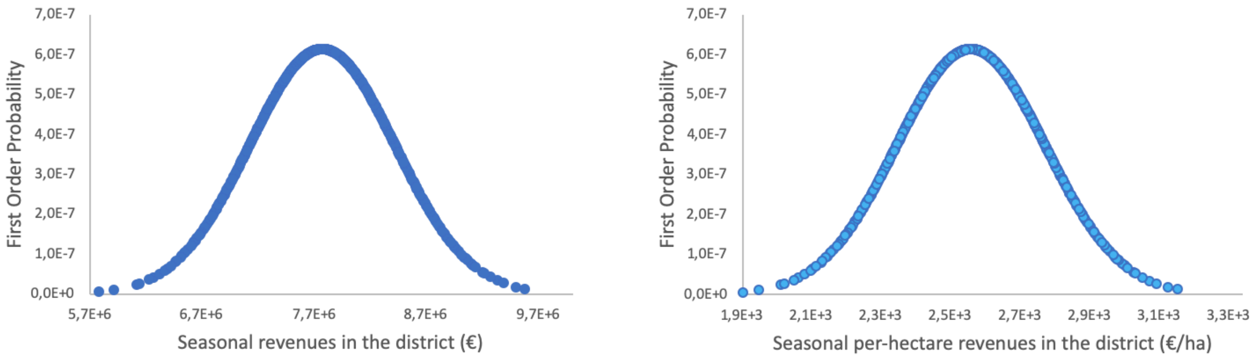

Figure 15: I Order PDF of revenues in the district for the period March-April

		Average		Standard deviation	
		€	€/ha	€	€/ha
I order PDF of seasonal revenues	March-April	7,769,648	2,563	652,969	215
	May-June	7,769,648	2,563	1,058,601	349
	July-August	7,769,648	2,563	1,053,017	347
	September-October	7,769,648	2,563	561,071	185

Table 5: Parameters of the I Order PDF representing risk in the district for one period

Since we did not have information on actors' perceptions either, Monte Carlo Simulation was used to simulate the II Order PDFs too (Figure 16). Here, averages correspond to the expected value in the relative I Order PDF, as assumed by Klibanoff et al. (Klibanoff et al. 2005). Standard deviations were determined assuming that the range of feasible distributions (Δ) varies within 30% of the I Order PDF. This assumption implies that errors in probability estimations are up to the 30%; such error is considered equal between actors. From Table 6 we can see that standard deviations are significantly higher than the correspondent I Order distribution due to the assumptions made on the range of feasible distributions. With regards to differences in ambiguity between periods, these reflect the differences in the I Order distributions: with higher variability in the I Order PDF we will have higher variability in the II Order PDF too. The simulated II Order PDFs, obtained for each actor and for each period, are then updated following the learning rule expressed in Eq. 17. This allowed mean-preserving contractions in the distributions, resulting with a lowering in standard deviation with time (Figure 17). Given the specific case considered, where the ICT is capable to correctly estimate all uncertainty in $\pi^{ICT}(x^s)$, standard deviation lowers after each TF, until ambiguity is solved.

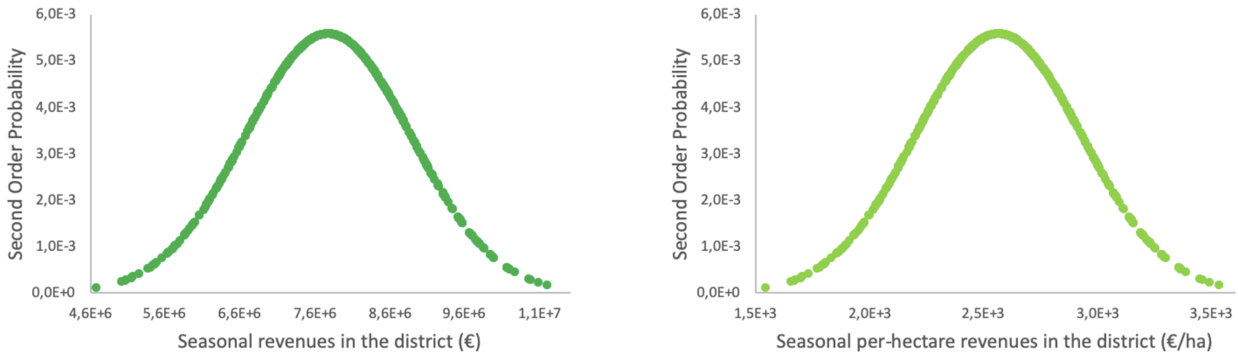

Figure 16: II Order PDF of revenues in the district for the period March-April

		Average		Standard deviation	
		€	€/ha	€	€/ha
II order PDF of seasonal revenues	March-April	7,769,648	2,563	1,108,993	366
	May-June	7,769,648	2,563	1,224,099	404
	July-August	7,769,648	2,563	1,119,908	369
	September-October	7,769,648	2,563	965,435	318

Table 6: Parameters of the II Order PDF representing ambiguity in the district

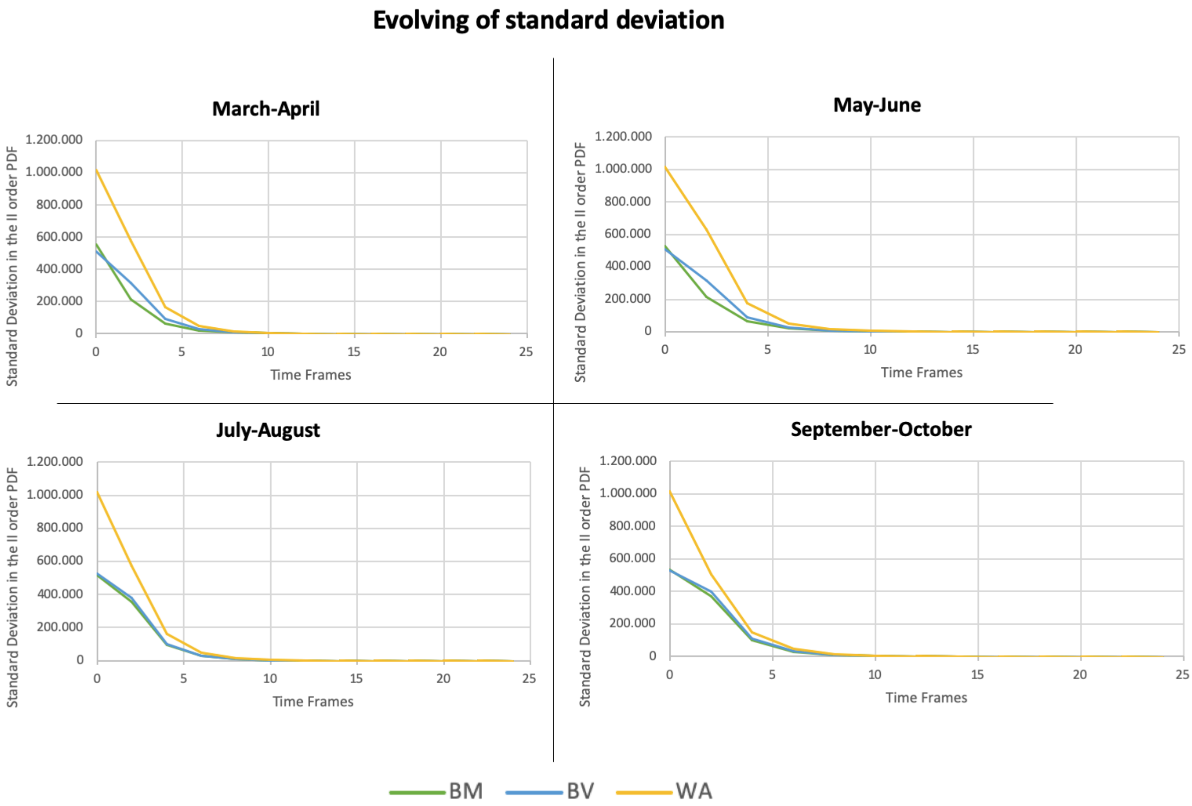

Figure 17: Standard Deviation of the II Order PDF

Finally, we applied Eq. 21 and Eq. 22 which gave as output the numerical estimations of the actor's demand for water in absolute terms and on a per-hectare basis. Because the developed model determines WD as function of variability in the II Order PDF, as standard deviation lowers also WD lowers in the learning process. To better understand model's output, we assessed the extent to which the simulated behavior differs from a situation in which the actor always implements the PP or the RP. As a result, in Figure 18 and Figure 19 we have WD of one actor which always implements the PP (WD_Precautionary); the simulated WD (WD_Simulated) and WD of an actor which is neutral to uncertainty and always implements the RP (WD_Neutrality). From both figures, it is evident how, with the learning process, the lowering in variance allows to lower the simulated water demand thanks to the progressive information implementation. The simulated behavior sees the actor implementing the PP in the first TFs, then as ambiguity lowers, he starts to implement information and reduce the water volumes he would use. Eventually, when ambiguity is solved the simulated WD gets comparable to the uncertainty-neutral actor's one. However, as can be seen in the graphs, WD_Simulated never coincides with WD_Neutrality. Although WD_Simulated gets constant when the actor is familiar with the ICT, it is always higher than WD_Neutrality. This is due to the elements of risk aversion in the simulated behavior which are absent in the uncertainty-neutral behavior. Therefore, when an actor is familiar with the ICT, the difference between WD_Simulated and WD_Neutrality represents a form of risk premium. This is expressed in m^3 of water the actor is willing to use in excess to get rid of part of the risk involved in the RP. Figure 18 is reported as an example to highlight how WD from one actor varies across periods; this is due to the different water requirements from crops across periods. Instead, in one period there are differences in WD between Basso Piacentino Monte and Basso Piacentino Valle (Figure 19) because of differential land use.

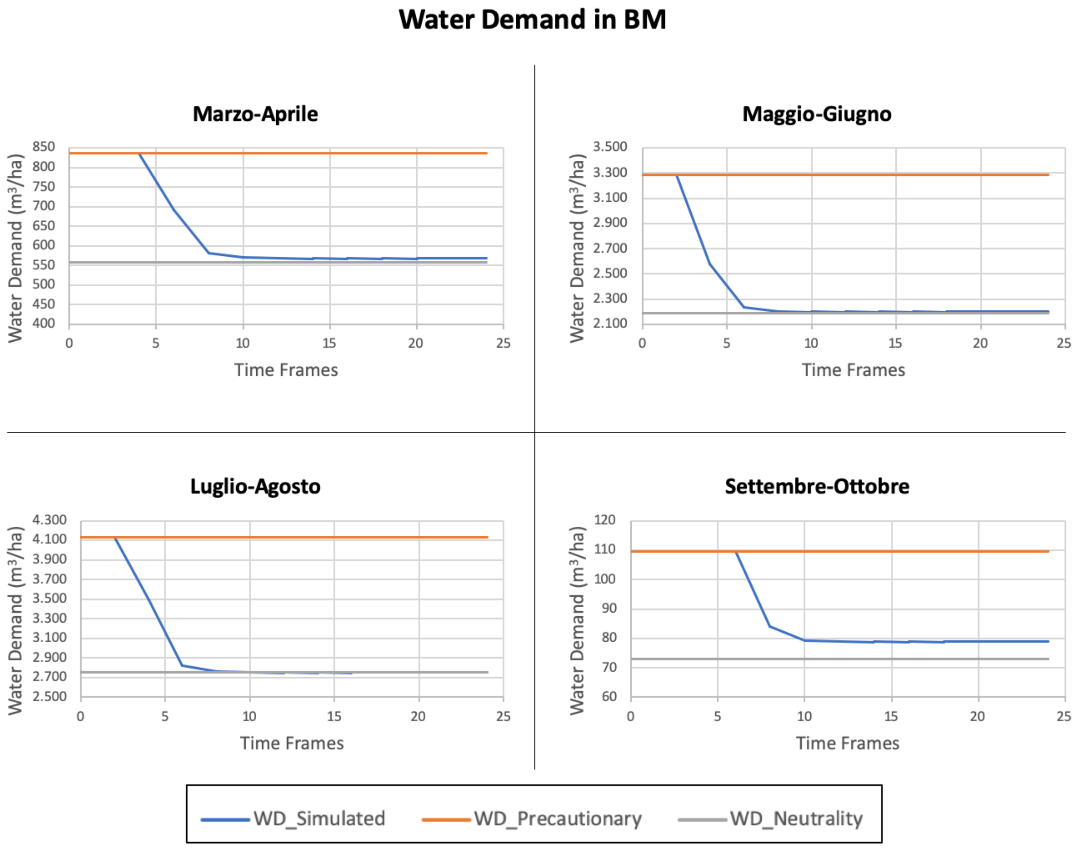

Figure 18: Comparison between periods of the evolving of WD in Basso Piacentino Monte

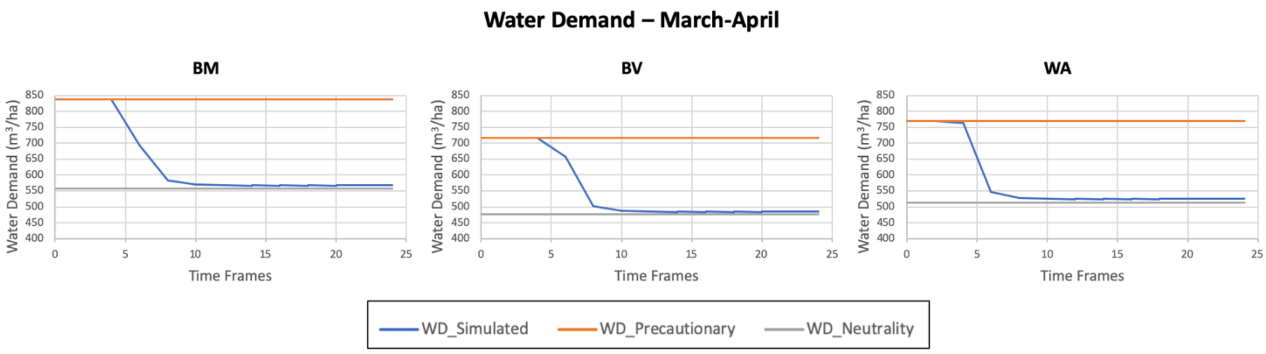

Figure 19:Comparison between actors of the evolving of WD in March-April

4.6 Governance issues and scenario analyses

By applying the above described assessment procedure, we were able to identify the water volume each actor wishes to use under his behavioral perspective. Now, to understand how this affects WU and WP at the district level, we have to take into account the relations between actors along the irrigation network. Accordingly, even in conditions of regular water availability, the volume an actor would use to irrigate might differ from the one at his disposal. This migh be due to the fact that, in the management of common resources, the decision of an actor is capable of affecting resource availability of another. This is the case of the irrigation management process described in the following paragraph.

The irrigation management process along the irrigating network can be represented as follows. The WA decides the water volume to be pumped in the network according to its demand (x_{WA}^{d}). In sub-district Basso Piacentino Valle, WU will correspond to ${x^{d}}_{BV}$ if ${x^{d}}_{BV} \geq x_{WA}^{d}$, otherwise, the DM irrigates up to x_{WA}^{d}. In the first case, after water has been used to irrigate in Basso Piacentino Valle, to Basso Piacentino Monte remains the available water. In the second case, it remains no water to Basso Piacentino Monte. In any case, if the remaining water in Basso Piacentino Monte is higher than CWD, there will be no impact from poor governance, otherwise water un-availability will cause revenues to be lower than expectations. Finally, if WU in Basso Piacentino Monte will be lower than water availability (${x^{d}}_{BM} + {x^{d}}_{BV} \leq x_{WA}^{d}$), part of the water pumped in the network reaches the end section of the district where it is discharged.

As made evident by the process above described, water demand is the key variable to highlight governance issues. However, it depends on the actor's subjective behavior, on which we did not have any information. To overcome this lack of data, we made hypothesis on behavioral coefficients and varied them in the following two scenarios, which are the most representative in determining the dynamics of WP:

1. Scenario 1: the WA starts to implement information earlier than farmers;
2. Scenario 2: farmers start to implement information earlier than the WA.

In both, we consider an actor to start implementing information when the water volume he decides to apply ($x_{farm_i}^{d}$ or x_{WA}^{d}) is lower than the precautionary one. These two scenarios are selected because they highlight the main two problems which can rise from poor coordination.

Accordingly, despite the infinite number of combinations between actors' behavior, their impacts on the district's efficiency can be divided in the two alternatives described later in this subsection. The actors' behavioral coefficients in the two scenarios differ only for the coefficients of ambiguity aversion (a), where in Scenario 1 $a_{WA} < a_{BM}$ and $a_{BV} = a_{BM}$; the opposite, in Scenario 2 $a_{WA} > a_{BM}$ and $a_{BV} = a_{BM}$ (Table 7 and Table 8).

In the first scenario, we suppose that the WA is the first actor to implement information received because of its lower ambiguity aversion (Table 7). As a result, the WA pumps in the network a water volume which is not sufficient for both farms if they implement the PP and irrigate at the field capacity. Because farmers' actions are not coordinated, it is likely that in Basso Piacentino Valle there will be excess use of water. This will cause the available water in Basso Piacentino Monte to be lower than CWD, so revenues will get lower than expectation with economic losses. If we analyze the occurrence of such losses with the passing of TFs (Figure 20), we see that in the first place no loss occur; because, notwithstanding excess-use in Basso Piacentino Valle, the remaining water in Basso Piacentino Monte is sufficient. Then, as the WA reduces the pumped volumes, losses occur; these are higher in the core of the irrigating season when crops are more susceptible to droughts. After actors have gained familiarity, no losses in Basso Piacentino Monte are manifested.

		Behavioral coefficients		
		Risk aversion (r)	Ambiguity aversion (a)	Update rate (w)
Actor	WA	2.0E-07	6.0E-05	2.0E-01
	Basso Piacentino Monte	2.0E-07	6.0E-04	2.0E-01
	Basso Piacentino Valle	2.0E-07	6.0E-04	2.0E-01

Table 7: Actors' behavioral coefficients in Scenario 1

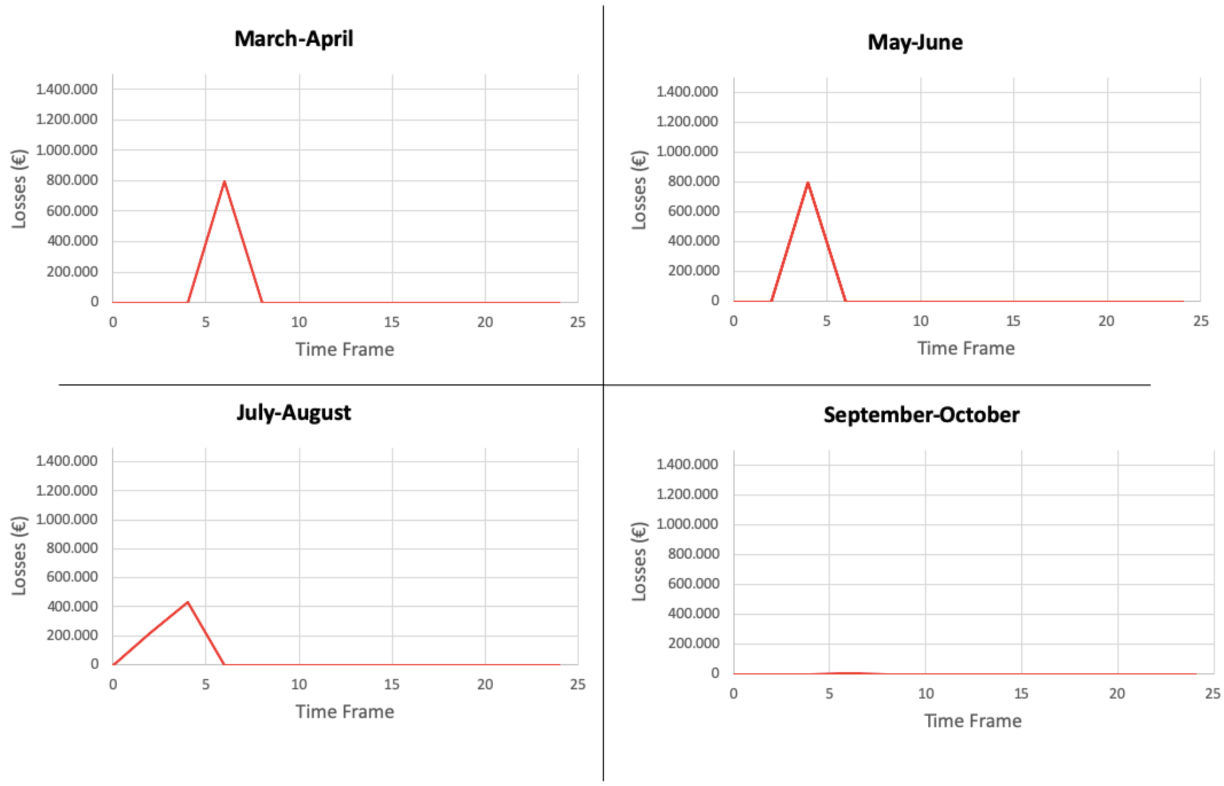

Figure 20: Losses in Basso Piacentino Monte due to over-use in Basso Piacentino Valle in scenario 1

The above explained inefficiency in water governance do not allow to maximize farms' revenues with the available water; this has strong impacts on WP. Accordingly, if we analyze the evolving of the district's WP during time (Figure 21), we see that, in the first TFs after the introduction of the ICT, WP is extremely low due to excess-use of water and production losses in Basso Piacentino Monte. However, in WP there is a positive trend and, as ambiguity is solved in the process of familiarity, WP reaches relatively high values. Has done with WD, to better understand model's output we also determined WP in a situation where all actors implement the PP (WP_Precautionary) and where all actors are neutral to uncertainty and always implement the RP (WP_Neutrality). Here again, the trend of WP reflects a progressive information implementation and, with it, a progressive achievement of ICT-benefits. In the first TFs, WP is low and coincides with the business as usual situation when all actors implement the PP and the district's efficiency is low. Then, WP rises as WU lowers and losses in Basso Piacentino Monte are less important; finally, WP reaches values comparable with the settings when all actors implement the RP. Again, WP_Simulated never coincides with WP_Neutrality, due to the remaining risk and the risk-aversion in the simulated behavior.

In Scenario 2 we hypothesize that DMs in the two sub-districts are the first to implement information because of their lower aversion to ambiguity (Table 8). Here, farms' efforts to save water are wasted at the district level because the WA pumps water in excess. Then, water will be wasted downstream the irrigating network, not being fully used by farmers. This translates into low WP up until the time when also the WA starts to implement information and progressively lowers water volumes pumped in the network. Accordingly, in the graph of Figure 21, we see WP in the first TFs being extremely low, then, as the WA progressively reduces water volumes, WP rises with a non-decreasing trend

		Behavioral coefficients		
		Risk aversion (r)	Ambiguity aversion (a)	Update rate (w)
Actor	WA	2.0E-07	6.0E-04	2.0E-01
	Basso Piacentino Monte	2.0E-07	6.0E-05	2.0E-01
	Basso Piacentino Valle	2.0E-07	6.0E-05	2.0E-01

Table 8: Actors' behavioral coefficients in Scenario 2

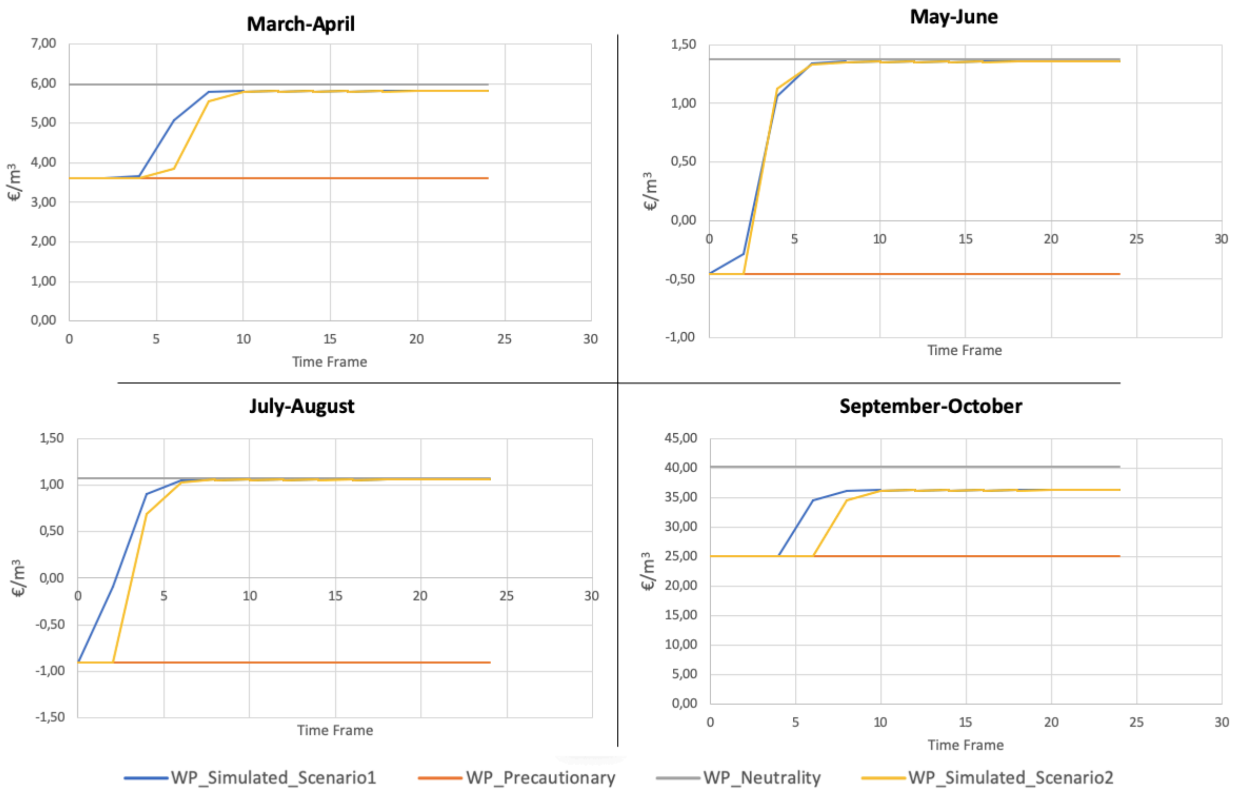

Figure 21: WP during time

In parallel with the assessment of the dynamics in WP, we estimated how, with the passing of TFs, water savings at the district level evolve (Figure 22). These are determined considering the simulated use of water in the district, having as benchmark WU with the PP. Reflecting the trend in WP, in the beginning no savings are achievable at the district level because actors decide to implement the PP. Then, the process of familiarity allows to lower water demand (Figure 18) and, with it, WU in the district.

Both in the assessment of WP and water savings, between the two scenarios values are comparable. However, we can see that in Scenario 1 higher levels in the district performance are reached few TFs earlier than with Scenario 2. This interesting pattern reflects the dominant role of the WA driving water use efficiency in in the whole district. Decision at the WA level are key because they not only condition water availability at the farm level, but also determine water use for the district. Accordingly, if farmers implement information but the WA does not (Scenario 2), there will still be water waste at the end section of the irrigation network.

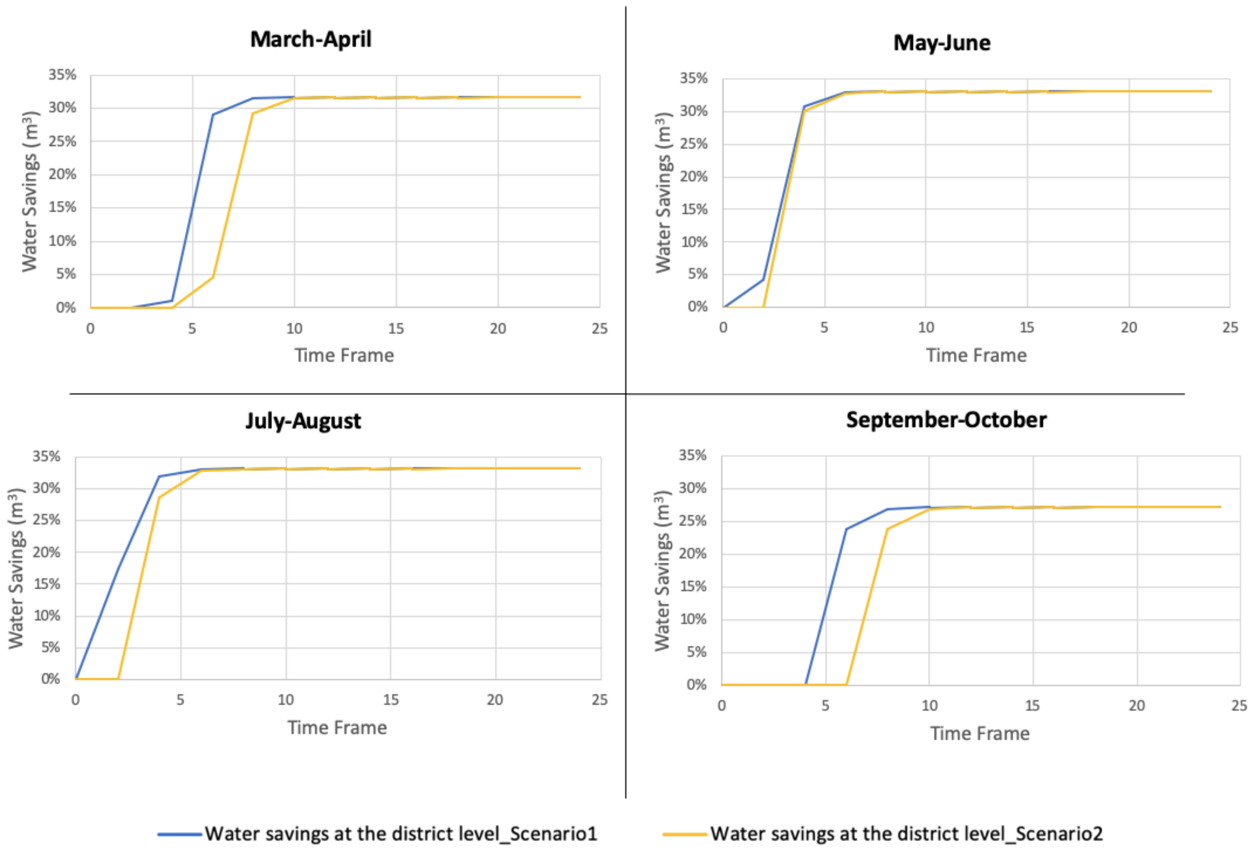

Figure 22: Water savings with the passing of TFs

A specific consideration must be made in the estimated values of WP. Here, the main highlights are: (i) in the periods March-April and September-October WP is much higher than in the rest of the season and (ii) in the first TFs of the periods May-June and July-August WP has negative values. The first highlight reflects the fact that CWD in the core of the irrigating season is much higher than in the shoulder season, given the same production levels. Negative WP values uncover the assumed nature of volumetric costs of water at the WA-level which include resource and environmental costs. Under the private perspective, having negative WP means irrigation has negative impacts on production levels and actors would spontaneously avoid water use in such circumstances. However, we raised the cost the WA has to face to pump water into the network to represent external costs. Therefore, a negative WP should be interpreted as a signal of the fact that in the business as usual conditions irrigation is not sustainable under the societal perspective, even if it is profitable for actors in the district. Nevertheless, because we made strong assumptions on the total cost of water, such conclusions cannot be made and WP values per-se are not reliable; in the scope of this research, the key focus is on the dynamics of WP. To further understand the effects of not including external costs in the decision environment, we have run a separate simulation. This helps to understand the differences in decision dynamics between a situation where cost of water is the only bill the WA has to pay and a situation with the assumed total cost of water. The results of the simulation are compared to the WP when all actors implement the PP or the RP. As can be seen from Figure 23, WP evolves with TFs as in the previous two scenarios. However, the maximum WP values are far from being comparable to the RP. Accordingly, given the small cost of water, the WA finds it more profitable to use water in excess than risking revenues and implement the RP. This is especially evident in September-October when information is never implemented because never profitable under the actors' private perspective.

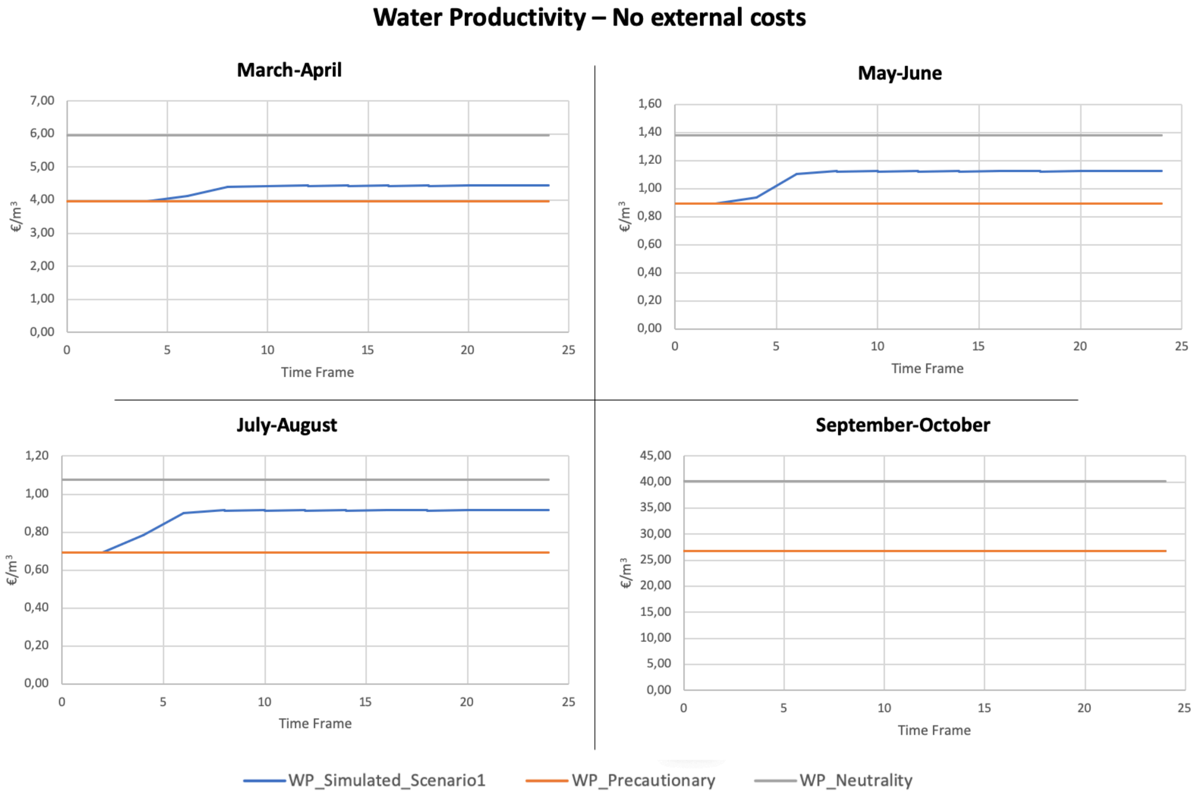

Figure 23: WP if no opportunity costs are considered

4.7 Discussion

In this paper we developed a behavioral model capable of representing the decision between inefficient but riskless irrigation plans or ICT-aided efficient irrigation plans with uncertain outcomes. The complex uncertainty settings involved in new ICT-information implementation are framed distinguishing between risk and ambiguity. This allowed to treat separately the probabilistic estimations provided by the ICT, which are exogenous and common between DMs, and the subjective perceptions on the ICT reliability. This separation opens the possibility to model the evolving of ambiguity over time as DMs get familiar with the new technology.

In literature, several learning models have been proposed to describe how familiarity takes place as new evidences become available in time. However, these models cannot be applied in our context for one of the following reasons: (i) they refer to data-generating problems, where the mere repetition of a test allows to objectively solve ambiguity; or (ii) they are developed to account for production technologies, where performance can be quantitatively measured. For these reasons we developed a new learning model where, at the end of each TF, the DM gets a binary signal from the environment. This signal describes whether information has been correct or not. It is used to update the prior II Order PDF on ICT reliability to obtain a posterior PDF, according to the updating model developed. With the passing of TFs, if the ICT proves to be reliable, ambiguity lowers and, with it, the variance in the II Order PDF. This will help ambiguity-averse DMs in ICT-information implementation.

Because behavioral attitudes under uncertainty are subjective, there will be differences among DMs in the time when they get familiar with the ICT and implement its information. Up until the time when every actor is not familiar with the ICT, differential ambiguous perceptions will cause un-coordinated WU in the district. By applying the model to a numerical example, we highlighted how this can undermine ICT benefits. Specifically, we considered two main scenarios assuming an accurate ICT and attitudes toward uncertainties being constant in time. Scenarios revealed that poor coordination among actors can not only cause allocative inefficiencies, but also drought losses at the farm level, with negative WP values. The issue is further exacerbated if we relax the assumption of constant attitudes between actors.

In both scenarios we see ambiguity and poor coordination between actors to undermine benefits form ICT. However, this is true only in the first TFs when actors have few or no insights on ICT reliability. If they were allowed to gain experience, considering the learning behavior hypothesized, eventually, they would observe the same performance. As a result, actors' actions will get coordinated by information provision on its own. This way, high WP values can be reached thanks to efficient ICT-aided irrigation plans. However, the learning process takes some time, an issue which will cause inefficiencies in the use of water at the district level. Further, with the modelled behavior WU and WP never reach the optimal values achievable when all actors implement the RP because, even after they get familiar with the ICT, RA remains. This makes actors willing to use water in excess to get rid of part of the risk specified by the ICT.

The limitations of these results are in the model's assumptions and simplifications. These are required by the complexity of the uncertainty settings. The first limitation is in the payoff function which includes only volumetric costs. This simplification is driven by the fact that costs for machineries and in-farm delivery systems are fixed in the short term and cannot be reduced by efficient ICT-aided irrigation plans. Therefore, we assume that they will not be taken into account in the implementation decision. This is true even at the WA-level, where fixed costs for irrigation network maintenance are mostly related to the characteristic of the infrastructure itself not to the operational volumes.

The research makes strong assumptions on behavioral coefficients. Here risk and ambiguity aversion coefficients are hypothesized in absolute terms and assumed to be equal between actors. This simplifies reality because differences in behavior are not only due to the mere differential perceptions, but also to differences in attitudes, with some DMs being more averse to uncertainty than others. However, these assumptions allowed us to focus on ambiguity, isolating the effects that AA has on decisions, rather than uncertainty attitudes as a whole. Further, we assumed the learning behavior being dependent only on subjective attitudes and, again, it is considered to be constant between actors.

Volumetric costs incorporate another limitation caused by the lacking available data. At the farm level we assumed the cost of water being known and proportional to the quantity of water used. This is not always true, especially in settings where water use is un-metered. However, other costs, such as fuel consumption, could be taken into account by the farmer when deciding whether to use less water (in light of new pieces of information) or not. At the WA-level, as assumed in the model, costs for water should include resource and external costs. However, such costs are difficult to be estimated and the available information was not sufficient; so, we hypothesized them being 50% higher than the costs at the farm level. To assume external costs of water being proportional to the in-farm water cost is a significant simplification. Opportunity costs might be somehow related to the in-farm water costs, but environmental costs are likely to be not. Therefore, the assumption is simplistic and might lead to strong biases in the estimation of water costs under the WA perspective. Nevertheless, it was not the purpose of this paper to focus on common good assessment and the main governance issues highlighted by the model are still in place even with sensible variations in the full cost of water. In addition, we run a separate simulation to highlight the differences in decision dynamics between a situation where the cost of water is made only by the water bill and a situation with the assumed total cost of water.

The main limitation of the model is in assuming that DMs can judge if information received was correct and in simplifying this judgment with a binary signal. With weather-related ICT, the DM might find difficulties in the ex-post assessment of information reliability. Climate parameters are hard to measure by DMs: multiple sources of information might be misleading and quantitative comparisons between forecasts and observations are frequently impossible at the end-user level. This can cause relevant elements of subjectivity in DMs' judgements on the signals received after each TF. However, this phenomenon will only be relevant in the first TFs and, as the number of TFs increases, its impact will be negligible. Therefore, we can still consider that, when DMs are completely familiar with the ICT, their judgements on ICT reliability will be comparable. Moreover, in case of differences in judgements, the issues of poor governance highlighted in this paper will be further emphasized.

Finally, the model considers ordinary settings for water management, with no constraints in terms of water availability. It would be interesting to develop the model by including DMs' behavior with extreme events such as droughts. In these conditions, decision payoffs are characterized by heavy tailed distributions where knowing only the expected state would lead to strong underestimation of downside risks. At this end, information on distribution's skewness would allow DM to be better able to plan their action consistently with the climate risks (Li, Xu and Zhu 2018). In such settings, it is evident how ICT would play a significant role; however, the impact of ambiguity can be expected to be significant too. Accordingly, the DM would not only doubt the probability of the average state, but also the shape of the whole distribution, given its relevance for the decision. This would require to further develop the model to relax the assumptions of normality in first and II Order PDFs and account for negatively skewed distributions of payoffs with climate shocks

4.8 Conclusions and policy advice

Despite being simplified, the model developed is capable of providing a complete picture of the impacts that subjective behavior under ambiguity has in undermining ICT potentials for efficient water management in irrigation districts. Ambiguity is found to be limiting ICT implementation because ambiguity-averse DMs find disutility from being exposed to the un-measurable uncertainty generated by not knowing ICT reliability. Further, through an empirical example, we showed that, if actors' decisions on ICT implementation are not coordinated, allocative inefficiencies and production losses can occur. Both of the above issues can only be solved thanks to the process of familiarity. By allowing the DM to gain experience on ICT reliability, he would solve his ambiguous perceptions and put information into action. Then, when all actors get familiar with the ICT, their action will get coordinated according to their observations. However, the process of familiarity can take time; this period might further discourage ICT uptake. Accordingly, if in a TF the DM implements information to save water, but his efforts get vanished due to those who decide to implement the PP, in the next TF he will be more unwilling take the RP. This would hinder a vicious circle and underlines the need for policy interventions.

Uncertainty-management policies would be needed to lower ambiguity on ICT reliability, speeding up the process of familiarity. This can be done by providing ambiguity-reducing information on the technology's performance (Ross et al. 2012) and allowing DMs to directly experience the reliability of the ICT trough demos and demonstration events. Having hands on the new technology, without necessarily implementing it at DM's own expenses, would allow users to gain information on ICT reliability.

Policies for efficient water governance would be needed too. Here, the main aim would be to avoid excess-use of water by some farmers, which might cause production losses to others. At this end, the only available tool would be to meter water consumption at the farm level and provide sanctions in case of excess-use. Nevertheless, this is possible just in few cases because the majority of irrigation networks are made of open-air canals where water consumption cannot be metered to implement volumetric pricing systems (Lika et al. 2016). In such conditions if the WA imposed to farmers the use of the ICT, it would not have any tool to assess whether information had actually been implemented or not. As a result, farmers downstream the network would remain subjected to the risk of water un-availability due to excess-use of water upstream. Given the risk of the sector to not exploit ICT because of these barriers, we believe to be a priority to further invest in ICT development to maximize the capabilities of these tools and to further disseminate their potentials. This would help fostering ICT uptake with a bottom-up approach, given the absence of policy tools to impose regulations for information implementation.

Chapter 5

5. Discussion

5.1 Summary of results

The thesis started considering the potentialities of ICT but also acknowledging the fact that ICTs cannot always be beneficial to irrigation management and even if ICT-information can provide benefits, there are constraints. To help understanding the problem, we distinguished between two classes of constraints limiting ICT adoption and ICT-benefits in irrigated agriculture. On the one hand, we identified with restrictions to information usability those constraints which occur when the ICT provides information that cannot be implemented or it is not profitable if implemented. Such restrictions cannot be overcome because they are intrinsic characteristics of the decision environment. On the other hand, we defined barriers to the achievement of ICT-benefits those constraints which can be overcome by: (i) modifying ICT-information to meet DMs' needs; (ii) adapting decision processes to implement information and achieve higher performances or (iii) providing ambiguity reducing information to solve behavioral barriers.

In the literature, there are several studies addressing the topic of ICT implementation in agriculture and water management (Jeuland et al. 2018; Meza et al. 2008). Nevertheless, results are contradictory, and none provides a comprehensive assessment addressing, with a holistic approach, the whole decision environment. In particular, to the best of authors' knowledge, no study was found addressing decisions at the WA-level and the issues of ambiguity and AA.

In this context, we deeply analyzed the decision environment around the choice for ICT implementation to aid irrigation management in the process of digitalization. The ambition of the thesis was to develop new decision models to fill the knowledge gaps on ICT implementation and answer the need for evidence-based policy advice. Specifically, we aimed at answering the need of evidences on information usability, on potential economic benefits from ICT and on barriers to the achievement of such benefits. To do so, the research has been carried out in three interconnected but separate parts. (1) The first is a literature review aimed at understanding the key issues for ICT adoption and at drawing the objectives and foundations on which to develop decision models to aid the sector. (2) In the second part of the research, we addressed the issues of restrictions to information usability and quantitatively estimated potential economic benefits from the ICT-informed decision process of irrigation management at the WAs level. Finally, (3) in the third part, we developed a behavioral model to assess the extent to which behavioral barriers under ambiguity have in undermining ICT potentials for efficient water management in irrigation districts.

(1) Results from the literature review highlighted how ICT benefits are strongly context dependent. ICT-information will only be usable when its content answers DMs' needs (Furman et al. 2011) and its form is compatible with technical restrictions (Vogel et al. 2017). Further, many works underline how subjective behavioral barriers are capable of compromising ICT implementation and ICT-benefits. The review also allowed to build the theoretical foundations for new behavioral decision models of ICT adoption under uncertainties in irrigation management. Here we introduce the concept of ambiguity. This arises from a lack of knowledge on information reliability and expresses the degree of confidence the DM puts on the risk estimations provided by the ICT. The uncertainty framing proposed allows to model the process of familiarity which occurs as the DM gains experience on the ICT. Familiarity is expected to play a key role in the ICT adoption decision as it favors uncertainty-averse DMs in ICT-information implementation.
(2) To answer to the issues of restrictions to information usability and unclear ICT-benefits, in the second paper we developed a theoretical model, based on BDT. Results from the implementation of the model to the case study allowed to estimate potential benefits from ICT-aided decision process of irrigation management at the WA-level. This is subjected to high variability in spatial and temporal distributions. The former variability is caused by differences in land use, where, with permanent or high added value crops, technical barriers or the high stakes in the decisions do not allow ICT implementation. Temporal variability is caused by the fluctuation of water savings during time along the irrigating season; when no rain is forecasted, savings are low. Over variability, benefits are also characterized by barriers of the decision environment which are capable of compromising information usability. In the specific context analyzed, the most relevant constraint is in the decision power of the WA. Here, the WA cannot act upon information received before the irrigating season because it cannot influence land allocation of permanent crops in the medium term. Moreover, due to the characteristics of the supply network, the WA is not able to precisely allocate water

according to needs. This limits ICT-benefits because of missed water savings opportunities. Finally, results proved how information form and quality affect its usability. Especially in irrigated agriculture, decisions follow the seasonal pace, therefore, it is important that messages are delivered at the right time during the decision process. With regards to the quality of ICT-information, a specific sensitivity analysis was carried out to show its relevance and the benefits from improvements in accuracy. Given the high stakes involved in irrigation management, it is fundamental that new ICTs provide information with the accuracy needed by the specific target decisions.

(3) Quality of information and ICT perceived reliability have been the core of the third part of the thesis. Here, we developed a behavioral model capable of representing the decision between inefficient but riskless irrigation plans or ICT-aided efficient irrigation plans with uncertain outcomes. The model allowed to account for perceptions on ICT reliability and attitudes toward uncertainty and showed how differential ambiguous perceptions can undermine ICT benefits. To assess the extent to which subjective behavior can compromise the efficiency of ICT aided irrigation plans, we applied the model to a case study. Here, we considered two main scenarios assuming an accurate ICT and attitudes toward uncertainties being constant in time. Scenarios revealed that poor coordination among actors can not only cause allocative inefficiencies, but also drought losses at the farm level. However, this is true only in the first TFs when actors have few or no insights on ICT reliability. If they were allowed to gain experience on it, their actions would eventually get coordinated and the potentials of ICT achieved.

5.2 Limitations and future research

Modelling decision processes for irrigation management under uncertainty is extremely complex. This posed limits in the results and in the models' capability to represent real-life decisions. Three main limitations are caused by three distinct sources of complexity: (1) uncertainty framing; (2) peculiarities of the irrigation sector; (3) subjective behavior of farmers and WA.

(1) Uncertainty framing: uncertainty on its own is unclear and its structure and impacts are often debated (Machina and Siniscalchi 2014). This is highlighted by the numerous theories developed in the economic literature, often one theory in contrast with the other. In this research we provided a representation of uncertainty where there is a clear separation

between risk, which is exogenous and captured with the accuracy of the ICT, and ambiguity which is a characteristic of the DM's subjective belief. This is a simplification of real decision processes, where uncertainty is not dichotomic and its multiple forms might be indistinctly perceived by DMs. Here, the theory of ambiguity and AA developed by Ellsberg (1961) was chosen by the authors without any empirical evidence. This might cause over-estimation of the impacts that uncertainty-aversion has on the decisions. On the one hand, other theories might be better explaining reality and further research carrying out comparative experimental tests would be useful to assess the theoretical background most suitable to represent behavior toward ICTs. On the other hand, the theory of AA is the only which allows to support the modelling of decision dynamics on ICT implementation occurring along the process of familiarity. Because we believe familiarity to be a key target for policies, we consider the theory of AA the most useful in representing the uncertainty settings of the study. Accordingly, the of uncertainty which is risk is hard to be modified because intrinsic to the decision environment. For example, risk can be due to: (i) the accuracy of the ICT, which in the short term cannot be raised more than what the state of the art model offers; (ii) or the variability of climate events, which are exogenous to the decisions. As opposite, ambiguity can be lowered in the short term by allowing DMs experiencing with the ICT and building knowledge on the ICT reliability. At this end, policies have the capability to ease the process of familiarity, speeding up information uptake.

(2) Peculiarities of the irrigation sector: the complexity of the sector adds further issues, which required simplifications. Irrigation management is peculiar and involves numerous disciplines, some knowledge of which is needed to understand decisions. This is confirmed by the multidisciplinary background of many WAs' boards and by the multiple stakeholders involved in the decisions. For example, we accounted for elements of hydraulics, where the WA must guarantee a threshold of minimum flow in canals and precise allocation is not feasible. However, because of the complexity of the systems we had to overlook other aspects of the decision environment and this might have caused biases on the estimation of ICT-benefits. Between these, in all models we overlooked or simplified environmental externalities, despite their relevance in the area where case studies are located (Cavazza et al. 2017). If research would be developed to estimate ICT-impacts on environmental variables, further support to ICT development could be motivated thanks to the resource-efficiency of ICT-aided irrigation plans. In addition, this would support policy-makers in

adapting the full cost recovery principle of the Water Framework Directive (60/2000/EC) to the context of virtuous WAs who choose to implement ICT. The peculiarities in the decision environment of the irrigation sector are also extremely variable between WAs due to differences in climate, land use, existing infrastructures and decision-making flexibility. Therefore, decision problems for irrigation management are local-specific. This poses limits to the models' applicability in different contexts and to the generalization of results; which would rather benefit of a wider testing exercise in areas with radically different decision-making conditions.

(3) Subjective behavior of farmers and WA: issues in modelling decisions on ICT information implementation are exacerbated when assumptions on the rationality of DMs' behavior are relaxed. Although being extremely relevant in affecting decisions, subjective behavior is complex and, to be represented in decision processes, it requires specific modelling techniques. In the literature there is ample variety of modelling approaches to represent DM's behavior when he is making decisions under uncertainty. Many model's applications are available highlighting the better performance of a model over another in a specific context (Machina and Siniscalchi 2014). Despite representing real life decisions with a sufficient degree of reliability, every solution proposed is significantly simplifying reality. Accordingly, combinations in behavioral traits are infinite and defining one behavioral pattern which fits for more than one DM implies to take the stereotype of the average DM and assume it fits for all actors in the same decision process. Moreover, behavior is driven by perceptions and attitudes which are difficult to be elicited because very context dependent (Machina and Siniscalchi 2014). For these reasons, in the first model, where we estimated ICT benefits, we assumed that the WA is rational when making choices on ICT-information implementation. This is done by the majority of work carried out on this topic (Aker et al. 2016) and allowed us to focus on the technicalities of the decision process, so that a better picture of information usability and potential benefits could be drawn. Despite the limits in all behavioral models, if not capable of faithfully representing reality, they can still provide better understanding of decision processes. Therefore, we modelled subjective behavior in the third part of the thesis to gain a better picture of its impacts on ICT-benefits. Here, the focus was not on attitudes per-se, but on the relative degree of uncertainty aversion between actors in an irrigation district. Accordingly, in the numerical implementation of the model, we made assumptions on all behavioral parameters.

Therefore, results provide a representation of the dynamics of the decisions and do not assess the real actors' behavior. To gain a better picture of behavior in the decision process, the model would benefit from experiments aimed at eliciting the coefficients of uncertainty aversion and perceptions toward ICT reliability. Several experimental games are available in literature, between these, the one developed by Attanasi et al. (Attanasi et al. 2014) is the most powerful to elicit AA in a way suitable to the modelling framework of this research. By calibrating the model with elicited parameters, its output would deliver results which could be better simulating the decisions. These results could be employed to design incentives aimed at compensating actors for their effort in bearing new uncertainties to save water.

Despite the above described limitations, together with the ones mentioned in each chapter of the present research, the results provided answers to many uncertainties on ICT adoption for irrigation management. The models allowed to highlight the main issues which hinder ICT implementation and ICT-benefits and provided an estimation of the potentialities of such tools. Both the models and the consideration derived from their implementation can be extended to the broader implementation of technologies in precision agriculture. Here, the use of new tools is widespread, but uncertainties on the real performances or reliability still affect implementation decisions. Further, the methodology proposed can be considered replicable in many other agricultural sectors where the digitalization process is taking place. Between these, we consider particularly relevant the topics of: (i) result-based payments to compensate farmers for the provision of ecosystem services and (ii) weather-indexed insurances developed on the basis of agrometeorological models to provide new opportunities for risk management. Environmental uncertainties cause information asymmetries between farmers and the regulator, in case of result-based payments (Derissen and Quaas 2013), or between farmers and the insurance company in case of weather indexed insurances (Vroege, Dalhaus and Finger 2019). ICT-information provision would have a potential key role in lowering uncertainties, while allowing the parts to be to be in the same informational settings. This is true for both result-based payment, where platforms can disseminate to the supplier and the regulator information on the current ecosystem status (Birge and Herzon 2019), and index-insurance, where ICTs allow to increase transparency and real time monitoring of losses (Ceballos, Kramer and Robles 2019). Nevertheless, the parts involved in the development of these tools might be unwilling to implement ICTs as they benefit from such asymmetries. Further, if lack of knowledge on the platform's reliability occurs, there will be differences in ambiguity perceptions. The impact of asymmetries in perceptions can be expected to lower the economic efficiency of these new insurance or policy tools.

5.3 Policy implications

The present dissertation was motivated by the need of evidences to support policy-makers in the design of new schemes to guide irrigated agriculture in unlocking ICT potentials. The results answered to this need and highlighted how to act in favor of the *Digital irrigated agriculture*. At this end, policy implications can be divided in three main categories: (1) ICT-development policies; (2) uncertainty-management policies and (3) agricultural and water policies. These are motivated by the potential economic benefits from ICT-aided irrigation plans and should favor an efficient digitalization process.

(1) ICT-development policies are needed to overcome issues of information usability and boost ICT-potentials. Many ICTs offer discrete technology components without providing any support to adapt the technology itself to real decision processes. The simple information provision is not sufficient to allow its implementation because of local specificities in the end-user's information environment. This is especially true for irrigation management, where climate and technical elements can vary significantly between decision contexts and can hinder ICT-information implementation. At this end, ICT are suggested to aim at delivering information tailored to farmers' or WAs' specific needs (Furman et al. 2011). However, most of ICT projects are characterized by a *top down* technological development where platforms are designed without involving end-users (Rotz et al. 2019). This causes phenomena such as the "loading dock" (Cash et al. 2006) where end-users are provided with relevant climate information which has no use in reality because its form is incompatible with actual decision making (Vogel et al. 2017). Further, this approach feeds skepticism toward ICT reliability, when DMs have never experienced the new platform (Rotz et al. 2019). Rather than a *top down* approach to ICT development, a bottom up involvement of farmers and WAs is suggested. If ICT developers gathered more information and feedbacks from end-users, they would be better assured that barriers to information usability are overcame. However, a participatory ICT development process is likely to be more complex, to be longer and to incur in higher costs. At this end, policy intervention is advised to facilitate the process, because public institutions have the role and the capability

to favor a better use of existing knowledge (Cash et al. 2006). The suggestion is to implement policy tools to help private initiative facing the high transaction costs of ICT implementation jointly with end users. At this end, Operational Groups funded by the Rural Development Programme (RDP) are a good example, bringing together different stakeholders with farmers. Similarly, the RDP's subsidies to investments on innovation implementation can be a powerful tool to directly finance investments on new platforms or indirectly by means of cross-compliance.

(2) Uncertainty-management policies would be needed to lower ambiguity on ICT reliability, speeding up the process of familiarity. Once new platforms are brought to the market, it would be ideal to offer long trials or demonstrative events. Rather than a plug and play approach, these initiatives would allow end-users to better understand how information can be implemented and to gain experience on ICT reliability. Having hands on the platform, without necessarily implementing its information at DM's own expenses, would lower ambiguous perceptions and potentially foster the diffusion of ICTs. In addition, even after ICT adoption, DMs can be encouraged in starting to use the new platforms for informative purposes before attaching real decision making on it; this way they would experience ICT reliability without risking losses. As we modelled in this research, ICT-information implementation often implies moving from inefficient PPs with sure outcome, to efficient ICT-informed RP with uncertain outcomes. Here, if a DM is willing to bear such uncertainties to save water, he would be needing support in his virtuous choice. Accordingly, even after ambiguity is solved, uncertainty remains in the form of risk. Therefore, ex-post risk coping policies would be helpful to compensate losses at the WA's or farms' level when the ICT failed in its predictions.

(3) Agricultural and water policies instruments are suggested to be evaluated also with respect to their effects on risk perception to promote ex-ante risk management solutions to increase the sector's resilience. Between these, at the farm level, policies could favor investments in resource-efficient crops and irrigation systems; at the WA level, there could be favored: reservoirs, to face longer periods of scarcity; and investment in the irrigation network to allow efficient water allocation between districts. Policies for efficient water governance would be needed too. Here, the main aim would be to avoid excess-use of water by some farmers, which might cause production losses to others. Further, we have to consider that the share of risk estimated by the ICT is subjected to climate variability. This complicates ICT-

informed decisions with CC, because every time the share of risk varies, the DM's expected utility from information implementation varies too. This issue will require DMs to take time to analyze case by case the uncertainty settings, before deciding. Therefore, policies for digitalization are suggested to account for such extra time and compensate adopters for their decision.

Finally, to clarify the settings in which specific policies are suggested to be implemented and which actor to target, in Table 9 we propose a schematic representation of the policy suggestions arising from the thesis. Here, we consider the combinations between high or low levels of risk and ambiguity affecting ICT-aided irrigation management decisions. If uncertainty is low because of low levels of risk and ambiguity, policy intervention can be limited at promoting ICTs and favoring familiarity or in providing incentives to adoption or incentives to water use reduction. The target for such policies can be limited to WAs, because they can implement ICT-information in their districts with low risks for farmers. On the other hand, if risk is high while ambiguity low, the target for policies is represented by farmers. Here, if the ICT is implemented at one of the two decision levels, farmers risk production losses due to the high variability of climate events, therefore ex-post compensation of such losses would be helpful. To better predict climate variability, investments on the accuracy of information would be useful too. As opposite, if it is ambiguity high while risk low, the target is both the WA and farmers. Both would benefit from ambiguity reduction initiatives, making them be more inclined in information implementation thanks to the process of familiarity. However, because of the high ambiguity, farmers are also exposed to losses caused by poor governance. Therefore, they would need ex-post compensation in case of in-farm losses due to excess-use in other farms. Finally, when uncertainty is high due to high risk and ambiguity, the policy maker is suggested to further investigate on the convenience of information implementation. As highlighted in this research, in not all decision processes ICT-information implementation is profitable. Here, rather than the mere promotion of ICT illustrated in Table 9, other insurance schemes or policies aimed at supporting irrigation management are expected to be more suitable. Otherwise, if uncertainty can be lowered trough information provision all the policy tools described in Table 9 would be needed to reach the ICT potentials.

		Risk	
		Low	High
Ambiguity	Low	Target actors: • WA Policy tools: • ex-ante ambiguity reduction initiatives and information	Target actors: • farmers Policy tools: • ex-ante: investment on accuracy of ICT; • ex-post: compensation of climate losses
	High	Target actors: • WA + farmers Policy tools: • ex-ante: ambiguity reduction initiatives and information • ex-post: compensation of losses due to poor governance	Target actors: • WA + farmers Policy tools: • ex-ante: ambiguity reduction initiatives and information + investment on accuracy of ICT • ex-post: compensation of losses due to poor governance + compensation of climate losses

Table 9: Scheme of policy tools to be used in different uncertainty settings

Chapter 6

6. Conclusions

The present doctoral dissertation rose in a context where CC is posing new challenges to irrigated agriculture. Here, weather patterns are increasingly unpredictable and highly variable, while climate shocks such as prolonged droughts are more frequent. Decreased predictability together with increased variability are posing significant uncertainties in decision processes and are exacerbating the sector's vulnerability to CC.

Many scholars agree on the capability of ICTs to help facing such problems by lowering uncertainty and improving decision processes through the provision of relevant information. Accordingly, in the *Digital agriculture revolution* we are living in, numerous innovations contribute to modify the decision environment by lowering uncertainty. Many examples are found in literature showing the ICT potentials to favor adaptation to CC. However, together with such potentialities new challenges emerge due to barriers to ICT-information implementation. This is especially true for irrigated agriculture which is one of the sectors most vulnerable to climate-related uncertainties. Irrigation management is characterized by peculiar decision processes where several barriers can undermine information usability and ICT benefits.

Given the risk of the sector to not exploit ICT potentials we considered a priority to support irrigated agriculture in the *Digital water journey*. At this end, we analyzed the most critical issues to ICT development and defined a theoretical framework which provides a complete picture of the uncertainties around ICT-information implementation. On this framework we based two decision models which helped to understand the decision dynamics of ICT-information implementation for irrigation management. The first model allowed to highlight restrictions to information usability and to estimate ICT-benefits. The second model was developed to assess the impacts that subjective behavior under uncertainty has in undermining ICT potentials.

The capability of decision models was then proved by two separate empirical examples. Results confirmed the hypothesis of ICT potentials, but underlined that benefits are extremely variable and subject to constraints. These are relative to the decision environment, to the form and quality of ICT-information and to the behavior of DMs. Within the decision environment, technical elements condition information usability; between these the most relevant are in the water delivery systems, land use and the WA's decision power. Because irrigation management decisions follow the seasonal pace and have high payoffs at stake, information must be provided at the right time and with the needed accuracy to be relied on. Finally, subjective behavior can limit ICT-benefits both because ambiguity-aversion lowers EU from ICT-informed actions and because irrigation efficiency is conditioned by all actors' actions for the management of the resource.

The main limitations of the results are caused by complexities in the decision processes of irrigation management and in the nature of the uncertainty settings. Complexities required many assumptions and simplifications, both in the decision environment and in the DMs' behavior. Despite the simplifications, models are still capable of representing the dynamics of decision processes and results allowed to provide policy-makers important advices to aid the sector. At this end, we highlighted the need of ICT-development policies to overcome barriers and maximize ICT potentials. Uncertainty-management policies are also suggested to lower the ambiguity raising from a lack of knowledge on information reliability and to support DMs when they choose to implement ICT-information and bare new sources of risk.

To conclude, thanks to the holistic approach adopted in this research to study ICT-informed decision processes for irrigation management, we can confirm that ICTs can be a viable tool to face new challenges posed by CC. However, the exploitation of such new tools by irrigated agriculture is not self-fulfilling. First of all, to ease the digitalization process, it is important to disseminate not only the capabilities of ICTs, but also their real limits and accuracy. This is expected to help avoiding false expectations which feed ambiguity and skepticism. In addition, the process is characterized by barriers which can be targeted and solved by policy makers; at this end, further research is suggested to efficiently design new policies and develop new ICT platforms. Finally, the authors wish to underline the natural evolution of ICTs which is through the provision of new pieces of information which will be more reliable and easier to be implemented. This is expected to allow irrigated agriculture to have always more opportunities to lower uncertainties affecting management decisions.

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Appendix

Appendix 1: Simplification for the CE computation

In this section we provide the extensive proof behind the simplification used to determine the CE of the RP starting from the expected utility equation of Klibanoff et al. (Klibanoff et al. 2005):

$$EU^{r,a}\left(f(x^s|\mathrm{x}^{\mathrm{ICT}})\right) = \mathbb{E}_\Delta \phi\left(u\left(\mathbb{E}_S f(x^s|\mathrm{x}^{\mathrm{ICT}})\right)\right) = \int_\Delta \phi\left(EU^r\left(f(x^s|\mathrm{x}^{\mathrm{ICT}})\right)\right) \mu\left(\pi(x^{\hat{s}})\right) d\pi(x^{\hat{s}})$$

For simplicity in notations we have the following elements: $x^s = s$; $\mathrm{x}^{\mathrm{ICT}} = x$. In the first step we assume negative exponential utility functions and normal distributions for both risk and ambiguity. By making explicit the distribution function of $\pi(s)$, with σ_s being the standard deviation and μ the average, is we obtain the following set of equation:

$$EU^r(f(s|x)) = \int -e^{-rf(s|x)}\pi(s)ds$$

$$EU^r(f(s|x)) = \int -e^{-rf(s|x)} \frac{1}{\sqrt{2\pi\sigma_s}} e^{-\frac{1}{2}(\frac{f(s|x)-\mu}{\sigma_s})^2} ds$$

$$EU^r(f(s|x)) = -\int \frac{1}{\sqrt{2\pi\sigma_s}} e^{-\frac{f(s|x)^2+\mu^2-2f(s|x)\mu+2r\sigma^2 f(s|x)}{2\sigma_s^2}} ds$$

$$EU^r(f(s|x)) = -\int \frac{1}{\sqrt{2\pi\sigma_s}} e^{-\frac{f(s|x)^2+\mu^2-2f(s|x)(\mu-r\sigma_s^2)+(\mu-r\sigma_s^2)^2-(\mu-r\sigma_s^2)^2}{2\sigma_s^2}} ds$$

$$EU^r(f(s|x)) = -\int \frac{1}{\sqrt{2\pi\sigma_s}} e^{-\frac{(f(s|x)-\mu+r\sigma_s^2)^2+\mu^2-(\mu-r\sigma_s^2)^2}{2\sigma_s^2}} ds$$

$$EU^r(f(s|x)) = -\int \frac{1}{\sqrt{2\pi\sigma_s}} e^{-\frac{(f(s|x)-\mu+r\sigma_s^2)^2+\mu^2-(\mu^2+(r\sigma_s^2)^2-2\mu r\sigma_s^2)}{2\sigma^2}} ds$$

$$EU^r(f(s|x)) = -\int \frac{1}{\sqrt{2\pi\sigma_s}} e^{-\frac{(f(s|x)-\mu+r\sigma_s^2)^2-r\sigma^2(r\sigma_s^2-2\mu)}{2\sigma^2}} dx$$

$$EU^r(f(s|x)) = -e^{-r\left(\mu-\frac{1}{2}r\sigma_s^2\right)}\int \frac{1}{\sqrt{2\pi\sigma}} e^{-\frac{1}{2}\left(\frac{f(s|x)-(\mu-r\sigma_s^2)}{\sigma}\right)^2} dx$$

$$EU^r(f(s|x)) = -e^{-r\left(\mu-\frac{1}{2}r\sigma_s^2\right)} = -e^{-r\left(\mathbb{E}_S f(s|\mathrm{x})-\frac{1}{2}r\sigma_s^2\right)}$$

Now, because the inverse of the risk preference function is the certain equivalent associated to the risky outcome, the CE is determined as follows:

$$CE^r(f(s|x)) = \mathbb{E}_S f(s|\mathrm{x}) - \frac{1}{2}r\sigma_s^2$$

Now we consider also ambiguity and repeat the same procedure to determine expected utility under risk and ambiguity:

$$EU^{r,a}(f(s|x)) = -e^{-a\left(\mathbb{E}_S f(s|\mathrm{x})-\frac{1}{2}r\sigma_s^2\right)}$$

This is followed by the associated certain equivalent:

$$CE^{r,a}(f(s|x)) = \mathbb{E}_\Delta(\mathbb{E}_S f(s|\mathrm{x}) - \frac{1}{2}r\sigma_s^2) - \frac{1}{2}a\sigma_\Delta^2$$

Appendix 2: Simplification for the computation of the optimal water volume

In this section we provide the extensive proof behind the simplification which is used to assess the optimal water volume to be used under the DM's behavioral perspective. The simplification starts considering the formulation of the CE determined in the previous section. To aid the comprehension, we follow the same notation of the previous section and the following: $R = \frac{1}{2}r\sigma_{\pi(s)}^2$; $A = \frac{1}{2}a\sigma_{\mu(\pi(\mathrm{x}^{\hat{s}})|t_i)}^2$; $m = \mu\left(\widehat{\pi(\hat{s})}\right) = \mu(\pi(\hat{s}))$; $p = \prod(\hat{s})$; $R_{farm_I}^* = v$; $c_{farm_i} = c$. This helps obtaining the equation:

$$CE\big(f(s|x)\big) = \mathbb{E}_\Delta\left(\mathbb{E}_S f(s|\mathrm{x}) - \tfrac{1}{2}r\sigma_s^2\right) - \tfrac{1}{2}a\sigma_\Delta^2 = \mathbb{E}_\Delta\big[\mathbb{E}_S\big(f(s|x)\big) - R\big] - A$$

Now, because the model of Klibanoff et al. (Klibanoff et al. 2005) is based on the assumption that second order acts in the space Δ yield the same CE as first order acts in the space S, we have that:

$$\mathbb{E}_{\Delta}\left[\mathbb{E}_S\big(f(s|x)\big)\right] = \widehat{f(s|x)} = V(X) - cx$$

Therefore, we obtain the following CE:

$$CE\big(f(s|x)\big) = V(X) - cx - R - A$$

Now, if we consider the equilibrium where the DM is indifferent between the RP and the PP, we have:

$$g(X) = CE(f(s|x))$$

$$V(X) - cX = V(x) - cx - R - A$$

$$X = x + \frac{A + R}{c}$$

Where X can be interpreted as the water demand from the DM, accounting for uncertainty and his behavior toward it. By employing the above equation, we can obtain the following simplifications considering different alternatives of perceptions and attitudes:

- Uncertainty-neutral DM:

$$X = x$$

- Ambiguity-neutral DM:

$$X = x + \frac{R}{c}$$

Appendix 3: Relation between irrigation and crop production

To estimate the relation between irrigation and crop production, we firstly consider evapotraspiration (ET) being function of irrigation (x). Although, studies in agronomics proved the polinomial nature in the relation between the two quantities (Linker et al. 2016), we assume a linear and constant relation. This is a strong approximation forced by the lacking available data. To determine the crop production as function of irrigation we employ a simple modification of the classic production function introduced in FAO Irrigation and Drainage Paper No. 33 (Doorenbos and Kassam 1979):

$$Y_t(x_t) = Y_t^*[1 - k_{y_t}(1 - \frac{ET_t(x_t)}{ET_t^*})]\frac{Y_{t-1}(x_{t-1})}{Y_{t-1}^*}$$

where: x_t e x_{t-1} are the decisional variables, that is, respectively the quantity of irrigation water at time t and the quantity of irrigation water at time: $t-1$; $Y_t(x_t)$ and $Y_{t-1}(x_{t-1})$ are respectively crop productions at time t and time $t-1$; Y_t^* e Y_{t-1}^* are respectively optimal crop productions at time t and time $t-1$; k_{y_t} is the crop coefficient which helps to convert evapotranspiration in crop production; as said, $ET_{\mathrm{t}}(x_t)$ represents the crop's evapotranspiration at time t; ET_t^* represents the crop's evapotranspiration at time t but withoud stresses from lacking irrigation. The proposed equation differs from its original form because it accounts for the impacts that prior drought stresses have on the optimal crop production in the current stage.