Agricultural Water Management 227 (2020) 105848

Contents lists available at ScienceDirect

Agricultural Water Management

journal homepage: www.elsevier.com/locate/agwat

The value of information for the management of water resources in agriculture: Assessing the economic viability of new methods to schedule irrigation

Francesco Galioto[a,*], Parthena Chatzinikolaou[a], Meri Raggi[b], Davide Viaggi[a]

[a] Department of Agricultural and Food Sciences, Viale Fanin 50, 40127, University of Bologna, Italy
[b] Department of Statistical Sciences, Via Belle Arti 41, 40126, University of Bologna, Italy

ARTICLE INFO

Keywords:
Irrigation scheduling
Uncertainty
Value of information

ABSTRACT

This study develops a methodology to assess the comparative advantages of new methods to plan irrigation with respect to prevailing existing irrigation practices. The methodology consists of a comparative cost-benefit analysis based on the Value of Information approach that makes it possible to analyse whether an improvement in the information available to farmers generates economic benefits. The method is applied to the problem of comparing computer irrigation models (providing irrigation advice based on measurements, water balance models and weather predictions) and prevailing irrigation practices (at times based on soil and plant observations, or on advanced technologies) in estimating and predicting crop water requirements, in pilot experiments located in four different European regions. The results reveal that the introduction of the alternative method improves the performance of irrigation practices in Mediterranean regions that are characterised by high weather variability and for those crops for which the consequences of failing to meet predictions are relatively low (i.e. tomato instead of maize, drip irrigated crops instead of sprinkler irrigated crops). Under favourable conditions, the use of the alternative technology generates a 0–20% increase in gross margin and a 10–30% water saving with respect to prevailing existing irrigation practices. The study concludes by addressing the conditions that justify the use of advanced information systems to schedule irrigation interventions and by offering some policy recommendations to drive their uptake. These include subsidising research at the evaluation stage and public investments aimed at knowledge creation (weather and shallow water table monitoring stations) and knowledge sharing (counselling) at the adoption stage.

1. Introduction

During the last decade, the agricultural sector in Europe has seen the introduction of information and communication technologies (ICT) that have the potential to increase farmers' access to public and private information, improving, among other aspects, their efficiency in using water resources (Aker et al., 2016).

The recent diffusion of ICT for agriculture in Europe is favoured by the Common Agricultural Policy (CAP), which dedicates financial support to improve irrigation scheduling and to promote the dissemination of water saving irrigation techniques, especially for water-sensitive areas. The adoption of Computer Irrigation Models (CIMs) is sometimes a prerequisite for farmers to receive subsidies (Galioto et al., 2017). CIMs provide messages to farmers about whether to irrigate and how much, often through smartphones (Bartlett et al., 2015), by coupling information from water balance models, field sensors and weather forecasts. Increased interest from the scientific community in developing new CIM technologies (amongst the others: Corbari et al., 2019; Li et al., 2018; Nguyen et al., 2017) has been documented worldwide, but a clear understanding of the actual usage of CIM technologies to plan irrigation interventions and the relevant impacts is still missing, hence weakening arguments in favour of the public value of supporting their adoption (Galioto et al., 2017; Nakasone and Torero, 2016). This is because of the intangible nature of the product generated by these technologies, namely 'information', and because of the impossibility of checking whether farmers formally adopting CIMs are actually using them. Consequently, the ambiguous performance of commercial CIM technologies does not help public authorities in the design of adequate policy interventions to convey their proliferation. Therefore, public authorities will at times provide incentives for the adoption when these technologies are not yet mature enough to be marketed, with the result of failing both to increase farmers' competitiveness and to trigger water

* Corresponding author.
E-mail address: francesco.galioto@unibo.it (F. Galioto).

https://doi.org/10.1016/j.agwat.2019.105848
Received 20 December 2018; Received in revised form 18 September 2019; Accepted 4 October 2019
Available online 19 October 2019

saving practices (Bartlett et al., 2015).

From an economic point of view, the decision by farmers to use CIMs to plan irrigation may be interpreted as dependent upon economic performance, i.e. the comparison of the benefits, identified as the value of information (VOI), against costs. Most farmers will decide to adopt new management practices and begin to purchase and learn to use the technology only when they are convinced that the time and money spent are justified by improved yields or reduced costs or risk. Thus, a farmer's decision to use a new information technology, especially to plan irrigation, starts from assessing the VOI associated with it. This value is influenced by the existing information status under which the farmer operates, the type and quality of the additional information made available to the farmer, and the consequences brought about by the use of the new information technology.

The objective of this paper is to develop and test a methodology to assess the comparative advantages of CIMs to plan irrigation with respect to prevailing existing irrigation practices. This is a challenging issue due to the uncertainty surrounding the information produced by CIMs and due to incomplete knowledge of its effects.

The method is based on applying the VOI approach (Bikhchandani et al., 2013) to assess the extent to which an improvement in the quality of the available information justifies the change in the criteria used by the farmer to schedule irrigation. The developed approach shows that better information does not necessarily imply changes in the criteria used to schedule irrigation. The transition to new information sources is in fact conditioned by the expected benefits of using such information. Such benefits are influenced by elements that are both intrinsic to the technology itself, such as the quality of the information provided, and extrinsic, namely the operational conditions under which the technology is implemented. An empirical implementation of the method is also provided with the aim of investigating the factors that motivate investments in such type of technologies.

Since the pioneering article of Raiffa (1974), a number of scholars have introduced methodologies and empirical analyses similar to the one developed in this study in different fields of research (Bouma et al., 2009; Cavazza et al., 2018; Galioto et al., 2017; Lindner and Gibbs, 1990; Liu et al., 2008). Yet, there is limited literature available that applies the VOI approach on issues related to water management (Cavazza et al., 2018; Galioto et al., 2017; Liu et al., 2008).

The existing literature highlights the potentialities of CIMs applied to the management of water resources both at the district level (Cavazza et al., 2018) and at the irrigation plot level (Galioto et al., 2017; Liu et al., 2008). In all cases, the VOI approach is used to evaluate the economic performance of new CIMs compared to the existing ones, without really exploring how new information contributes to triggering changes in water management practices and, most importantly, without applying this approach to real case studies.

The methodology presented in this paper differs from previous studies both in the method and in the empirical implementation. From a methodological perspective, this study applies a VOI approach to analyse the role played by information in influencing decision making, disentangling the process of value creation brought about by the introduction of new pieces of information and providing a theoretical explanation of the conditions that might favour the use of new information technologies in the field of irrigation scheduling. In addition, the method is tested using data from field experiments in the framework of irrigation scheduling, a practice particularly sensitive to the availability of information, but not yet studied in the perspective offered by the present study.

Thus, the present study might contribute to fill existing gaps in the dedicated literature, that to the best knowledge of the authors, do not provide a clear understanding of the real benefits brought about by the introduction of CIMs in agriculture.

The remainder of the paper is organised as follows: the literature review (section 2) discusses how uncertainty is approached in the agricultural economic literature, motivating the criterion used to assess the viability of new sources of information. The methodology (section 3) describes the assessment approach that was adopted, while an empirical example is provided in section 4, where we compare different sources of information to schedule irrigation interventions at an experimental level. Section 5 discusses the main implications of the results obtained. Section 6 concludes, whilst providing some policy recommendations and hints for further research on the topic.

2. Literature review

Lack of access to information is considered to be a major problem in the agricultural sector as it contributes to maintaining unsustainable agricultural practices and pressure on resources, especially water resources (Nakasone and Torero, 2016). In fact, a considerable number of studies in recent decades have analysed the management of water resources under uncertain information environments (Perry and Narayanamurthy, 1998) both at the district level (Anon, 2014; Chung et al., 2009; Das et al., 2015; Qin et al., 2007; Sabouni and Mardani, 2013; Wang and Huang, 2012) and at the farm level (Carey and Zilberman, 2002). These studies support the idea that the natural variability of production, not depending on the management of water resources, hampers the adoption of advanced water supply and irrigation technologies because of the uncertain outcomes. Nevertheless, in the real world the high risk of extreme outcomes triggers the adoption of advanced water supply and irrigation technologies. The discrepancy between what is argued by the cited scholars and what is happening in the real world can find a possible explanation in the fact that such scholars did not explicitly include in their assessment methodology the adoption of information technologies. Such technologies contribute to influencing the perception of uncertain events by decision makers and, consequently, the decision maker's capacity to manage uncertain events.

In fact, information helps farmers to develop strategies for mitigating the possibility of adverse events (Harwood et al., 1999). When making decisions under uncertainty and risk, there is the possibility of receiving different degrees of information prior to making the decision. More information reduces the uncertainty and facilitates improved decision-making.

The VOI is used as a generic term for the increase in value resulting from better informed actions (Raiffa, 1974). Generally, the greater the uncertainty of the outcome, the higher the value of information. Additionally, the more it will cost to use the information to make decisions, the lower the price of the next-best substitute for the information, the lower the value of information (Laxminarayan and Macauley, 2012).

To the best of our knowledge, the VOI approach has seldom been applied to the agricultural sector[1] . A first attempt at applying the VOI approach in agriculture was made by Adams et al. (1995). Specifically, they applied this approach to estimate the economic effects on agriculture of an improvement in the capacity to predict extreme weather events prior to the growing season in the southeastern US. They found that increases in the accuracy of weather predictions have substantial economic value to agriculture, making it possible to take precautionary measures with regard to land use, hence mitigating damages.

More recently, Liu et al. (2008) developed a methodology to assess the VOI in precision farming. Specifically, they developed a methodology to assess economic improvements in applying nutrients through

[1] The concept of the value of information has been applied in various fields, such as economics, finance, medicine and engineering (Chiang and Feng, 2007; Koerkamp et al., 2006). Furthermore, the value of information has been estimated by different studies dealing with environmental resource management and disaster prevention (Bouma et al., 2009; Trigg and Roy, 2007). Only few studies dealt with agriculture (Liu et al., 2008; Galioto et al., 2017; Cavazza et al., 2018).

variable rate application and a methodology to assess economic improvements in rationalizing land uses by applying technologies to discriminate management zones with different production potential. Later, Galioto et al. (2017) applied the VOI approach to assess the value generated by new irrigation technologies that improve information about soil characteristics and weather conditions based on simulation modelling. Cavazza et al. (2018) developed a methodology based on the VOI approach to evaluate how the combination of different information technologies contribute to influencing sequential decisions for the management of water resources at the district level (based on simulation modelling).

However, such studies do not provide any empirical evidence and the role played by information in improving farm performance in the field of precision farming is still unclear. In fact, there is no clear evidence that precision farming increases profit or decreases environmental impacts (Long et al., 2016).

The value of the information approach is particularly relevant when analysing decisions regarding water management (Cavazza et al., 2018) and, especially, irrigation scheduling (Galioto et al., 2017). The use of CIMs to schedule irrigation can increase irrigation efficiency. This is because CIMs are supposed to offer better information about crops and their environment with the potential to help farmers in taking decisions closer to the optimal as the use of water and energy is concerned. CIMs provide farmers with information about when, and how much, to irrigate, coupling real-time micro-weather stations, plant-based sensors (e.g., reflectance, infrared temperatures or video) and numerous real-time soil water sensors scattered around the field at key locations to feed a set of predictive models. CIMs potentially ensure higher economic returns, principally by triggering a more rational use of inputs (Delgado and Bausch, 2005; Hedley et al., 2009; Meisinger and Delgado, 2002; Sadler et al., 2005; Tas et al., 2016), and, sometimes, increasing yield and production quality (Cambouris et al., 2014; Fallahi et al., 2010, 2011, 2015; Montesano et al., 2015).

With respect to input uses, scholars agree that the use of CIMs make it possible to save labour, energy for pumping water, water and fertilizer consumption. Moreover, the possibility to differentiate the field in management zones can reduce the risk of having areas in the same field that are either too wet or too dry, hence rationalizing the use of pumping energy and the consumption of water for irrigation (Li et al., 2018). CIMs are also considered to be a primary management tool to reduce N leaching (Delgado and Bausch, 2005; Meisinger and Delgado, 2002; Nguyen et al., 2017) and to minimize the need for continuous and expensive monitoring, reducing labour efforts (Bartlett et al., 2015; Sadler et al., 2005). With respect to crop production, recent studies demonstrate that with irrigation scheduling services it is also possible to increase product quality. Recent results in this direction have been reported for tomatoes (Montesano et al., 2015), potatoes (Cambouris et al., 2014) and especially for fruit (Fallahi et al., 2015).

Several studies have found that the magnitude of the benefit brought about by the use of water saving practices is conditioned by a number of factors, especially: the type of crop (Evett and Schwartz, 2011), the type of irrigation systems (Caswell and Zilberman, 1985; Genius et al., 2013), field characteristics (Sadler et al., 2005; Sunding and Zilberman, 1999), climate conditions (Sauer et al., 2010) and the quality of information (Sadler et al., 2005; USAID, 2012). However, farmers are often hesitant to use new practices to schedule irrigation and especially to drive irrigation by way of CIMs (Long et al., 2016). This is because of different uncertainties regarding the economic value of better irrigation information, in particular if the availability of irrigation water is also uncertain (Botes et al., 1995; Nguyen et al., 2017) and due to the perception of more complicated management procedures and learning needs considered to increase transaction costs for the farm (Galioto et al., 2017). These conditions substantiate the need to identify an appropriate methodology to evaluate whether an improvement in the quality of information to schedule irrigation introduced by the availability of new technologies justifies the use of such technologies.

3. Methodology

3.1. Set-up

The approach presented here values the economic benefits of possible improvements in the quality of information to plan irrigation at what can be called the evaluation stage, i.e. when the famer decides the type of information support to adopt for the scheduling of irrigation.

The method seeks inspiration and uses data from empirical experiments conducted in the framework of the European FP7 project FIGARO, aimed at the development of new information tools to schedule irrigation (further detail is provided in the next section). In the FIGARO project, the consortium developed a new CIM technology to support irrigation scheduling. To verify the marketability of the new technology, the consortium ran a set of experiments to compare it with the prevailing irrigation practices in different regions. In this respect, in each experimental site, the consortium identified a number of fields with similar characteristics (similar soil texture, morphology and size) all of which were growing the same crops (i.e. processing tomatoes, maize, etc.) and using the same irrigation technologies (i.e. sprinkler, drip, etc.). For each experimental site, irrigation was scheduled through the Irrigation Advice (IA), provided by the new CIM technology on half of the fields and with the prevailing irrigation practice (PI) on the other half. During the irrigation season the consortium monitored soil moisture before and after each irrigation intervention, the amount of water applied for each irrigation intervention and the yield obtained in all experimental fields. Additional information on crop prices and unit irrigation costs from each experimental site was collected.

In this paper, we use this information to develop two comparative approaches to assess the performance of the new technology. The first one is a conventional cost-benefit analysis to assess the relative performance of the new technology; this is implemented using available information from the test fields. The second step introduces an alternative assessment approach aimed at estimating accuracy thresholds about the new CIM, and providing a better understanding of the suitability of this tool depending on contextual production and climate conditions. This makes it possible to underscore the role of information in the process of value creation. It builds on the same information used above, but also requires additional assumptions, as the original information was not specifically collected for this purpose.

3.2. Comparative cost-benefit analysis

The collected information made it possible to compare differences in a small set of selected performance indicators *i*, namely: yield, water uses and gross margins (the difference between revenues and irrigation costs) among the alternative irrigation scheduling systems. To guarantee comparability across treatments we computed the following relative indicators for each performance parameter:

$$R_i^{IA} = \frac{I_i^{IA}}{I_i^{PI}} - 1 \tag{1}$$

Where, R_i^{IA} is the relative performance of IA compared to PI for the i_th performance indicator; I_i^{IA} and I_i^{PI} are the i_th performance indicators for the comparing irrigations scheduling systems. When $R_i^{IA} = 0$ there are no comparative advantages with the new technology. IA perform better than PI if $R_i^{IA} > 0$ for yield and the gross margin and if $R_i^{IA} < 0$ for water uses. The relative performance of the gross margin is influenced by the relative level of the other two indicators. A higher yield affects gross margin positively through multiplication by the price; higher water use affects it negatively through multiplication by the cost per cubic meter of irrigation water. The compensation among indicators can in principle result in better performance for either PI or IA. Namely, the positive economic performance of IA compared to PI is associated to increases in water use efficiency, i.e. higher average productivity of water. This does not necessarily imply water saving.

3.3. Comparative VOI approach

In this second step, we refine and generalise the assessment approach presented above by developing a method to identify message accuracy thresholds that incorporate and operationalise the value of the information advice provided by the CIM and compare it across decision support tools. This value depends on the quality of information provided by the CIM, on the existing information environment under which the farmer operates, and on the magnitude of the impacts associated with the decisions at stake. The term 'quality of information' in the present empirical framework is used as a synonym for the accuracy of the messages provided by the irrigation methods under comparison (probability to correctly predict States).

In order to proceed, we first have to better formalize the description of the decision problem by introducing the concept of Messages, States and Actions. Messages represent the irrigation advice offered by a generic information service, providing estimates about the probability of occurrence of States in the near future (next decision-making period). States represent the different environmental conditions under which the crop is grown and that influence crop water requirements. Actions are the possible choices the farmer can make to satisfy crop water requirements. Without loss of generality and for the sake of simplicity, we consider a binary representation of the problem with two Messages ('irrigate' and 'do not irrigate'), two States ('rain', 'no rain'), and two Actions ('irrigating' and 'not irrigating').

Messages, Actions and States occur into a sequential process where: first, the farmer receives a message from the information service; second, the farmer decides among a set of alternative actions; third, the farmer faces a set of alternative 'States' depending on which the consequences of his actions (pay off) are determined. Thus, following a backward induction process, the farmer takes decisions and faces expected consequences on the basis of his expectation with respect to the existing information status of a comparable technology. Consistently with the VOI approach, we refer to the farmer's expectation as the farmer's expectation regarding the occurrence of forthcoming States that are conditional to the message received. The sequential process described above is depicted by the decision tree in Fig. 1 for the message 'do not irrigate'.

To formalize our problem, we use: the term m for a generic Message supplied by the information service; s for the occurrence of the State predicted by the message and $\bar{s}$ for the occurrence of the State not predicted by the message; a for the Action 'follow the message' and $\bar{a}$ for the action 'do not follow the message'. In this framework, a is coherent with m and $\bar{a}$ is not coherent with m, likewise s is coherent with m and $\bar{s}$ is not coherent with m.

In addition, we use the term $p_{s|m}$ for the probability of occurrence of the State predicted by the message and $p_{\bar{s}|m}$ for the probability of occurrence of the State not predicted by the message and such that: $p_{s|m} + p_{\bar{s}|m} = 1$. If the information provided by the message is perfect, $p_{s|m} = 1$ and, consequently, $p_{\bar{s}|m} = 0$ for each message provided by the information service. On the other hand, if the information provided by the message is not perfect, $p_{s|m} < 1$, consequently, $p_{\bar{s}|m} > 0$.

Finally, we use the term $l_{a,s}$ for the losses faced by the farmer when taking the right action and $l_{a,\bar{s}}$ for the losses faced by the farmer when taking the wrong action. Actions cause a loss when these are not consistent with States ($l_{a,\bar{s}} \geq 0$) otherwise the loss is null ($l_{a,s} = 0$). The expected loss associated with each action taken by the farmer, $\{a, \bar{a}\}$, is, then, conditioned by her expectation about the likelihood of the upcoming States. The value of the expected loss associated with each action is, then, obtained by the following equation:

$$R_{a|m} = l_{a,s} p_{s|m} + l_{a,\bar{s}} p_{\bar{s}|m} \quad \forall \ m \in M \tag{2a}$$

$$R_{\bar{a}|m} = l_{\bar{a},s} p_{s|m} + l_{\bar{a},\bar{s}} p_{\bar{s}|m} \quad \forall \ m \in M \tag{2b}$$

Where: $R_{a|m}$ is the expected loss associated with the action "follow the message" and $R_{\bar{a}|m}$ is the expected loss associated to the action "do not follow the message". The first term on the right-hand side of Eq. (2a) is null for the action "follow the message" and the second term on the right-hand side of the Eq. (2b) is null for the action "do not follow the message" because actions are coherent with States. It is worthwhile to follow the message only if the expected losses associated with the action 'follow the message', $R_{a|m}$, are lower compared to the expected losses associated with the action 'do not follow the message', $R_{\bar{a}|m}$, such that:

$$R_{a|m} < R_{\bar{a}|m} \ or \ \frac{p_{\bar{s}|m}}{p_{s|m}} < \frac{l_{\bar{a},s}}{l_{a,\bar{s}}} \ or \ \frac{P_m}{L_m} < 1 \quad \forall \ m \in M \tag{3}$$

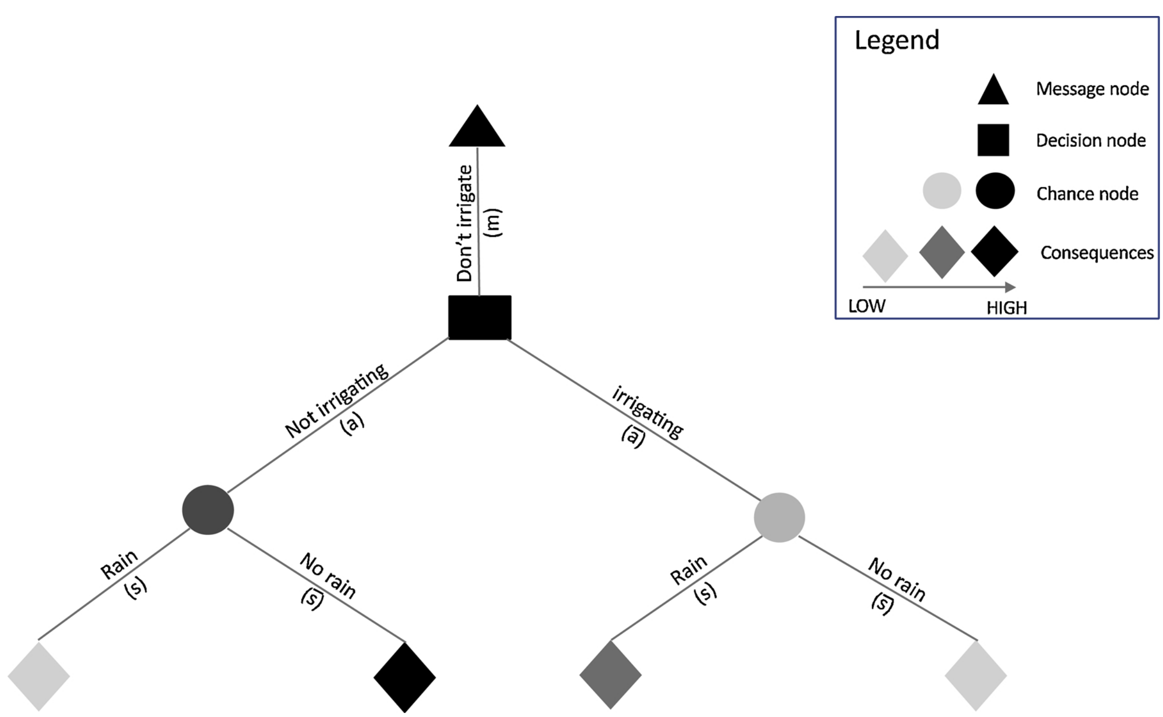

Fig. 1. Decision tree to schedule irrigation once the farmer receives the message 'do not irrigate' from the information advice.

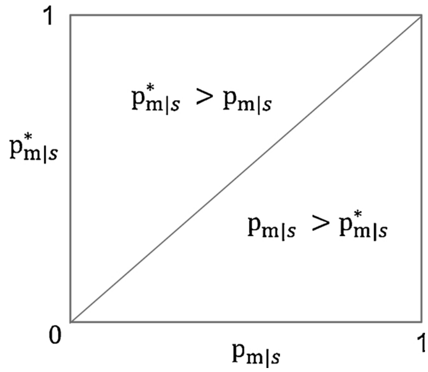

Fig. 2. Relation between the probability of correctly predicting events, $\boldsymbol{p_{s|m}}$, and the reference accuracy threshold, $\boldsymbol{p^*_{s|m}}$, for message *m*.

where: P_m is the relative error probability, wrong predictions divided by right predictions about the occurrence of State *S* provided by the message *m*; L_m is the relative loss, losses associated with the action 'do not follow the message', $l_{\bar{a},s}$, divided by losses associated with the action 'follow the message', $l_{a,\bar{s}}$.

When the ratio between the relative error probability and the relative loss, $\frac{P_m}{L_m}$, is below 1, the expected loss associated with the action 'follow the message' is lower than the expected loss associated with the action 'do not follow the message' and messages can be considered accurate enough to drive decisions. From the former Eq. (3) it is possible to calculate a reference accuracy threshold ($p^*_{s|m}$), the minimum probability to correctly predict events needed to justify the action 'follow the message':

$$\frac{p^*_{\bar{s}|m}}{p^*_{s|m}} = \frac{1 - p^*_{s|m}}{p^*_{s|m}} = L_m \; and \; p^*_{s|m} = \frac{1}{1 + L_m} \quad \forall\ m \in M \qquad (4)$$

$p^*_{s|m}$ is an inverse function of L_m. The value of $p^*_{s|m}$ is high when L_m is small and low when L_m is high. When the probability to correctly predict States is greater than the reference accuracy threshold, $p_{s|m} > p^*_{s|m}$, it is worthwhile to follow the message (Fig. 2).

L_m is zero if there are no consequences when disregarding the message. That implicitly means that there are no rational reasons to take the action 'follow the message', even though the message delivered by the new technology is extremely accurate. In these extreme circumstances the reference accuracy threshold equals 1.

Based on common sense experience of economic parameters linked to irrigation, yield and water uses, it can be expected that the magnitude of the L_m parameters are highly dependent on the type of message delivered by the new technology. When the message is 'do not irrigate' and the action is 'follow the message', then the losses suffered when failing to meet the prediction are that the farmer is missing an irrigation intervention when irrigation is actually required, with direct consequences on crop yield. On the contrary, when the message is 'irrigate' and the action is 'follow the message', then the losses suffered when failing to meet the prediction are that the farmer is misusing water when irrigation is actually not required, with direct consequences on water uses and irrigation costs, but not very much on yields (except for very high amounts of water). Thus, the relative loss is likely higher for the message 'do not irrigate' and lower for the message 'irrigate'. That implies that higher accuracy is required to drive decisions for the messages to which higher losses are associated. This is the message 'do not irrigate' in our problem. Hence, in light of the L_m calculated from Eq. (5) for each message it can be expected that: $L_{\{don't\ irrigate\}} < L_{\{irrigate\}}$. As a result, $p^*_{s|\{don't\ irrigate\}} > p^*_{s|\{irrigate\}}$. In general, the message service is more valuable if those messages to which higher losses are associated are accurate enough to drive decisions, namely when $p_{s|\{don't\ irrigate\}} > p^*_{s|\{don't\ irrigate\}}$.

The analysis made so far provides a rationale to assess if messages are accurate enough to be used to schedule irrigation. The approach presented here reveals that the usability of the information technology under evaluation is influenced by factors that are both intrinsic (the accuracy of the irrigation advice) and extrinsic to the technology itself (the magnitude of losses is influenced by factors such as crop type, climate conditions and irrigation technologies).

While this is true for a single decision about irrigating, comparing information technologies entails calculating the performances of the messages delivered across the whole season. In our case, the problem is to compare the performances obtained by scheduling irrigation through the information advice, IA, provided by a new CIM technology with the performances obtained with existing prevailing irrigation practices, PI, in a given region. IA performs better than PI if the following condition is satisfied:

$$\sum_{m=1}^{M} p_{\bar{s}} R^{IA}_{a|m} < \sum_{m=1}^{M} p_{\bar{s}} R^{PI}_{a|m} \qquad (5)$$

where: the superscript IA and PI represent the comparing information sources; the subscript m1 and m2 are the messages offered by the comparing information sources, respectively "irrigate" and "do not irrigate"; the subscript a1 and a2 are the actions that are coherent with the messages delivered by the comparing information sources; the subscript s1 and s2 are the States "need to irrigate" and "no need to irrigate". This last step makes it possible to verify if the new CIM technology is competitive with respect to the prevailing existing irrigation practices, that is, if it is capable of improving the quality of the information environment under which farmers operate. In the following, we introduce a case study in which we applied the methodologies developed thus far.

4. An empirical application

4.1. Data sources

The methodology described in section 3 above was tested using the data collected in the context of the FP7 FIGARO project. We compared two treatments: a first treatment that followed a 'prevailing existing irrigation practice' (PI) and a second treatment where irrigation was scheduled by means of the 'irrigation advice' (IA) of the CIM developed in the project. The first is considered to be the benchmark strategy whereby irrigation is performed by checking the status of soil and vegetation conditions and using meteorological predictions provided by local meteorological stations, and sometimes with recourse to additional soil water or weather information. The latter incorporates advanced instruments (such as local weather stations, soil moisture sensors and agronomic models) to estimate and predict crop water requirements in the near future during the irrigation season.

The comparison was performed for five different pedo-climatic regions (Denmark, South Portugal, South Spain, Northern Greece and Northern Italy) and five major water-demanding crops (maize, processing tomato, cotton, potatoes and citrus) from 2013 to 2015

Table 1
Information on field experiments.

Region	Crop Typology	Irrigation technology	Seasons (s.)*	Treatments (t./s.)**	Replication (r./t.)
Greece	Cotton	Drip	2	2	1
Greece	Cotton	Sprinkler	2	2	1
Denmark	Potato	Drip	2	2	4
Italy	Tomato	Drip	2	2	2
Spain	Citrus	Drip	3	2	3
Italy	Maize	Drip	2	2	2
Portugal	Maize	Sprinkler	3	2	1

* From 2013–2015.
** the treatments are irrigation carried out by IA and irrigation carried out by CIM; s. – season; t. – treatment; r. – replicate.

(Table 1). Specifically, 2 treatments, one for PI and one for IA, were carried out in each region over 2 consecutive years, with the exception of the Spanish and the Portuguese region where the experiments where prolonged for an additional year. Each treatment was replicated once for the Greek and Portuguese regions, twice for the Italian region, 3 times for the Spanish region and 4 times for the Danish region. Differences between IA and PI were estimated by comparing each replication of the alternative treatments for each experiment and year. For example, the presence of 1 replication per treatment makes it possible to perform only 1 comparison between the two treatments for each year of experiment (this is the case of the Greek and Portuguese experiment), the presence of 2 replications per treatment allows for 4 comparisons (this is the case of the Italian experiment), the presence of 3 replications per treatment makes it possible to perform 9 comparisons (this is the case of the Spanish experiment), and the presence of 4 replications per treatment allows for 16 comparisons (this is the case of the Danish experiment). As a result, we have 82 comparisons considering the whole period of field experiments, of which 36 comparisons in 2013 and 2014, and 10 comparisons in 2015.

Experimental sites were selected following three key criteria: 1) the existence of significant temporal variability in factors influencing irrigation interventions (by cultivating summer crops); 2) the presence of adequate equipment to monitor the status of water content in the soil (soil moisture and plant sensors); and 3) the direct control of crop management practices by the project staff (in some cases field experiments were conducted on commercial farms).

Such criteria did not guarantee perfect homogeneity in the selection of experiments. Indeed, field experiments where selected by the project consortium members who in some cases relied on their own field experiments (Denmark and Italy), by using commercial sites, and in other contracting the cultivation of specific crops with farmers (Portugal, Spain, Greece). The crops selected for the comparison between IA and PI were chosen on the basis of their representativeness in the surrounding region of each experimental site. The PI identified in each area was associated to: 1) the most performing CIM available in the region for experimental sites directly managed by the project staff; 2) the practices used by the farmers directly cooperating in the experiments for the other sites.

Specifically, the Danish experiment was carried out on experimental fields and the new CIM technology was compared with an existing CIM technology that is used to schedule irrigation for potatoes in the region (DAISY decision support system, https://daisy.ku.dk/). In Italy, the new CIM technology was compared with IRRIFRAME, the most popular decision support system used by farmers in the region to schedule irrigation (https://www.irriframe.it/irriframe/home/Index_er). For the other experimental sites the new CIM technology developed in the project was compared with existing farm practices, mainly based on farm experiences and local weather forecast.

Thus, the CIM technology developed in the project was compared with different technologies under very different agro-ecological conditions, hence making it possible to assess the intrinsic value of the technology under heterogeneous real-world conditions, which allow for analyses of the circumstances under which the new technology is potentially capable of increasing the performance of the existing irrigation practices.

The experimental sites managed by contracting farmers where strictly monitored by the project staff. For each experiment, information was collected on:

- Soil moisture before and after irrigation using tensiometers scattered in each experimental field to estimate variations in the humidity level of the soil using the technologies under analysis;
- Water use by installing water meters at the pump outlet on each experimental site (including commercial sites) and monitoring the entire season in such a way as to obtain the precise number of irrigation interventions and the amount of water used per irrigation intervention for each season of treatment;
- Yield, estimated by monitoring canopy growth (which is useful to understand at which phenological stage water stress is suffered by the crop) and then by sampling cropping areas at harvesting.

In addition, information was collected on management practices (specifically, frequencies, duration and amount of water applied for each irrigation intervention) and on prices, using a protocol developed by the authors. Specifically:

- Economic information on energy prices, crop prices and labour costs, collected using official statistical information when available from local statistical sources, otherwise from the EUROSTAT database (http: //ec.europa.eu/ eurostat) and the FAO database (http://faostat.fao.org/);
- Technological characteristics of the irrigation system, including the hydraulic head of the pumping system, the flow rate of the water delivered to the field, the pumping efficiency and the power of the pump to estimate energy consumption per cubic meter of water applied;
- Man-hours to equip each irrigation intervention, number of irrigation intervention, timeframe of each irrigation intervention, scheduled through the protocol during the whole irrigating season.

The inconsistency of soil moisture measurements during the entire irrigation season in most of the experimental fields (breakages, errors of measurement, etc.) made it such that it was not possible to assess water in excess and water at fault for the technologies being compared. For this reason, to implement the VOI approach, we relied on the information used to perform the cost-benefit analysis, on the number of irrigation interventions for each treatment and year and on the following assumptions needed to indirectly estimate the probability to wrongly predict events:

- The target number of effective irrigation events, n^*, is set equal to the number of irrigation events of the best performing experimental plot, for each experiment and each year of investigation;
- The actual number of effective irrigation interventions for each experimental plot, $n_{s|\{irrigate\}}$, is set equal to the target number of effective irrigation interventions multiplied by the ratio between the yield obtained in the experimental plot and the maximum yield for each experiment and each year of investigation.
- The total number of decision events, n^T, is set equal to the ratio between the length of the irrigation season and the minimum period between two consecutive decision events for the whole period of investigation.

The information collected and the assumptions made allowed for a rough estimate of the quality of information from the technologies being compared, which were used to drive irrigation interventions, and of the associated impacts.

To implement the methodology developed here, which is based on discrete choices (whether or not to irrigate, rather than how much to irrigate), the number of missing irrigation interventions, the absence of watering when irrigation is actually required, for each treatment was computed by calculating the differences between the target number of effective irrigation interventions and the actual number of effective irrigation interventions between the technologies being compared. This is formalized in the following equation:

$$n_{\bar{s}|\{don't\ irrigate\}} = n^* - n_{s|\{irrigate\}} \tag{6}$$

Eqs (6) to (9) are defined for each observation (replication of each treatment being compared). The subscript in brackets defines the message delivered to the farmer that in our study overlaps with the actions taken by the farmer (in our experiment both messages rendered by IA and PI drive actions). The number of missing irrigation interventions equals the difference between the target number of irrigation events and the actual number of effective irrigation interventions (the number of irrigation interventions where the State 'no rain' is coherent with the Action 'irrigate').

Furthermore, the number of irrigation interventions where water is misused was calculated by computing the difference between the actual number of irrigation interventions and the actual number of effective irrigations carried out by the treatments being compared. This is formalized by the following equation:

$$n_{\bar{s}|\{irrigate\}} = n_{\{irrigate\}} - n_{s|\{irrigate\}} \tag{7}$$

In Eq. (6), $n_{\bar{s}|\{irrigate\}}$ is for the number of irrigation interventions where water is misused (the State 'rain' is not coherent with the Action 'irrigate'). This number equals the difference between total number of irrigation interventions made by the farmer and the number of irrigation interventions that are coherent with the State 'no rain'.

Finally, the probability of wrongly predicting 'no need to irrigate' was computed by the ratio of the number of missing irrigation interventions and the target number of effective irrigation interventions.

$$p_{\bar{s}|\{don't\ irrigate\}} = \frac{n_{\bar{s}|\{don't\ irrigate\}}}{n^{*}} \tag{8}$$

Similarly, the probability of wrongly predicting 'need to irrigate' was obtained by the ratio of the number of irrigation interventions where water was misused and the difference between the total number of decision events and the actual number of effective irrigation interventions.

$$p_{\bar{s}|\{irrigate\}} = \frac{n_{\bar{s}|\{irrigate\}}}{n^{T} - n^{*}_{s|\{irrigate\}}} \tag{9}$$

This information was then used to estimate the economic impact of taking the wrong action, that is: a) missing irrigation interventions when irrigation is needed; or b) irrigating when irrigation is not needed. Missing irrigation causes water stresses with direct consequences on the crops, and hence also on revenues. Misusing water causes unnecessary expense with direct consequences on irrigation costs.

Impacts where estimated differently if the technology predict 'need to irrigate' when irrigation is not needed and if the technology predict 'no need to irrigate' when irrigation is needed. The first error results in water misuses and consequently unnecessary costs (specifically, labour and energy costs), the second error results in a reduction in yield, and consequently income losses.

The reduction in yield associated with a missing irrigation intervention is estimated by averaging the ratio of the differences among the highest and the lowest yields obtained in treated plots and the differences amongst the associated effective irrigation interventions. The lost income is then calculated by computing the differences between lost revenues (crop prices multiplied by the estimated reduction in yield) and irrigation costs per irrigation intervention.

Finally, the cost associated with water misuses, such as unnecessary irrigation interventions, is calculated by computing the average amount of water applied per irrigation intervention multiplied by the unit irrigation cost (pumping cost per cubic meter of water applied).

4.2. Results

4.2.1. Comparative cost-benefit analysis

Fig. 3 reports boxplot results for each experiment. The boxplot is built using multiple values generated by computing all of the possible differences in water uses (A), yield (B) and economic performances (C) between IA and PI. Thus, 2 points for each experiment carried out in Greece, 32 points in Denmark, 27 points in Spain, 8 points in Italy and 3 points in Portugal.[2] IA performs better than PI when the difference between IA and PI is greater than zero for the yield and the revenue (values above the dotted line crossing the y_axis to 0 in Fig. 3(B) and (C)) and lower than zero for water uses (values below the dotted line crossing the y_axis to 0 in Fig. 3(A)). The figure does not offer clear evidence that IA performs unambiguously better than PI. Notably, the use of IA seems to perform better than PI for drip irrigation (except for drip irrigated potatoes in Denmark), while performances reverse when comparing IA with PI for sprinkler irrigation. The improvement of economic performance using IA (showed by the box plots moved up from the dotted line in Fig. 1C, representing the experiments conducted in Italy for tomato and maize, Spain for citrus and Greece for drip irrigated cotton) is mainly attributable to water savings (shown by the box plots below the dotted line in Fig. 3B). The impact on yield is less evident (shown by the box plots below the dotted line in Fig. 3B). In general, results reveal that the use of the alternative technology generates a 0–20% increase in gross margin and a 10–30% water saving with respect to existing irrigation practices.

Specifically, IA proved to perform better for drip irrigated cotton in Greece, where, unlike the other experimental sites, an appreciable reduction in water uses was not noticed, but rather an increase in yield. Conversely, IA performed worst for drip irrigated Potatoes in Denmark, where, on average, a reduction in yield was recorded, whereas no water savings were noted compared with the local PI.

4.2.2. Comparative VOI analysis

Table 2 depicts the performance of the irrigation technologies under comparison. Specifically, the table includes information about the number of effective irrigation interventions (the applied irrigation interventions that satisfy crop water requirements), the number of ineffective irrigation interventions (the applied irrigation interventions that are not required) and the number of missing irrigation interventions (the irrigation interventions that are required but not performed), for both PI and IA. The data reported in the table represents average values for the whole period of investigation, grouped by treatment. Results from Table 2 shows that the information service developed in the project seems to be relatively robust for the experiments carried out in Spain, Italy and Greece, and less accurate for the others. The degree of robustness is expressed by the magnitude of the coefficient of variation (cv) provided for each variable in Table 2. The robustness decreases with increasing variability, or increasing cv. Specifically, the experiments conducted in Italy and Spain showed great variability between the different years of investigation (higher coefficients of variation). That is, the service performance was very different among the different replications and for the different irrigating seasons.

These results offer a first rough approximation of the service reliability; however, this information alone is far from offering an evaluation of the service capacity to generate net economic benefits. Indeed, we also need to account for the consequences suffered when taking wrong decisions.

The estimation of revenues and costs per irrigation intervention is reported in Table 3. Costs are generally less variable among different seasons than revenues (the coefficient of variation is lower). Indeed, costs presumably depend mainly on technological aspects that are controlled by farmers[3], while revenues are extremely variable and

[2] Multiple values are generated by multiplying the number of replicates times the number of treatments times the number of years, using the information reported in Table 1. For example, in the Greek experiments we had 1 replicate, 2 treatments, and 2 seasons that made it possible to obtain 2 values (differences in values between IA in the first year and PI of the first and differences between IA in the second year and PI in the second year).

[3] Energy price is not likely to vary significantly over a small number of consecutive years. Water use is likely to vary significantly among consecutive years, but less variable is the amount of water applied per irrigation intervention, as this mainly depends on field capacity.

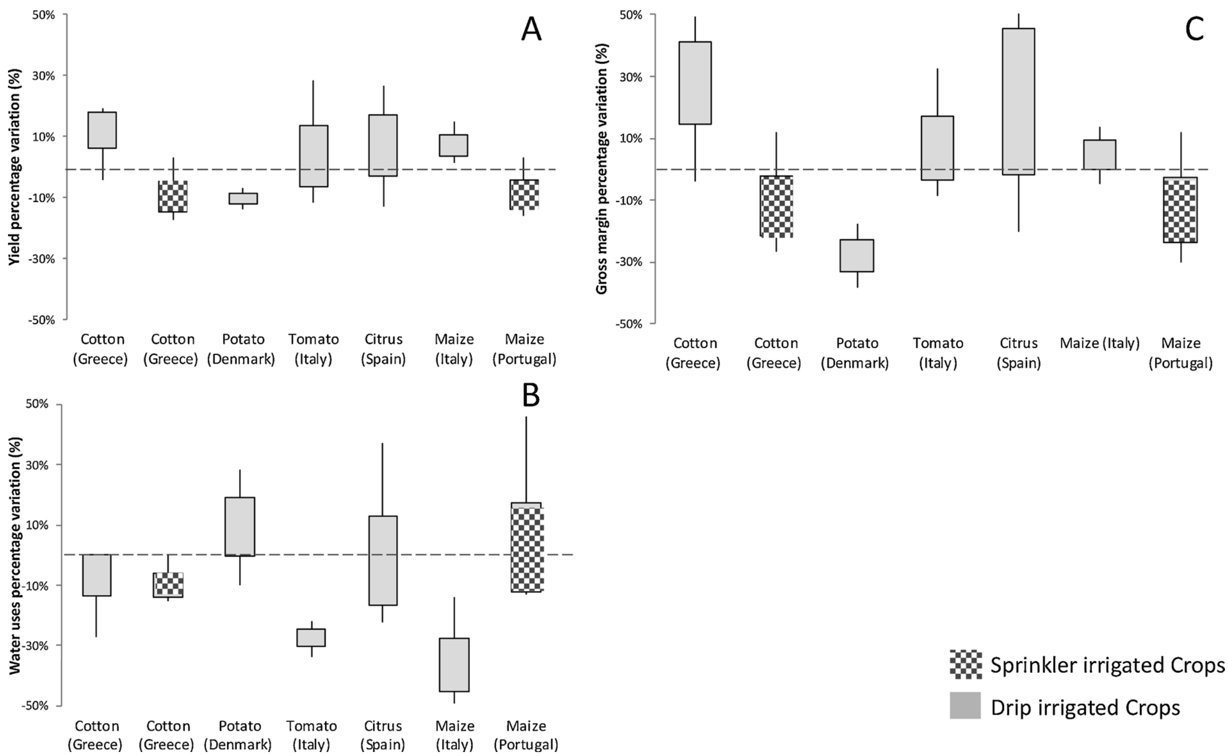

Fig. 3. Differences in the performance of irrigation provided by IA and PI for different experiments during the period 2013-2015. Differences in yield are reported in Fig. 3(A); differences in water uses are reported in Fig. 3(B); differences in gross margin are reported in Fig. 3(C).

Table 2
Performance of the technologies under comparison to plan irrigation (the coefficient of variation is reported in italics).

Region	Crop Typology	Irrigation technology	IA Effective irrigation interventions (number)	 Ineffective irrigation interventions (number)	 Missing irrigation interventions (number)	PI Effective irrigation interventions (number)	 Ineffective irrigation interventions (number)	 Missing irrigation interventions (number)
Greece	Cotton	Drip	11.95	2.05	0.95	10.24	4.10	2.66
			0.44	*0.52*	*0.85*	*0.56*	*0.57*	*0.78*
Greece	Cotton	Sprinkler	7.46	1.33	2.74	9.01	1.40	1.19
			0.64	*0.71*	*0.76*	*0.62*	*1.21*	*0.64*
Denmark	Potato	Drip	8.51	4.82	4.99	8.54	5.89	4.96
			0.11	*0.41*	*0.20*	*0.29*	*0.42*	*0.51*
Italy	Tomato	Drip	28.63	3.68	2.55	4.09	1.14	1.01
			0.44	*1.61*	*1.55*	*0.71*	*1.11*	*0.81*
Spain	Citrus	Drip	109.81	5.20	0.57	134.26	0.76	0.86
			0.27	*1.25*	*2.78*	*0.30*	*2.24*	*4.10*
Italy	Maize	Drip	35.85	0.95	0.45	22.17	0.00	12.83
			0.07	*0.99*	*1.14*	*0.20*	–	*0.35*
Portugal	Maize	Sprinkler	23.50	5.17	4.70	26.80	5.53	1.40
			0.29	*0.09*	*0.62*	*0.16*	*0.55*	*0.82*

conditioned by a number of factors that are out of the control of the experiments, such as pests and temperatures.

By comparing the average revenue and cost per irrigation intervention of the different experiments, it appears that for some of them revenues are significantly above costs (i.e. drip irrigated tomatoes in Italy, drip irrigated cotton in Greece and sprinkler irrigated maize in Portugal) and for some others revenues are just slightly above costs (such as citrus in Spain and potatoes in Denmark).

The difference between revenues and costs is the average productivity of an irrigation intervention and it represents a loss when the irrigation intervention is missed. Analogously, costs represent a loss when the irrigation intervention is unnecessary. The ratio between the losses associated with the two types of errors (wrongly predicting 'need to irrigate' and wrongly predicting 'no need to irrigate') influences the level of the reference accuracy threshold (minimum probability to correctly predict events), consistently with Eq. (3).

Fig. 4 compares the reference accuracy threshold, $p^*_{s|m}$, and the probability of correctly predicting events, $p_{s|m}$, for the messages provided by the information service. The results depicted in Fig. 4 are obtained for each replication of each pair of treatments being compared and for each year, for a total number of 82 comparisons. IA performs better than PI for the points located below the bisector in Fig. 4, chart A and B. The figure shows that the probability of correctly predicting events is likely to be higher than the reference accuracy threshold for the message with lower failure consequences, 'irrigate' (most of the points in Fig. 4 B are below the bisector), and lower for the message with higher failure consequences, 'do not irrigate' (most of the points in Fig. 4A are above the bisector).

In any case, the quality of information provided by the technologies under comparison must be weighted against the probability of States

Table 3
Revenues and costs per irrigation interventions (the coefficient of variation is reported in italics).

Region	Crop Typology	Irrigation technology	Average Revenues (€/irrigation)	Average Costs (€/irrigation)
Greece	Cotton	Drip	107.38	24.96
			0.62	*0.16*
Greece	Cotton	Sprinkler	99.53	55.02
			0.49	*0.09*
Denmark	Potato	Drip	50.68	33.23
			0.05	*0.48*
Italy	Tomato	Drip	372.63	67.70
			0.84	*0.77*
Spain	Citrus	Drip	19.93	6.88
			0.48	*0.57*
Italy	Maize	Drip	74.41	42.02
			0.51	*0.01*
Portugal	Maize	Sprinkler	98.23	27.31
			0.83	*0.18*

occurrence (the climate condition under which the new technology is tested) and the consequences of failing to meet predictions (the operational condition under which the new technology is tested) to ultimately verify the marketability of the new technology. Such a comparison leads to the results provided in Fig. 3.

5. Discussion

The study presents a methodology to assess the economic viability of new methods to schedule irrigation interventions under different conditions. The method is applied to the problem of comparing computer irrigation models and existing irrigation practices in estimating and predicting crop water requirements. The main novelty of the study concerns the assessment approach based on the VOI concept, highlighting the role played by information in conditioning the usability of new irrigation technologies. To the best of our knowledge, compared with previous studies (Cavazza et al., 2018; Galioto et al., 2017) the empirical example presented here is the first attempt to model the role played by information in triggering changes in irrigation practices at the evaluation stage (that is, preceding first use of the technology), providing original theoretical insight and evidence about regarding the frontiers of application of CIM technologies to plan irrigation.

Specifically, the empirical example provided by this study compares a new CIM technology with the prevailing irrigation practices for different crops and under different operating conditions. The results show that, taking the overall average, there is no substantial difference in performance of the new CIM technology compared to existing ones. However, the new technology performs better for drip-irrigated crops and in semi-arid regions. Conversely, the new CIM technology can perform worse than existing practices in su**b**-humid regions and for sprinkler irrigation.

Performance improvements are mainly attributable to water saving. The impact on yield is less evident. Negative performances were recorded for the Danish experiment for drip irrigated potatoes, the Portuguese experiment for sprinkler irrigated Maize and for the Greek sprinkler irrigated cotton. Such unsuccessful applicative examples may result from the fact that for the Danish experiment, the new CIM technology was tested in an operational environment where farmers were already using an advanced CIM technology, well adapted to local conditions. In Greece and in Portugal the new CIM technology was compared with current farm practices. In these cases the success of the new CIM technology seems to be highly influenced by the type of irrigation system to which the technology is associated: sprinkler and drip irrigation. The negative performance of the new CIM technology with sprinkler irrigation seems to arise mainly from the fact that this system is associated with low frequencies of irrigation interventions. Here, missing an irrigation intervention leads to greater losses than it would happen for drip irrigation. Namely, the reference accuracy threshold is likely to be higher for sprinkler irrigation than for drip irrigation, all other conditions being constant. This might explain the reason why we recorded good performances for drip irrigation for those experiments located in Mediterranean regions. Here, positive performances were recorded when comparing IA both with traditional practices (Spain and Greece) and with existing CIM technologies (Italy).

Besides the difficulties in finding suitable comparable technologies as highlighted above, the present study faced various limitations and challenges, especially regarding the application of the method. The evidence reported on a case study basis lacks a sufficient number of observations in time and space, hence making it impossible to generalise the results provided here. Three years of investigation and analysis were insufficient to achieve robust results; accordingly a longer testing period with more replications should be sought in the future. In addition, from a methodological point of view, the probability of correctly estimating water requirements should be calculated by directly measuring soil moisture content before and after each irrigation intervention and not approximated by comparing differences in yield, as we did in this study. Differences in yield can be used as valuable costless proxies for water stresses if no other factors than water interfere in conditioning them. This is not usually the case in real world conditions.

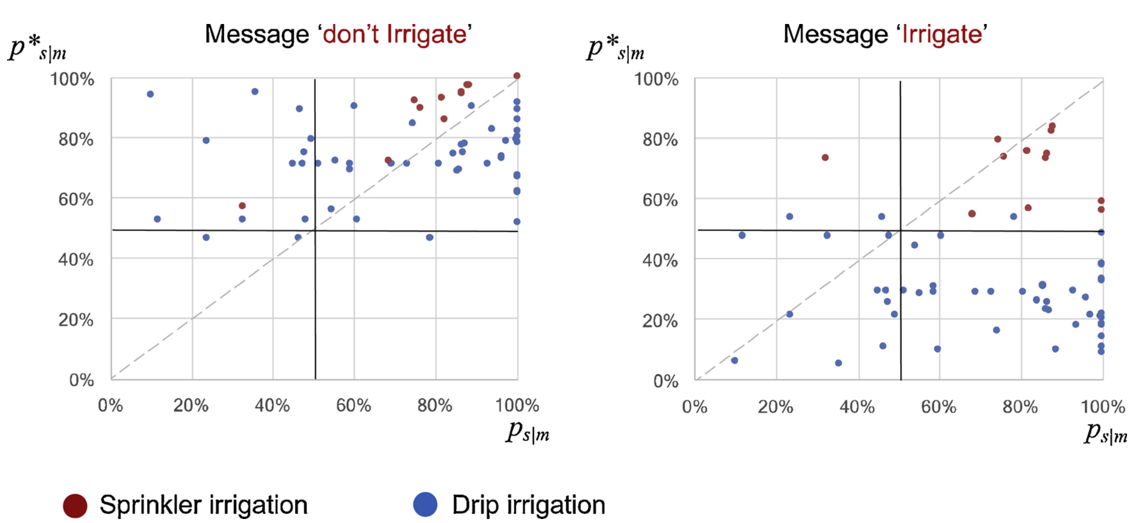

Fig. 4. Relation between the reference accuracy threshold, $p^*_{s|m}$, and the probability to correctly predict events, $p_{s|m}$, for the messages provided by the irrigation advice, IA.

In addition, the methodology provided here is designed for discrete choices, such the application or non-application of water, and losses are assumed to vary linearly with forecasting errors (losses associated with two forecasting errors account for twice the losses of one forecasting error). Thus, a further refinement of the approach presented here could link the probabilities of forecasting errors to water stress levels rather than irrigation interventions.

6. Conclusions

The present paper analysed the role played by information technologies in the scheduling of irrigation in agriculture. The paper depicts a simplified analysis with an eye to displaying the process by which information can contribute to building realistic expectations about future events, hence influencing strategic decisions.

The results obtained reveal that a given CIM technology does not perform in the same way in different regions (Mediterranean and continental regions), for different crops (maize, processing tomatoes, cotton, citrus) or different irrigation systems (sprinkler and drip irrigation). This highlights that such type of tool must be fine-tuned to local conditions before considering their broader dissemination.

The assessment procedure developed in this study could help public authorities to identify the right set of instruments to drive the uptake of CIM technologies at the local level. For example, the subsidisation of research aimed at improving the quality and usability of new CIM technologies and/or subsidizing investments in public infrastructures to guarantee accessibility to the relevant information (i.e. meteorological station networks, water table level monitoring stations, etc.), could be suggested in those cases where it is found that the technology is not yet ready to be disseminated among end-users. Subsidies for dissemination and advisory services might be worth implementing to trigger the adoption in those cases where it is found that the technology has already good performance but needs to be better known and appreciated by potential end-users. In cases of low adoption, it can also help to understand if the problem is the technology itself or external conditions (e.g. water or agricultural product prices) and the extent to which a policy is needed at all.

In any case, the results obtained with this study suggest that CIM technologies can actually contribute to increase substantially the efficiency of irrigation practices:

- in sub-humid and sub-arid regions where the presence of climate variability justifies the use of advanced technologies to drive irrigation interventions in the near future;
- for drip irrigated crops where the consequences of failing to meet irrigation requirements are low compared to sprinkler irrigated crops.

In addition, other studies (Montesano et al., 2015; Cambouris et al., 2014; Fallahi et al., 2015) demonstrated that the use of such technologies is particularly welcome for crops where the amount of water applied influences the quality of the production (which can be linked to the role of prices in our model).

A further improvement of this study would be that of extending the method from the evaluation stage of the information technology to the early adoption stage and to analyse the linkages between farm risk attitudes and the quality of information and the relevant impact on water and land uses as well as issues related to knowledge sharing and familiarity (Cabantous, 2007).

Declaration of Competing Interest

None.

Acknowledgments

The research leading to these results received funding from the European Community's Seventh Framework Programme under grant agreement No. KBBE-2012-311903 (FIGARO). The authors gratefully acknowledge the FIGARO consortium as a whole, with particular reference to representatives of the Canale Emiliano Romagnolo (Italy), Aarhus University (Denmark), the University of Lisbon (Portugal), and the Regional Union of Municipalities of Eastern Macedonia-Thrace (Greece) for having provided data and other technical information.

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