Changes in the information environment of water management: the role of ICT

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Numerous Information and Communication Technologies (ICT) have been developed in irrigated agriculture. While there are studies focusing on ICT impacts at the farm level, no research deal with this issue at the level of Water Authority (WA). With the present study, the authors developed a theoretical framework based on Bayesian decision theory to assess the economic benefits brought by the introduction of ICT. An empirical example is provided with the aim of showing any potentialities and limitation of ICT for the management of water supply networks in agriculture. The adoption of ICT by WA have the capacity to achieve water savings and favor climate change adaptation. Site specific constraints as decisional power, water availability and technical issues do not allow the full exploitation of information services. A sensitivity analysis showed that by improving the quality of information, such constraints can be overcame. Policy remark is to favor ICT development jointly with end users, answering decision maker's information requirements.

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1. Introduction

Climate Change (CC) is an issue of growing importance in irrigate agriculture. It requires new approaches combining adaptation and mitigation strategies to realize the goal of sustainable development. With mitigation the International Panel on Climate Change refers to "options and strategies for reducing GHG emissions and increasing GHG uptakes by the Earth system" (IPCC 2014). Whereas adaptation is considered as the "process of adjustment to actual or expected climate and its effects" (IPCC 2014). Adaptation and mitigation are the two pillars for facing CC (Burch, Cohen, and Robinson 2010). In this regard, weather and climate services can help decision-makers in taking informed decisions to improve adaptation capacity by assessing and forecasting existing and emerging risk (Vogel, Letson, and Herrick 2017). Since all adaptation actions depend on the availability of adequate information, the rapid diffusion of Information and Communication Technologies (ICT), such as mobile phones and the Internet, poses new opportunities to face CC. ICT provide a way for disseminating relevant information such as weather forecasts, hazard warnings, market information, information sharing, and advisory services. In irrigated agriculture, one of the most important problem brought by CC is the raise in the level of uncertainty of decisions regarding the management of water resources. This is due to the increased variability of weather patterns and increased frequency of extreme weather events. Variability by itself does not necessarily imply decrease in profits if it is anticipated and acted upon. Nevertheless, Decision Makers (DMs) must take decisions beforehand to manage of water resources. Under such circumstances, decisions are to be taken as an optimal compromise for the full set of possibilities (Meza, Hansen, and Osgood 2008). This condition causes a moving-target problem. This is generated by the fact that ex-post and ex-ante decisions rarely coincide, with negative consequences on profits (Hallstrom 2004). At this end, ICT could provide timely information regarding future climate and weather conditions, diminishing the perceived uncertainty by reducing the spread of possible outcomes for the upcoming season. So, ICT have the potential to contribute for a better planning of preventive actions, hence attenuating the moving-target problem (Fernandez et al. 2016). Farmers and Water Authorities (WA) might benefit from using such instruments to support timely decisions to reduce losses from climate shocks and to take advantage from favorable or average years (Deichmann, Goyal, and Mishra 2016; Guerra et al. 2017).

In this paper, we refer to adaptation strategies that involve the use of ICT. Such technologies are considered a mean for reducing the perceived uncertainty and building the capacity of WA to cope with CC impacts by improving decisions. In this respect, a theoretical model is designed and implemented to investigate the mechanisms conditioning the adoption of ICT for the management of water resources in agriculture. The theoretical model presented here integrates insights from the Bayesian Decision Theory (BDT) and expected utility maximization. It assesses the economic benefits brought by new pieces of information, influencing the DM perception of uncertain events with direct consequences on it's strategic decisions. Specifically, the model investigates the role plaid by information in supporting WA to rationalize the management of water resources and the prevention of extreme weather events impacts. The methodology account of the timing factor as decisions on land and water allocation differ with the time when information is provided and are influenced one by the other. 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. The reminder of the paper is organized as follow: in Section 2 we review the recent literature inherent the adoption of ICT; in Section 3 we define the theoretical framework; in Section 4 we describe the empirical example where we tested the theoretical model; in Section 5 we discuss the main findings and in Section 6 we draw final remarks.

2. State of the art

In agriculture, numerous ICT have been developed and disseminated (Aker, Ghosh, and Burrell 2016). Great potential is found for such technologies in contributing to food security and climate change adaptation in the agricultural sector (Nakasone and Torero 2016; Vogel, Letson, and Herrick 2017). Qualitative studies sowed their impacts for both developed and developing countries (Martin 2016). Findings bring to radically different conclusions (Macauley 2006; Aker, Ghosh, and Burrell 2016). This suggests that ICT impacts on decisions outcomes are highly variable. One reason of this variability lies in the findings of Aker, Ghosh, and Burrell (2016) and Nakasone and Torero (2016). According to them, ICT development initiatives are primarily successful only when they address a key information need. In addition, many ICT projects do not reach the expected success because developers take for granted information to be useful (Vogel, Letson, and Herrick 2017). This implies a lacking consultation with end users on topics as information's form, time provision and dissemination. With regards to quantitative analysis, few are found in agricultural economic literature. This is especially true at the WA level. In models information is treated like any other production factor, with both a value and a cost (Plant 2001). The Value of Information (VOI) can be defined as an increase in expected value arising from the introduction of a new piece of information in the decision process (Keisler et al. 2013). As addressed in literature, the VOI is not conditioned only by the information content, but also by the following main drivers (Meza, Hansen, and Osgood 2008):

a) The level of uncertainty in the decision environment: the more the condition under which the DM operates are uncertain, the higher will be the benefits brought by information.
b) What is at stake in the decision process: the higher variance of decisions' outcome the more the DM is willing to use information for reducing the uncertainty regarding the optimal choice.
c) The change in beliefs after the information: the additional information must be as accurate as to induce change in DM beliefs.
d) The informativeness/accuracy of the message: the more conclusive the message service is, the smaller will be the risk of failures and the higher the VOI.
e) The timing of information provision: information must be provided at the right time in the decision process. Late messages have no value.

As a result, each element characterizing the information itself or the information environment have the potential to set the VOI to zero. 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 and the information environment (Tyrychtr et al. 2016). Assessments are based on the framework of BDT and expected utility maximization (Bouma, van der Woerd, and Kuik 2009). Time is a critical factor influencing both the accuracy of information and the decision to be taken (Hardaker et al. 2004). Usually, information provided well in advance to the occurrence of an event might condition strategic decisions but it will not be so accurate. Whereas, if information is provided with a short advance, the decisions influenced by information will not be so strategic but the information will be 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. The cost of waiting is often identified with losses due to sub-optimal decision performances (Bikhchandani, Hirshleifer, and Riley 2013). Taking into account of 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. 2004).

Developing and applying a method to assess the economic value of ICT which provides weather and climate forecasts, seems to be an interesting topic of research for agricultural economists (Tyrychtr et al. 2016). The novelty of the present paper is twofold, both in the theoretical model and in its empirical application. To the best of authors' knowledge, the former stands apart 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: this rarely tackled topic has potentialities contributing to investigate new instruments to face the challenges brought by CC.

3. Theoretical framework

The present section introduces an analytical approach describing a decision making process to select the best alternative among a set of actions upon receiving new information. The approach includes insights from the BDT, to integrate the role played by information in the decision process. As mentioned above, the model is applied to assess the VOI brought by the use of new sources of information by WA to manage water procurement and supply for agriculture. The decision process modelled involves two or more inter-correlated decision steps occurring during time. In a chronological order the first decision influences the second which in turn can mitigate or exalt outputs of the first. The decision process is modelled 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.

3.1 Definition of the model

The model 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 of the world (states, form now onward), 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 denote a specific action among the set of possible actions and the subscript s denote a specific state among the set of possible states. Now, the actions taken by the DM have uncertain consequences. This uncertainty is determined by the fact that a period of time elapses between the moment actions are taken and the time when states are incurred. A state can emerge once the action is taken with a probability π_s. A rational DM will choose the action that maximizes his expected utility. Expected utility 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, van der Woerd, and Kuik 2009). Without any information service, the maximization of the expected utility is obtained by the following equation (eq. 1):

$$max_{(x)} U(x, \pi_s) = \sum_s \pi_s v(c_{x,s}) \qquad \text{eq. 1}$$

In case of ICT adoption, the DM can receive a message, μ, among a set of messages, M, with a probability π_μ. Messages provide information regarding the emerging states of the world. Messages modify the DM information environment altering the uncertainty associated to each state of the world. The variation in the DM information environment is then measured by the probability of states occurrence conditional to the messages received, $\pi_{s|\mu}$, also known as posterior probabilities. In light of the new piece of information, the DM has to choose the action that maximizes his expected utility for each of the messages delivered by the information service. Here again, the decision is based on the concept of expected utility maximization. This is given by the message probability and the posterior probability weighted average of payoffs in each state of the world and for each message (eq. 2):

$$max_{(x_\mu)} U\left(x_\mu, \pi_{s|\mu}\right) = \sum_\mu \pi_\mu \sum_s \pi_{s|\mu} v(c_{x_\mu,s})$$
eq. 2

While for the problem described in equation 1 the DM is in condition to choose only one action amongst a set of alternative actions, for the problem described in equation 2 the information environment is enriched and the DM can take as many actions as many messages he receives. Now, we take in exam a decision problem involving T decision time steps. 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 by multiplying the all the possible combination of actions and messages in each time step, t, for the subsequent combination till the final decision step. Since decision steps, states and messages are independent, the expected utility maximization problem can be reformulated as it follows (eq. 3):

$$\underset{(x_\mu^t)}{max} U\left(x_\mu^t, \pi_{s^t|\mu^t}\right) = \prod_t [\sum_{\mu^t} \pi_{\mu^t} \sum_{s^t} \pi_{s^t|\mu^t}] v(c_{x_\mu^t, s^t}) \quad \text{eq.3}$$

Hence, during time in the decision process, the final choice made by the DM 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, the VOI is defined by the difference between the expected value of the best informed action, $x_\mu^{t^*}$, and the expected value of the best un-informed action, $x_0^{t^*}$ (eq. 3):

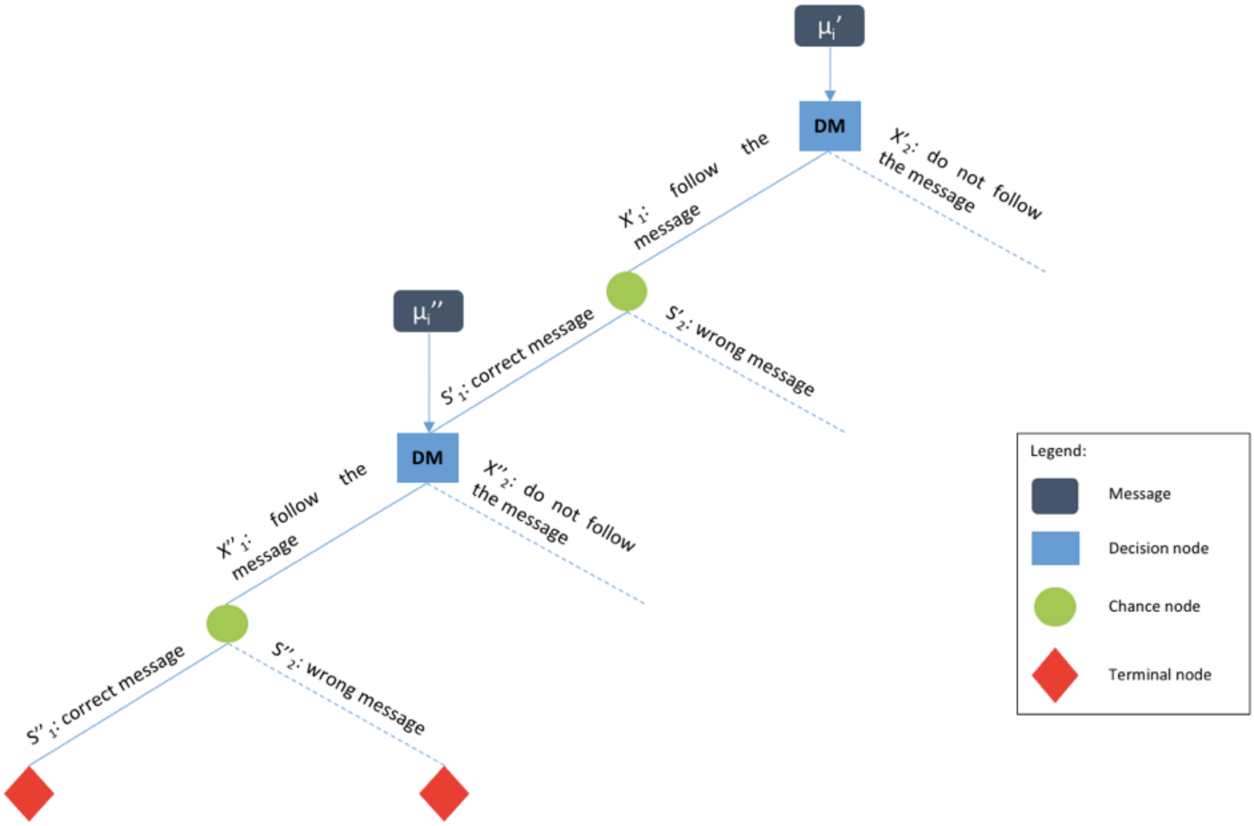
$$\Delta U(\mu) = U\left(x_\mu^{t^*}, \pi_{s^t|\mu^t}\right) - U\left(x_0^{t^*}, \pi_{s^t}\right) \quad \text{eq. 3}$$

The VOI associated to each message is positive only when the posterior probabilities of the states predicted by messages are higher than their prior. Otherwise messages would be uninformative, not justifying the use of ICT by the DM.

3.2 Graphic representation of the model

To graphically represent the decision model above described in a two steps informed decision process, we followed the standard formulation of the decision trees. Decision alternatives branch form square nodes; the probabilities of uncertain events branch form round nodes and terminal nodes express consequences of actions in states of the world (Fig. 1). In each decision step information is provided thru a message. The DM has to decide whether to follow the message or not. In turn, the message can emerge to be correct or not. At the end of the decision process, the combination of the set of actions with the set of the states of the world determines the associated set of consequences.

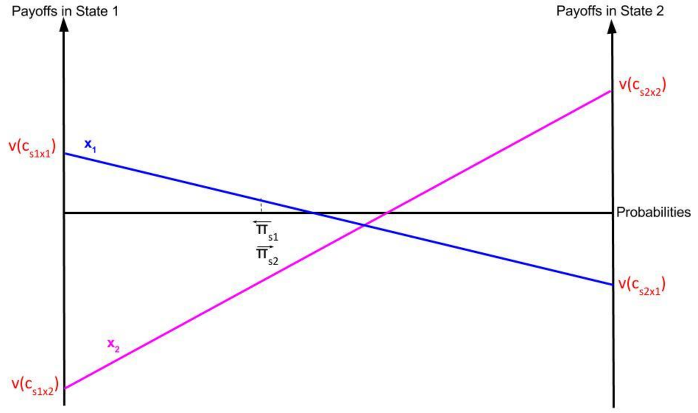
Figure 1: Theoretical framework for the decision tree



Source: own elaboration form Hardaker and Anderson 2004

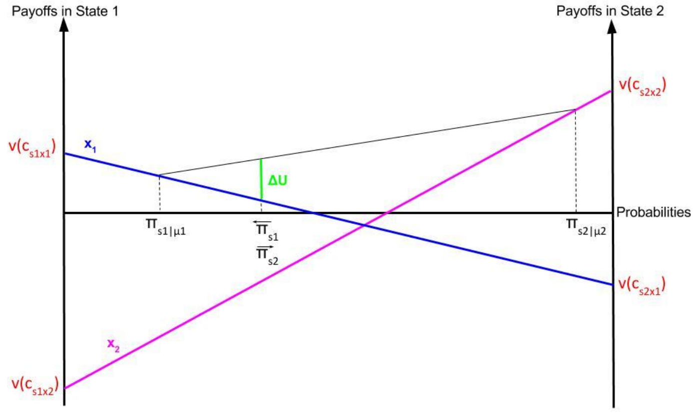
Consider now a simplified model with only two alternative states (s_1 and s_2), two alternative actions (x_1 and x_2) and one decision time step. This model can be represented in a diagram, where utility in each state is measured vertically and probability horizontally, ranging in a bi-directional segment limited from zero to one. Since states are alternative, meaning that one excludes the other, the relevant probabilities of occurrence are complementary ($\pi_1 + \pi_2 = 1$). Hence, a point along the segment represents both probabilities of states occurrence. In the diagram of figure 2, 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 expected value for that action as a function of probabilities. Similarly, the pink line, which joins $v(c_{s2x2})$ and $v(c_{s1x2})$, represents the expected value of action x_2 for any probability. For a given unconditional probability, the expected value of the best un-informed action is displayed by the vertical distance from a point in the horizontal segment of probabilities to the line joining consequences of actions in states. Taking into examination an information service that can generate two possible messages μ_1 and μ_2, either message will lead to a revised posterior probability vector, $\pi_{|\mu} = (\pi_{s1|\mu}\ ,\ \pi_{s2|\mu})$. The line joining the expected value of the best action if μ_1 is received and if μ_2 is received, defines the expected value of the message service. Again, mathematically represented by the probability weighted average of the value of consequences for both actions and messages. Hence, following eq. 3, the VOI is graphically represented by the vertical distance from the line of the expected value of the message service to the expected value of the best un-informed action. In figure 3 is represented the model, where the green segment is the graphic representation of the value of the message service.

Figure 2: Graphic representation of the decision model in case of un-informed decision



Source: own elaboration from (Bikhchandani, Hirshleifer, and Riley 2013)

Figure 3: Graphic representation of the decision model after receiving a new message



Source: own elaboration from (Bikhchandani, Hirshleifer, and Riley 2013)

4. **An empirical application**

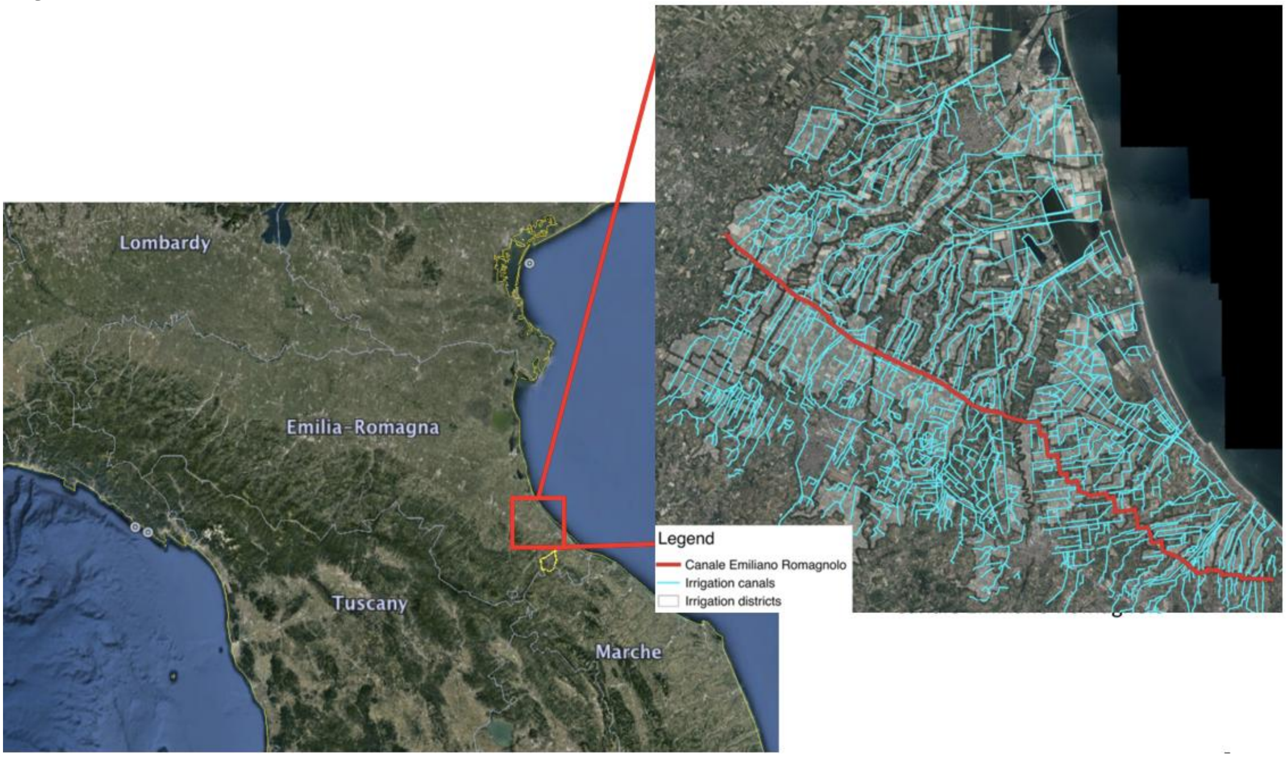
In the present section, we introduce an application of the methodology developed in section 3. The methodology is applied to assess any economic benefits brought by the introduction of new sources of information for the management of water resources in agriculture. Specifically, we selected an empirical example from the MOSES H2020 European project. This project was set up to develop a Decision Support System (DSS), then tested by different WAs around Europe and other Mediterranean countries to assess its usefulness and implementability.

In the present study, because of the availability of information, we focus our analysis on the MOSES project pilot Demonstration Area (DA) which is located in the Emilia Romagna region, Italy. In the following we describe: the characteristics of the agricultural region under investigation and the management of the irrigation network; the DA information requirements; the type of data that we collected and the assessment procedure that we adopted; the results obtained by implementing the method developed in section 3.

4.1 The management of water resources in an Italian agricultural region

The DA is managed by a reclamation and irrigation board named Consorzio di Bonifica della Romagna (CBR) (Fig. 5). The area is characterized by a highly intensive agricultural production in the Po river basin. The climate is continental (summer maximum temperatures above 30 °C), mitigated by the sea influence in the North-Eastern part. Drought events are relatively 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 drought.

Figure 5: Demostration Area

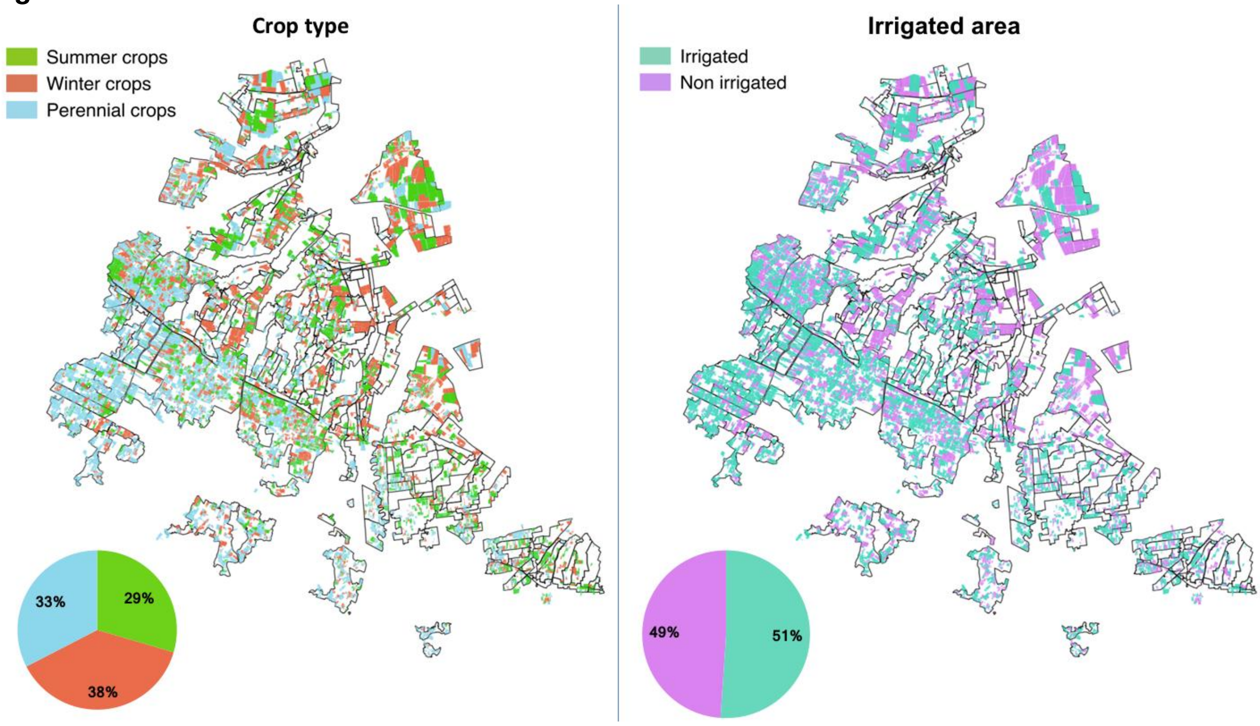


Source: own elaboration

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 irrigated area corresponds to 9,865 hectares, 51% of the cultivated area in the whole basin (Fig. 6). Winter crops are prevailing (i.e. wheat, barley and meadow), followed by perennial crops (i.e. alfalfa, orchard, vineyard) and summer crops (i.e. maize and sorghum). 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. In case of a dry season, the DM applies restrictions on the supply of water, depending on levels of water scarcity. Such restrictions may require enforcement of turns, reduction of water supply and/or reduction in the duration of water delivery. The main indicator used to define the level of water scarcity is the water level in the Po river in the section where the

CER has its origin[1]. If the water level in the Po river goes below a given threshold level, a warning state emerges and turns are imposed.

Figure 6: Land use in the DA



Source: own elaboration

4.2 Information provision and requirements

MOSES DSS provides information to WAs regarding future climate and crop water requirement states in a specific area of interest. MOSES provides two kinds of services:

- Seasonal climate and crop water requirement forecasts: provided from 3 to 6 months before the irrigating season. It gives a quantitative assessment on whether the following three months will be dry in respect to the climate average.
- In-season weather and crop water requirements forecasts: provided daily for the upcoming 3 to 7 days during the whole irrigating season. This information is detailed on a spatial scale of 10m x 10m.

To produce such messages, MOSES combines as input a wide range of data and technological resources. Earth observation data are used to assess land use and crop transpiration. Agro-meteorological models are applied to provide probabilistic seasonal forecasting; numerical weather prediction and crop water requirement forecasts. These outputs are elaborated and disseminated to the WAs by means of a web GIS platform.

As emerged from consultations with stakeholders, it can be expected that MOSES information services are likely to be used. In April, yearly concessions to irrigate crops are provided by the WA. Up until now, the WA never limited significantly concessions due to the lacking information. Hence, land allocation schemes for irrigated crops are rigid, because based on historical water use. If the WA used MOSES's seasonal forecast it could decide to follow such information and manage land allocation scheme. Specifically, in view of a regular period concessions for irrigable areas might be released in a business as usual situation. If the opposite is expected, water authority could potentially limit concessions to irrigate and advise farmers and agro-industries about any drought risks. The arable land would then be allocated mainly to dry or low water requiring crops. Available water would be guaranteed only to orchard and other

[1] Thresholds levels of water scarcity are: level > 3.25 m: normal operation; level 3 - 3.25 m: warning state; level < 3 m: alarm state.

permanent crops. By this way, the demand of water is managed by controlling land allocation. Losses caused by water requirements higher than the availability are reduced or avoided. Such kind of losses are due to a higher comparative performance of dry crops in respect to irrigable crops in case of no water availability. In addition, by guaranteeing water to permanent crops, permanent damages to plantations are avoided. Despite these potentialities, since information is not perfect, in case of errors major losses can emerge. Wrong information can rise with to two types of errors:

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

The former error leads to water requirements higher than the availability, with losses described before. Consequences of this type of error can be mitigated during the irrigating season by maximizing the efficiency of water allocation. The latter error causes a sub-optimal use of land and water resources. Accordingly, if land is allocated to dry crops, the available water during the regular season is used with a comparative lower performance by dry crops in respect to irrigable crops. As a result, the profitability per unit of land and water is lower than the optimal one, attainable in such climate conditions with irrigable crops. No mitigation of this sort of losses is possible during the irrigating season due to agronomic constraints.

Information from the in-season forecast would influence decisions on water allocation. Water allocation plans could be drawn delivering water according to actual crop water demand. Specifically, if during the following week no irrigation need is forecasted for a district, the WA may deliver water under the threshold of minimum flow for that district. This way, farmers in that district will not receive water and the remaining could be saved or allocated to districts where it is needed. Because of hydraulic constraints, the water flow in canals cannot get below specific thresholds, varying with the season and with the district. Thus, the decision is binary: the DM has to choose whether to deliver water to a district or not. Within districts, no water allocation proportional to needs is possible and the attainable efficiency is low. Despite such constraint, a management supported by MOSES would allow to save water in regular periods and to efficiently allocate scarce water in dry periods. Here again, the information provided is not perfect. Errors in regular periods can cause water scarcity (production losses) in some districts and waste of water in others. During dry periods, wrong information can enhance drought losses.

4.3 Data collection and assessment procedure

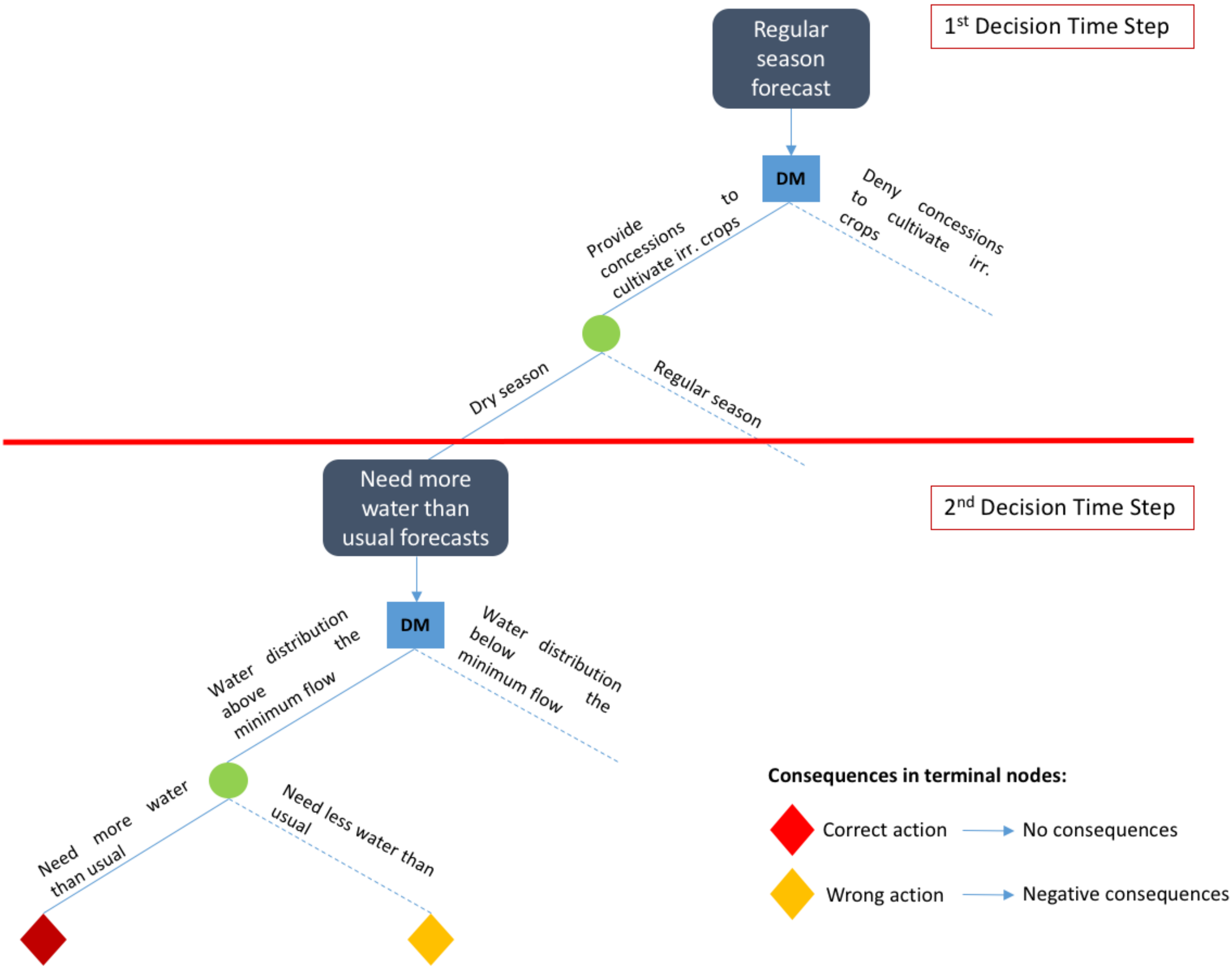
Information on the case study have been collected at different stages during MOSES project. The objective was to gather data for the estimation of the decisions' outcomes and the accuracy of information. An ad-hoc questionnaire was used to collect primary data. It included sections on irrigation infrastructures, cropping patterns and water management system. Secondary data on prices and yields, from public databases were used as well (RICA – Rete di Informazione Contabile Agricola, 2017: http://rica.crea.gov.it/public/it/index.php). Finally, the water authority made available shapefiles with aerial photo and weather observations. The WA decided to narrow the scope of investigation to a sub-group of districts. Specifically, only 33 of the 81 districts managed by the CBR where selected to calculate the potential benefits generated by the use of the MOSES DSS. Such districts have the common characteristics of a unique water source (represented by the CER) that is managed on demand, and of a water supply systems characterized by open-air canals.

To assess the accuracy of information, MOSES outputs of the 2017 irrigating season were compared with observed data. The aim of this analysis was to assess the frequency of correct messages for both the seasonal and in-season irrigation forecast. This estimation of the accuracy of information is given by the ratio between the number of correct messages on the overall messages received by the DM. Specifically, three comparisons were carried out: (i) comparison of MOSES crop maps with aerial photos, (ii) comparison of weather forecasts with weather observation, (iii) comparison of crop estimated water requirement with observed crop water requirements.

Thanks to a deep interaction with DMs in the CBR, several versions of the decision process were tested to build the most representative decision model. The whole decision process modelled is represented in the decision tree of figure 7. In the two decision time steps (before and during the irrigating season) information is provided in the form of seasonal forecast and in-season forecast. The decision process is binary: for each message received, the DM can choose to follow or not the message. Decisions are made based on the messages' reliability, probability to correctly forecast the emerging states, and on the consequences brought by the decisions themselves. At the end of the irrigating season, the combination of the set of actions and states for each decision step, determines the final outcome. The performance of the decision process is higher when messages received are correct. Decision consequences get worse with increased errors in the information provided.

Finally, agricultural income (Annex 1 and 2) and water consumption (Annex 3) were estimated in each state of the world and for each decision. Then, decision outcomes were measured in terms of agricultural and water losses[2] and a contingency table is determined. For each decision between the set of actions it expresses outcomes per set of states of the world. Every time the decision is not suited for the set of states additional management costs occur (production losses, energy and water losses). Optimal decision in each step does imply null additional management costs. Hence, the objective function of the model's decision process is in the minimization of the expected costs.

Figure 7: Decision process of MOSES adoption by the CBR



Source: own elaboration

[2] Water price: 0.0264€/m^3

4.4 Results

The methodology described before is used to analyze how MOSES information services might condition WA to drive strategic decisions for the management of water resources. The assessment of the accuracy of information gave as output the probability matrix of table 3 and 4. Overall accuracy of each message is expressed by the probability to detect irrigated crops times the probability to predict water requirements.

Table 3: Probabilities to detect irrigated/non irrigated crops

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

Source: own elaboration

Table 4: Probabilities to predict water requirements

		MOSES irrigation forecast	
		Need to supply water	**No need to supply water**
Observed data	**Need to supply water**	0,80	0,06
	No need to supply water	0,20	0,94

Source: own elaboration

With the input of the collected data and the support of the decision tree, decision outcomes are estimated through the model described in section 3. The matrix in table 5, represents payoffs of each combination of set of actions in set of states of the world. Each cell of the matrix gives an estimation of terminal nodes in the decision tree. As can be seen, optimal decisions are given by the choice of the optimal action for each state in each decision step. These combinations have no management cost since they represent the optimal management strategy given the climate conditions. Great variability in decision outcomes can be found because of the stake in the decisions. Accordingly, when the revenue from high added value crops (i.e. orchard) is at stake, no water provision due to wrong information can cause great losses. The opposite can be found with more resilient/extensive crops.

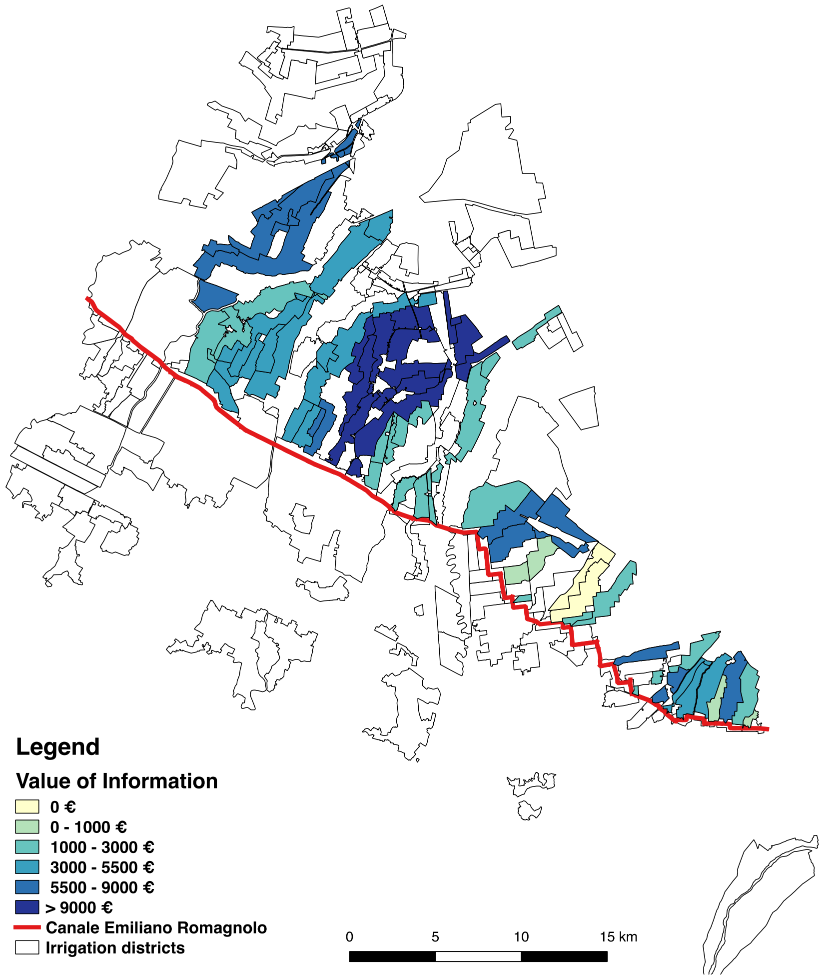
Table 5: Payoffs generated by MOSES adoption in the decision process of CBR (€)

			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	-199.481	-	-366.491	-252.155
	x'_2	x''_1	-252.155	-1.112.491	-	-860.336
		x''_2	-366.491	-252.155	-312.700	-

Source: own elaboration

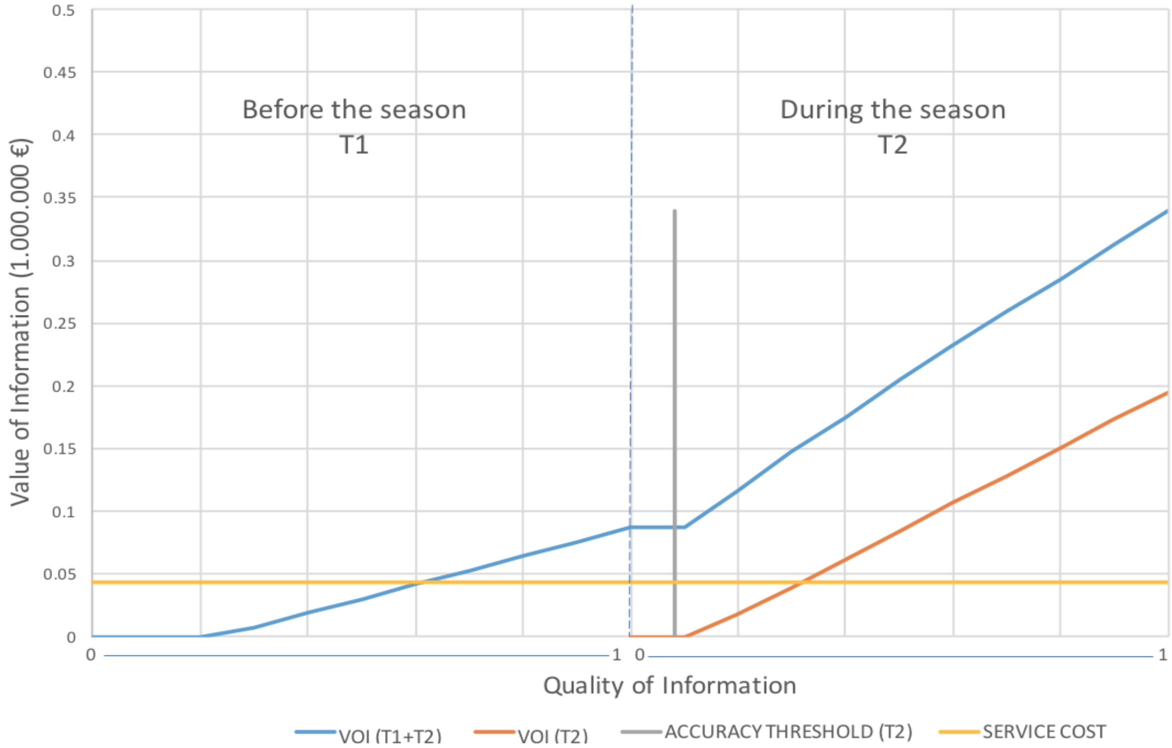
The developer of the platform estimated the cost of producing the service to be of 4.272€ (0,3€/ha). This includes data acquisition, modelling development, data analysis and platform management. The VOI is assessed as 156.462€/year (11€/ha) for the 33 districts. The spatial distribution of the VOI (Fig. 8) is highly variable. Some districts have a null benefit from the implementation of such technologies, other very high. Because the accuracy of information is estimated using inputs from only one irrigating season, it was considered useful to run a sensitivity analysis. This is method frequently adopted in literature (Keisler et al. 2013). By varying the accuracy of information in both decision steps, we determined the VOI in each condition of the information environment. Results show the VOI as a function of the Quality of Information Index (QII), given by the average of the messages accuracy (Fig. 9). As expected, the VOI has its minimum in un-informed conditions (QII=0) and reaches its maximum with perfect information (QII=1). The graph in figure 8 shows a VOI with a non-decreasing trend with the increase of the QII. Kinks take place when a new piece of information is introduced with a level of accuracy high enough to determine a change in the decisions. In other words, when a message is provided with the required accuracy, it causes a revision of DM belief and an improvement in water management. Arguably, for each piece of potentially useful information there will be a threshold over which the accuracy is high enough to cause the revision of DM belief. In example, in the graph of figure 9 it was drawn the threshold for the in season forecast information in the decision time step 2.

Figure 8: Distribution of the VOI between irrigation districts



Source: own elaboration

Figure 9: Sensitivity analysis for the VOI



Source: own elaboration

5. Discussion

Results from the model show positive impacts form ICT adoption but with a high heterogeneity in its spatial distribution. This is caused by different cropping patterns between districts. In districts with high added value crops, the accuracy of information might be too low to cause a change in DM belief. Accordingly, the stakes are higher with added value crops in respect to other crops. Thereby, losses caused by wrong information are relatively higher, diminishing the convenience to follow MOSES advices. Moreover, in districts where permanent crops are predominant, the decisional power of the WA is not enough to influence land allocation in the medium term. This factor limits the efficiency of land allocation scheme informed by seasonal forecasts. Finally, due to the open-air characteristics of the canals, the WA is not able to precisely allocate water according to needs. At this end, decisions are simply on whether to undergo the minimum threshold of water flow or not. Due to this constraint, together with the ones above described, the potential of MOSES services is not fully exploited.

The complex nature of decision making for water management poses limits in the modelling capabilities to represent the decision problem. Modelling limitation are rooted in the overlook of transaction cost in information processing and implementation (Nurmi, Perrels, and Nurmi 2013). In addition, the analyses showed a decision process that involves high risky prospects with decisions having extreme consequences at stake. Because of this, the model finds its main limitation in neglecting risk preferences of the DM. 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 decision analytic literature (Keisler et al. 2013). 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 impact of such emotional factor is considered limited in the medium/long term. This work, as well as the recent literature on the topic, do not consider the potential external benefits of improving DM's knowledge. These are not necessarily translated into higher yields, efficiency, outputs or profits (Aker, Ghosh, and Burrell 2016). A research theme apparently very interesting to deepen. Finally, as the decision problem 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. The sensitivity analysis not only overcame the problem of having data only for the 2017 irrigating season. It showed the accuracy threshold levels decisions are influenced by a new piece of information. Finally, 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.

6. Conclusions

The methodology proposed 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 in determining decisions on choosing to adopt ICT or not. This paper has shown that a combination of BDT and expected utility maximization can offer a suitable approach to deal with complex VOI modelling such as ones of WA. This approach seems promising as it links the information with the time it is provided in a sequential decision process made by more decision steps. The implementation of such methodology showed that ICT 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 constraints due to local characteristics of the decision process: (i) site specific condition (land use and water delivery system); (ii) the decisional 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 ICT for WA, these constraints strongly affect actual applications. Moreover, since many ICT offer discrete technology components without providing any support to adapt the technology itself to each specific reality, this undermines ICT usability. VOI is strongly affected by the information environment and ICT should aim at delivering information tailored to DM's specific needs (Furman et al. 2011). Specifically, requirements in terms of accuracy of information; timing of information provision and constraints 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) and is not sufficient for successful ICT (Vogel, Letson, and Herrick 2017). Hence, future ICT development in irrigated agriculture should aim at better answering to WA specific needs of information. An approach based this way will foster WA's adaptation capacity. In conclusion, policy intervention is advised to help private initiative facing high transaction costs in ICT implementation jointly with end users (Lemos et al. 2014). This is especially true in the case of ICT for WA, given their growing high demand for climate information (Vogel, Letson, and Herrick 2017).

7. References

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Annex 1: Land use in districts

District name	Wheat	Kiwifruit	Corn	Alfalfa	Apple	Peach	Vineyard	Total
Acquara alta	0.0	1.2	81.3	22.0	0.0	0.0	0.4	104.9
Baldone	0.0	0.0	35.0	9.7	0.0	0.0	0.0	44.7
Cannuzzo	0.4	3.1	59.8	47.7	5.6	4.2	0.6	121.4
Cappella	0.0	0.0	18.3	10.3	0.0	8.7	0.0	37.4
Carpena	3.1	2.3	69.7	350.7	10.8	20.8	80.5	537.9
Cavaticcia	0.0	0.0	3.3	2.0	0.0	0.2	0.2	5.7
Cervaro	0.0	0.0	14.7	10.7	0.0	0.0	0.0	25.4
Dismano est	0.0	0.0	9.9	4.2	0.0	3.7	0.0	17.8
Fiumicello superiore	0.0	1.6	104.6	96.0	1.2	17.4	0.7	221.4
Fossatone del bevano	0.0	0.0	7.7	8.7	0.0	0.0	0.0	16.4
Fossatone del rigoncello	1.7	0.0	20.0	12.6	0.0	0.0	0.0	34.3
Fossatone del rigoncello	1.7	0.0	20.0	12.6	0.0	0.0	0.0	34.3
Lagnano	0.0	0.0	0.0	0.6	0.0	0.0	0.0	0.6
Lama superiore	0.0	0.0	13.3	83.8	0.5	3.2	6.1	106.9
Lupara	0.0	0.0	22.4	23.1	0.0	5.8	0.0	51.3
Masiera	1.6	0.0	1.6	5.6	0.0	0.0	0.0	8.7
Matrice vecchia	0.0	0.0	11.1	0.0	0.0	0.0	0.0	11.1
Mesola del montaletto	0.0	0.0	7.8	29.9	0.0	0.0	0.0	37.7
Olca	0.0	1.8	32.4	23.3	11.0	5.0	1.2	74.7
Pradazzi	0.0	0.0	48.1	35.1	0.0	11.5	0.0	94.7
Re	0.0	0.5	27.7	21.2	2.8	0.3	20.3	72.8
Rigoncello	0.0	0.0	8.8	18.2	0.0	0.0	0.0	27.0
Rio della valle	0.0	0.0	28.1	22.2	0.0	0.0	0.0	50.3
Ronco grosso	0.0	0.0	22.4	2.0	0.0	3.4	0.0	27.8
Salto	0.0	0.0	2.4	1.7	0.0	0.0	0.0	4.1
Saraceta	0.0	0.0	5.5	21.2	0.0	0.0	0.0	26.7
Spadolaro pieve quinta	0.0	0.0	0.0	8.8	0.0	0.0	1.9	10.7
Tratturo fosso ghiaia	0.0	0.0	24.0	8.5	0.5	0.9	0.4	34.3
Vecchio	0.0	0.0	4.8	12.0	0.0	0.0	0.0	16.8
Vena grande	0.0	0.0	3.1	0.9	0.0	0.0	0.0	4.0
Veneziana	0.0	0.0	51.7	60.8	0.0	0.0	2.5	115.0
Via cupa	0.8	0.0	42.4	103.7	0.8	26.1	58.7	232.5
Violone della mesola	0.0	0.0	16.8	9.8	0.0	7.4	0.0	34.0

Annex 2: Agricultural data

Reference crop	Not irrigated yield (100kg/ha)	Irrigated yield (100kg/ha)	Production costs (€/ha)	Price (€/100Kg)
Corn	90.66	109.65	681.84	18.71
Alfalfa	62.87	96.98	162.61	10.95
Kiwifruit	39.27	138.83	1468.77	61.86
Vineyard	605.00	792.14	2799.11	8.45
Wheat	60.00	60.00	1468.77	30.00
Peach	415.00	619.80	1175.95	3.98
Apple/Pear	415.00	619.80	1175.95	3.98

Annex 3: Potential water savings by adopting MOSES services in the 2017 irrigating season

District name	Water saving (m^3)
Via cupa	690,420
Lama superiore	185,116
Ronco grosso	283,620
Tratturo fosso ghiaia	323,829
Re	507,138
Carpena	178,205
Fiumicello superiore	3,297,819
Acquara alta	3,474,330
Spadolaro pieve quinta	403,868
Dismano est	186,174
Fossatone del bevano	495,168
Saraceta	219,990
Veneziana	623,470
Cappella	329,723
Masiera	-
Lagnano	276,432
Violone della mesola	266,088
Pradazzi	-
Mesola del montaletto	790,252
Olca	644,390
Fossatone del rigoncello	937,606
Rigoncello	675,181
Fossatone del rigoncello	937,606
Baldone	501,248
Lupara	492,453
Cavaticcia	632,932
Vecchio	48,992
Matrice vecchia	873,620
Vena grande	309,933
Salto	-
Cannuzzo	174,165
Cervaro	-
Rio della valle	-
TOT	**18,759,766**