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# Assessing the Potential Economic Viability of Precision Irrigation: A Theoretical Analysis and Pilot Empirical Evaluation

Francesco Galioto <sup>1,\*</sup> , Meri Raggi <sup>2</sup>  and Davide Viaggi <sup>3</sup> 

<sup>1</sup> Department of Agricultural Sciences, University of Bologna, Viale Fanin 50, 40127 Bologna, Italy

<sup>2</sup> Department of Statistical Sciences, University of Bologna, Via delle Belle Arti 41, 40126 Bologna, Italy; meri.raggi@unibo.it

<sup>3</sup> Department of Agricultural Sciences, University of Bologna, Viale Fanin 50, Bologna 40127, Italy; davide.viaggi@unibo.it

\* Correspondence: francesco.galioto@unibo.it; Tel.: +39-051-209-6115

Received: 1 November 2017; Accepted: 15 December 2017; Published: 20 December 2017

**Abstract:** The present study explores the value generated by the use of information to rationalize the use of water resources in agriculture. The study introduces the value of information concept in the field of irrigation developing a theoretical assessment framework to evaluate whether the introduction of “Precision Irrigation” (PI) practices can improve expectations on income. This is supported by a Stakeholders consultation and by a numerical example, using secondary data and crop growth models. The study reveals that the value generated with the transition to PI varies with pedo-climate, economic, technological and other conditions, and it depends on the initial status of the farmer’s information environment. These factors affect the prerequisite needed to make viable PI. To foster the adoption of PI, stakeholders envisaged the need to set up free meteorological information and advisory service that supports farmers in using PI, as well as other type of instruments. The paper concludes that the profitability of adoption and the relevant impact on the environment cannot be considered as generally given, but must be evaluated case by case justifying (or not) the activation of specific agricultural policy measures supporting PI practices to target regions.

**Keywords:** Precision Irrigation; value of information; adoption; Stakeholders consultation

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## 1. Introduction

Climate change is bringing several new challenges to European agriculture. These effects are, by their very nature, strongly different across macro-regions as well as micro-areas. In Northern Europe, climate change may produce positive effects on agriculture through the introduction of new crop species and varieties, higher crop production and the expansion of suitable areas for crop cultivation. In Southern Europe, the possible increase in water shortages and extreme weather events may cause lower harvestable yields and higher yield variability. These effects may reinforce the current trends of intensification of agriculture in Northern and Western Europe and extensification in the Mediterranean and southeastern parts of Europe [1,2]. The new Common Agricultural Policy (CAP) reform explicitly addresses this aspect, dedicating funds for advisory weather services, training and supporting investments to adapt farm structures and production methods [3]. This changing environmental and institutional context is encouraging the development of new technologies and modify their patterns of diffusion, with particular reference to irrigation practices.

Good management of irrigation water can increase crop yields, improve crop quality, conserve water, save energy, decrease fertilizers requirements and reduce nonpoint source pollution [4]. A new frontier for optimizing the use of water resources is sought in the concept of “Precision Irrigation” (PI).

PI is a practice, rather than a technique, that can be applied to any type of irrigation method in any region of the world. PI provides a means to support end users' decisions with regard to how much to irrigate, and when, through data acquisition from monitoring devices (sensors) and forecasting tools (weather predictions), data interpretation, system control, and evaluation mechanisms [5]. PI has the potential to increase certain economic efficiencies of operations by optimally matching input to yields in each zone of a field and reducing costs [6]. Thus, PI can refer either to irrigation which is scheduled precisely (meets crop demand taking into account weather) or irrigation which is adjusted spatially (in order to account for differences in soil), or both. Any control strategies applicable to irrigation may be either: (i) "sensor-based", for which the (simulated) irrigation application is directly adjusted according to the measurement response (e.g., learning control); and/or (ii) "model-based", which use a calibrated soil and plant model for irrigation management (e.g., mathematical programming and model predictive control). These strategies differ fundamentally in their data requirements and their use of the crop model [1]. However, whatever is the PI approach adopted and whatever are the instruments used to apply PI, the effect of this promising innovation is still unclear due to its limited diffusion and to the varying accuracy of available monitoring devices. Both canopy cover [7] and soil moisture sensors [8] are often inaccurate and the spatial variability within each management zones is often significant [9], affecting the reliability of the information used to manage irrigation. However, a few empirical studies worldwide demonstrate that PI at least enables to lessen the risk of experiencing adverse situations of crop production and income [6,10,11].

With the adoption of PI, the main changes occur in the way to handle available information which in turn may affect farmers' ability to rationalize the use of water resources. A measure of the value of information (VOI) brought with PI can be estimated by comparing the consequences of the decisions made using PI with the consequences of the decision made using traditional sources of information [12]. The magnitude of the consequences brought with PI may be determined by several factors, which, consequently, may affect positively or negatively its diffusion within a given region [6].

The objective of this paper is to provide a methodology to assess the potential economic viability of PI in different environments introducing a literature on factors affecting the adoption of PI and a theoretical framework to calculate the value of the additional information brought with the adoption of PI. The theoretical framework is supported by a stakeholder consultation involving a structured group of experts from different geographical European regions and a pilot empirical example to assess the economic viability of PI. The Stakeholder consultation made it possible to explore divergences and convergences of factors that may determine the adoption of PI, while the empirical example offered a dimension of the potential economic and environmental relevance of PI. The paper concludes with a discussion of the extent to which PI can be considered an instrument capable of meeting the main concerns addressed by the Water Framework Directive (WFD) and the new CAP reform.

## 2. Literature on Factors Affecting PI Adoption

Nowadays, the paradigm of innovation for irrigation is shifting from technologies associated to the way to irrigate (i.e., from sprinkler irrigation to drip irrigation) to technologies related to the way to handle information for scheduling irrigation intervention (from hand-control irrigation systems to automated irrigation systems). Currently, however, there is very little literature analyzing the factors affecting the adoption of PI, while a broad literature contributes to identifying the main factors influencing the transition from traditional to modern irrigation technologies (MIT); that is, the transition from sprinkler to drip irrigation. These two different ways to innovate share the common goal to optimize the use of water resources in agriculture. Factors that affect the optimization of the use of water resources by the means of MIT [13] may be expected to play a role also in affecting the viability of PI [6].

The transition from traditional to modern irrigation technologies (MIT) appears to be affected by environmental, regulatory and structural factors. Climate conditions [7], the quality of land, soil water holding capacity (WHC) and orography [13–15] are addressed as the most important environmental

factors conditioning the transition to MIT. In addition, subsidies [8,16–19], water pricing [20–23], and enforcement and monitoring capacity [22,24] are regulatory factors that may further affect the transition to MIT. For their part, structural factors such as the type of crops [17,20], farmer networks [25,26], farmer skills [27,28], the cost of substituting inputs (labor and energy) (for instance, labor and energy can be considered substituting inputs when considering the transition from furrow irrigation to sprinkler or drip irrigation systems: furrow irrigation is highly labor intensive, while the other types of irrigation systems are energy intensive) and output prices [21], and land ownership [7] contribute to further substantiate under which circumstances the transition to MIT is more likely to occur.

With respect to the environmental factors, scientists have found that the adoption of modern irrigation technologies (from sprinklers to drip irrigation) is conditioned by the climatic conditions of a region and by the main types of irrigation water sources. For example, most of the crops for which it is possible to apply drip irrigation systems (fruit and vegetables) tend to be concentrated in tropical and temperate climate regions. Moreover, in those regions where underground water is the main source of irrigation water, the adoption of modern irrigation technologies increases as the unit cost for pumping water increases. In addition, increasing heterogeneity of field morphology and decreasing soil WHC increases the benefits brought with MIT. MIT guarantees a more homogeneous application of water, particularly on irregular fields, and allows to save water, particularly for fields with low WHC, requiring small amounts of water per intervention and high frequencies of interventions.

With respect to the regulatory factors, scientists have addressed instruments such as subsidies on investments, water pricing (tariffs) and rules of use (licensing for drilling wells, turns and quotas, etc.). These instruments can have varying impacts both on the adoption and the resulting water savings and nutrient leaching reductions. A point of attention where water saving is considered a public concern, is that subsidies alone may lead to the so-called Jevons paradox. That is, with increasing irrigation efficiency, also water availability with respect to needs increases, hence favoring the diffusion of more water intensive crops. To avoid the risk of such an effect, scholars suggest combining subsidies with water pricing. However, there is little evidence that water pricing affect water uses even when volumetric water price is applied; the main reason water price is not acting as an incentive to MIT adoption, however, is that in Europe water is rarely priced, and, when it is, tariff is just paid for the possibility to use water for irrigation and not for the real amount of water applied [24]. Besides direct incentive effects, water pricing, which is an instrument commonly adopted by local water authorities to recover supply costs [29–31], could be also applied to co-finance investments on modern irrigation technologies [22]. Finally, most of the authors agree that the possibility of imposing rules of use, with particular reference to quotas and turns, could favor the adoption of modern irrigation technologies, in order for the farmers to better comply with such type of constraints.

With respect to the structural factors, the authors found that the type of land tenure conditions the adoption of modern irrigation technologies, as landowners are usually more willing to make long-term investments than tenants. Besides this, the most important structural factor conditioning the adoption of MIT is the type of crop. Moreover, the adoption of MIT tends to increase with the increasing costs of the substituting inputs and output prices and is also conditioned by the quality of human capital, with particular reference to farm skills and networking capacity.

Unlike MIT, with PI climate and crop factors are less important in conditioning the potential diffusion of the technology as, theoretically, PI can be applied to any type of irrigation system (modern and traditional) and in any area of the world where irrigation is practiced [5]. However, presently, most of PI technologies have been developed without considering the knowledge levels, skills and abilities of farmers and service providers to effectively and economically manage them. In addition, the equipment is expensive [6]. Accordingly, a farmer's skills and financial capacity, coupled with his/her networking capacity and opportunity to consult service providers are considered the main factors conditioning the adoption of PI.

These cost-side considerations should be matched with benefits from adoption. PI should guarantee higher economic returns, mainly thanks to a more rational use of inputs (such as energy for

pumping water and fertilizers) and higher yield, minimizing the risk of having areas in the same fields that are either too wet or too dry [32,33]. The adoption of PI may be expected to favor higher economic returns and higher environmental benefits, minimizing nutrient leaching losses and irrigation water wasted, with increased heterogeneity in field morphology.

One of the most recent novelty in the field of PI is to combine crop growth models estimating yield responses to water uses with measures of crop evapotranspiration and soil water content and weather forecasting tools to precisely schedule irrigation in relatively homogeneous regions of a field, named management zones [34]. The management zone is a sub-region of the field that exhibits a relatively homogeneous combination of yield limiting factors for which a single rate of specific crop input (in the present methodology and water) is appropriate [35]. However, it has not been easy to demonstrate consistently the economic returns from adopting these technologies as the bulk of the scientific reporting refers to pioneer applications of PI at the case study level [6]. The limiting factors of this approach are found in the availability of cost effective support tools and instrumentation for decision-making.

Remote sensing is the most innovative technique to estimate crop evapotranspiration and, thus, spatial pattern in canopy cover, crop biomass and potential crop yield. The quality of the information provided through remote sensing is conditioned both by the spatial resolution and by the return frequencies of images [16]. Because of this, satellite remote sensing is significantly less accurate than proximal remote sensing. Moreover, remote sensing from satellite images includes biases due to interferences from soil reflectance at low canopy densities and interferences from cloud cover that may compromise measures [8]. However, most of these biases in the field of remote sensing have been consistently reduced since the spatial resolution of satellite images passed from 80 m (with Landsat 1 in 1979) to sub-meter resolution (with WorldView in 2009) and the return visit frequency has improved from 18 days to 1 day. Yao et al. [36] summarized the major challenges for using satellite remote sensing for precision agriculture.

The limitation of satellite remote sensing for precision agriculture and PI can be overcome by applying proximal remote sensing, i.e., measurements made with tractors and hand-held sensors [37]. However, satellite images are significantly less costly than proximal images and the quality of information provided through satellite images is steadily increasing. Particularly relevant in the field of PI is thermal remote sensing, based on emission of radiation in response to temperature of the leaf and canopy, as it captures water stress in crops [38].

To date, a wide range of sensors is also used to measure soil moisture [17]. Even recent research continues to show that these sensors takes point measurements that are seldom representative of the average soil moisture conditions of the field, especially for those fields with heterogeneous soil textures. However, all sensors give information about trends that can be usable for irrigation scheduling. Scholars suggest to locate sensors in those areas of the field with lowest WHC at the rooting depth to avoid reaching a water stress level in the other parts of the field [4]. In addition, low cost tools (e.g., tensiometers) do not provide consistently precise and accurate data on soil moisture status and require considerable maintenance. To date, a breakthrough in the field of soil sensors was the introduction of sensors measuring the soil electrical conductivity that have been applied to map spatial patterns in soil salinity [39], clay content and soil moisture content [40]. However, tools that provide precise and relatively accurate measurements of soil moisture are generally too expensive for a grower to utilize in multiple locations at multiple depths across a given field [6].

In any case, whatever is the accuracy of the instruments used to map spatial patterns in soil moisture content within a field, the issue of handling spatial variability remains. Practical limitation on the number of management zones collides with spatial variability with a consequent impact on the accuracy of the information provided [36].

With respect to weather forecasts, the accuracy of seasonal and long-term weather forecasts remains quite low despite access to satellite data and improved forecasting models. In addition, the longer the time frame, the higher the possibility of deviation from the forecast. In addition,

the absence of local weather stations negatively affect downscaling from global climate models (by the means of weather generators), with additional losses of accuracy [41], especially for predicting extreme events [42].

The considerations made so far are to highlight that both the spatial and the temporal accuracy of information contributes in conditioning the reliability of the information itself and consequently the practicality of PI.

Despite these limitations, a few empirical studies worldwide highlight that farmers who receive quality, up to date information, and who can use that information, are able to lessen the risk of experiencing adverse impacts on crop production and income [6,11,43]. It is expected that the diffusion of PI will play a role in bridging the information gap and in reducing the information differentials that exists between farmers and between regions. In other words, PI can play the role of better informing decision makers with regard to the value of data and information. Willingness to pay for information can be thought of as a derived demand, or demand emanating from the value of services or information [44].

### 3. Theoretical Framework

In the following, we develop an analytical approach combining the findings of scholars who have contributed to the analysis of the development of modern irrigation techniques with those of studies on new information systems for irrigation [6,7,13,14,44]. Specifically, Miranowski [13] collected a number of studies highlighting the factors that condition the adoption of MIT and, based on this, he developed a methodology that up until recently has provided support a number of empirical applications [7,14]. According to the relevant literature [6], some of these factors seem also to hold for PI, in particular land quality. With increasing soil WHC, PI is less likely to favor higher performances and less likely to reduce energy and water consumption.

The methodology below describes an assessment procedure to evaluate the economic consequences generated by the use of new sources of information to schedule irrigation. We assume that initially the farmer is not in the condition to handle both spatial and temporal variability and he is applying a fixed calendar irrigation scheme based solely on its past experience. The new source of information is assumed to allow the farmer to split the field in management zones characterized by different WHC levels and to provide better forecasts about water requirements in the near future. This allow the farmer to plan water requirements for the different management zones of its field.

Other relevant assumptions are: (1) the number of management zones is determined a priori; (2) the amount of water applied is the only decisional variable (no other crop inputs are considered here); (3) the probability to correctly estimate crop water requirements (quality of information) is conditioned by both spatial and weather uncertainty (no distinction between the two main sources of bias); and (4) the probability of correctly estimating crop water requirements is known to the farmer.

To introduce our analytical approach, we start assuming a deterministic environment where crop income is a function of the amount of water applied for a given irrigation technology. Under such conditions, a profit maximizing farmer needs to find the optimal allocation of water considering the heterogeneous WHC of its field. This problem is addressed by the following maximization:

$$\text{Max } \prod(x_z) = \sum_z \gamma_z [\mu y_z(x_z) - vx_z] \quad (1)$$

where  $z$  is a subscript indicating the single management zone of the field;  $\prod(x_z)$  is crop income;  $x_z$  is the decisional variable, per hectare amount of irrigation water applied to the field for each management zone,  $z$ ;  $y_z(x_z)$  is the yield, which is function of the amount of water applied;  $v$  is the unit cost of water for irrigation;  $\mu$  is the unit yield price; and  $\gamma_z$  is the share of field assigned to each management zone. To simplify notation, we do not include any additional cost not depending on irrigation decisions.

By maximizing Equation (1), we derive the optimal amount of water to be applied in each management zone of the field:

$$\mu y'(x_z^*) = v \quad \forall z \in Z \tag{2}$$

The maximization of Equation (1) is obtained by computing the partial derivative with respect to the decisional variable  $x_z$  and equating it to 0. Here,  $y'(x_z^*)$  denotes the partial derivative of the production  $x_z$ . Thus, the equilibrium is reached when marginal productivity equals marginal costs for each management zone of the field. This is valid as long as there is no restriction on the amount of water available for irrigation and assuming that the farmer perfectly knows how much water to apply in each region of the field.

In fact, the information actually used by the farmer to estimate crop water requirements is far from being perfect. Under such circumstances the farmer may fail to apply irrigation efficiently. The following equation better explains farm behavior with respect to irrigation intervention in a sub-optimal information environment, where it is not possible to handle field heterogeneity:

$$\text{Max } \tilde{\Pi}(\tilde{x}) = \sum_z \gamma_z [\mu y_z(\tilde{x}) - v\tilde{x}] \tag{3}$$

Equation (3) differs from Equation (1) mainly for the decisional variable  $\tilde{x}$ . Here, it is assumed that the farmer is not able to distinguish different regions of its field and to modulate water application accordingly. Under such circumstances the farmer will choose to drive the application of water by mainly referring to that quota of the field which guarantees higher economic benefits:

$$\sum_z \gamma_z \mu y_z'(\tilde{x}^*) = v \tag{4}$$

Thus far, the amount of water applied by the farmer moves away from the optimum the more increases field heterogeneity, or decrease land quality. Likewise, with decreasing land quality levels (increasing number of regions of the field with increasing differences in WHC) increases the potential value of any additional information acquired to handle irrigation intervention.

The difference between the profit obtained by maximizing Equation (1) and the profit obtained by maximizing Equation (3) determines the maximum benefit caused by the use of information instruments to plan irrigation intervention.

The VOI in the present problem is conditioned by the accuracy level of the information itself, that is, by the capacity to correctly estimate crop water requirement in different region of the field. This value is calculated by comparing the consequences associated with farmer’s decision of whether or not to irrigate with and without a new information source.

To move from a deterministic to a stochastic approach, we now also assume that the farmer faces different states of the nature. States refer to the real water requirement in each sector of the field during the irrigating season. A probability of occurrence is associated to each of these states,  $p_{z,s}$ . This probability is assumed to reflect farmer’s expectation on states occurrence. Thus, Equation (3) can be reformulated as follows:

$$\text{Max } \tilde{\Pi}(\tilde{x}) = \sum_{z,s} p_{z,s} \gamma_z [\mu y_{z,s}(\tilde{x}) - v\tilde{x}] \tag{5}$$

Let us consider Equation (5) as the benchmark irrigation management condition before receiving any additional information. Under such circumstances the farmer will choose to drive the application of water by mainly referring to those state conditions that are more likely to affect production in the most sensitive region of its field:

$$\sum_{z,s} p_{z,s} \gamma_z [\mu y'_{z,s}(\tilde{x}^*)] = v \tag{6}$$

Equation (6) reveal that the amount of water applied moves even further away from optimality than what is shown for Equation (4), to the detriment of crop profitability. The more heterogeneous are the state of the nature faced by the farmer in each management zone of the field, the more sub-optimal would be the allocation of water.

In the presence of information, once it has received the information the farmer is assumed to apply different irrigation criteria in each management zone of its field. This assumption implies that the accuracy of the information and the heterogeneity in the WHC are both known.

With respect to the benchmark condition, the farmer can receive a set of messages,  $m$ . messages inform the farmer about the amount of water to be applied in each sector of the field during the irrigating season. messages predict/estimate states of the nature,  $s$ . Each message is delivered with certain probability,  $p_{z,m}$ , and with a certain degree of reliability. The degree of reliability is measured by the probability of occurrence of the predicted state,  $p_{z,s|m}$ . By assumption, with respect to the benchmarking conditions, the information service combines more accurate weather forecasts with more accurate estimations of crop water requirements per field unit, or management zone. Consequently, under uncertainty, the maximization problem described in Equation (1) for an informed farmer can be reformulated in the following equation:

$$\text{Max} \prod (x_{z,m}) = \sum_{z,m} p_{z,m} \sum_s p_{z,s|m} \gamma_z [\mu y_{z,s}(x_{z,m}) - v x_{z,m}] \tag{7}$$

Differently from the problem described by Equation (5), the informed farmer differentiates the application of water in the different regions of its field through the messages delivered by the information service. Indeed, by differentiating Equation (7) with respect to  $x$ , we obtain the following equilibrium:

$$\sum_s p_{z,s|m} \gamma_z [\mu y'_{z,s}(x_{z,m}^*)] = v \quad \forall z \in Z, m \in M \tag{8}$$

Equation (8) reveals a differentiation on the management of irrigation in the different regions of the field. The informed condition generates a more efficient outcome than the uninformed condition when the probability of occurrence of the states predicted by the information service (or states conditional probabilities) is greater than the relevant states prior probability. With perfect information, the probability of the state predicted by the message equals 1 and the equilibrium of Equation (8) equals the equilibrium reached in the ideal condition described by Equation (1). On the other hand, the informed condition generates less efficient outcomes when the probability of the state predicted by the message is lower than its prior, justifying the non-use of the service.

Now, let  $\pi_{z,s}(x_{z,m}^i)$  denote the best income obtained by an informed farmer who differentiate the irrigation intervention in the different regions of its field through the information service;  $\pi_{z,s}(\tilde{x}^u)$ , the best income obtained by irrigating as usual. The value associated to the new source of information (VOI) is obtained by the difference between maximum expected profits of using and not using the new information source,  $\Omega$ :

$$\Omega = \sum_{m,z} p_{z,m} \sum_s p_{z,s|m} \gamma_z \pi_{z,s}(x_{z,m}^i) - \sum_{z,s} p_{z,s} \gamma_z \pi_{z,s}(\tilde{x}^u) \tag{9}$$

From Equation (9) it can be deduced that for each message delivered by the information service the value of the service is then depending on the differences between “informed” and “uninformed” expectation on income. The farmer is assumed to choose the action that maximize its profits. This is conditioned by the consequences faced by the farmer for each of the possible actions under the different possible states and by the accuracy of the messages delivered by the information service. If the farmer decides not to follow the message then its actions would equal the actions he would made in the absence of information.

The probabilities of receiving messages and the probabilities of state occurrences conditional to messages, known also as posterior probabilities, are related to the probabilities of states occurrence (known also as prior probabilities) and the probabilities of receiving messages conditional to states by the Bayesian rule [12], such that:  $p_{z,m}p_{z,s|m} = p_{z,s}p_{z,m|s}$ . This equation can be rewritten as follows:  $p_{z,s|m} = p_{z,s} \frac{p_{z,m|s}}{p_{z,m}}$ . The second term on the right hands side of this last equation,  $\frac{p_{z,m|s}}{p_{z,m}}$ , is the marginal informativeness of message  $m$  given state  $s$ . The message provided by the information service is uninformative when the marginal informativeness equals 1, as posterior probabilities collapse to prior probabilities. In addition, the more the marginal informativeness is higher than 1, the more posterior probabilities will differ from prior probabilities, hence improving the farmer's ability to predict future events. Prior probabilities may be further distinguished in an objective component, the probability of occurrence of state  $s$ ,  $h_s$ , and a subjective component whose value is conditioned by farmer's risk attitudes,  $w_s$ , such that:  $p_s = w_s h_s$ , and  $\sum_s w_s h_s = 1$ . The farmer is risk neutral when  $w_s$  equal 1 for each state. This way, rather than directly tying risk to farmer's payoff (Von Neumann-Morgenster Utility), we portray farmer's risk as a subjective components conditioning farmer's expectation about the occurrence of averse states. This way, the more the subjective component of farmer's prior belief increases the perceived uncertainty the more conservative (or cautious) will be the action undertaken by the farmer decreasing its expectation on crop income.

Finally, the strategy of profit-maximizing irrigation involves a sequential process. First, optimal expected water use levels under the two informative systems are determined. Then, resulting profits are compared. The new information system is selected if  $\Pi(x_{z,m}^*) \geq \Pi(\tilde{x}^*) + r$ , where  $r$  is representing the present cost of the equipment needed to shift from the conventional information system to the new information system and the transaction costs faced by the farmer in approaching the new information technology. The traditional technology is used when the difference on expected income between "informed" and "uninformed" actions is lower than zero.

#### 4. Empirical Analysis: Methods

##### 4.1. General Approach

The empirical analysis was carried out following a two steps approach: (1) identification of the key factors that may affect the adoption of PI through a Stakeholder consultation; and (2) pilot economic evaluation to test the theoretical assessment framework and to weight impacts based on some of the information collected in the first step. The Stakeholder consultation offers a broad overview about the technological limitation of current PI instruments, about external environmental and institutional factors that may condition the adoption of PI and about policy instruments that may speed up the diffusion of PI. This explorative analysis is motivated by the fact that most of the literature on PI is referring to application of PI in North America, while we focused on European experts to explore issues specific of this geographical context. The numerical example offers an estimation of the benefits that may be brought with the use of PI for a given crop, a given irrigation technology and given climate conditions following the theoretical approach described above. Finally, impacts from the empirical application are weighted based on the information provided by experts.

##### 4.1.1. Stakeholder Consultation

The consultation was directed to a group of 18 experts of irrigation systems from across Europe selected through some dedicated European networks (Water European Innovation Partnership—EIPWATER, European Fruit Research Institute Network—EUFRIN) and from local networks selected through the Flexible and Precision Irrigation Platform to Improve Farm Scale Water Productivity (FIGARO) consortium. The group of experts was mainly characterized by researchers and agronomists, who are already familiar with the concept of PI and its application in the real world and who can provide insights into where and when these practices will likely yield relevant benefits for farmers and for the environment.

The eliciting procedure adopted is a mixture of different techniques [45]. In a first phase of the consultation process, we adopted a Delphi method. This was followed by a roundtable in a second phase. The criterion adopted for deciding on sample size for constructing an experts panel was not a statistical one. The literature on this subject suggests that good results can be obtained with a small panel of 10–15 individuals with a homogeneous group of experts.

Anonymity was guaranteed during the first phase of the consultation process minimizing the tendency to follow-the-leader and other psychological barriers to communication. The Delphi Study was carried through a web survey including two rounds, representing two different stages of the consultation process, the “exploration phase” and the “evaluation phase”. In the first round, experts were invited to identify the main limits to the diffusion of Precise Irrigation in the regions where they operate and to suggest any action, policy measures, that might be implemented to overcome the observed weaknesses. In the second round, experts had the opportunity to compare their view surrounding a given issue with other views and were asked to specify whether they agree with alternative positions.

In the second phase, anonymity was removed and experts had the opportunity to carry out side conversation and to compare their experiences in a dedicated workshop enriching their motivations surrounding any convergences/divergences of opinions highlighted in the first phase. First, experts were asked to motivate their interest on PI. Motivations are a key component of the policy analysis because they justify the identification of Priority of intervention and the selection of instruments. Then, experts were asked to explain the conditions under which PI practices can generate appreciable benefits, identifying target regions and target users, and to highlight the problem that can prevent farmers from the adoption of PI practices, even when these conditions are satisfied. Finally, experts were invited to identify/explain any set of actions/measures that might be implemented to overcome any limitation.

This analysis made it possible to identify an ideal scenario highlighting Strengths, Weaknesses, Opportunities and Threats (SWOT) with respect to the potential diffusion of PI. Strengths and Weaknesses are characteristics intrinsic to the technology, whilst Opportunities and Threats relate to external factors. The combination of Threats and Weaknesses helps identify the main barriers to adoption. Based on this, experts elaborated some policy suggestions to overcome any barriers.

Finally, an in-depth analysis was carried out asking experts to rank the degree of desirability and of practicality attached to the selected actions by experts to face any barrier. Three aspects were considered to assess the practicality of the selected actions: Targeting, the ability to focus actions on target regions and target users; Effectiveness, the capacity to affect changes in water use attitudes; and Transaction costs, the costs that might encounter a regulator with the introduction of new measures plus the costs needed to monitor compliance.

#### 4.1.2. Pilot Economic Evaluation

In the second step of the methodology, we tested the information economics model described in the previous section by: (i) selecting a crop with specific physiological characteristics cultivated in a specific location with a given irrigation technology and under given water and out pricing condition; (ii) estimating crop water requirements under different soil and weather conditions to calculate the probability that crop water requirements are above and below specific threshold values, defining different states of the nature; (iii) estimating a crop–water production function for each state of the nature and for each soil type; (iv) setting hypothesis about the information environment, level of field heterogeneity, level of risk aversion, irrigation costs and output prices; and (v) implementing the above methodology to estimate different VOI scenarios.

For the first point, we decided to focus our analysis on processing tomato cultivated in a field experiment located in Mirandola, Italy. The decision to select such location and crop for our analysis is motivated by the availability of information. Specifically, we used: (1) the tomato model parameters published by Linker et al. [46]; (2) a historical series of climatic data from the past 20 years (1993 to

2013) collected by a local meteorological station, available online [47]; and (3) other techno-economic information from the technical literature [48].

For the second point, we estimated crop water requirement by the means of AQUACROP [49,50], a well-known FAO crop growth model, using the published parameters for processing tomato. Then, we altered the soil parameters using the default ones for “Clay” and “Silty” soils from the AQUACROP library with the aim to create an artificial heterogeneous field condition, keeping constant other factors (crop variety, irrigation system, shallow water table level, weather conditions, etc.). The model was then run for the two soil conditions using the weather data collected for each year of the selected period. The estimated crop water requirements enabled the calculation of a probability density function by assuming a normal distribution. This procedure allowed to attach a probability to each estimates of crop water requirements for the simulation period. To keep calculation simple, we assumed that the farmer is in condition to modify the irrigation strategy when crop water requirement is 20% above and below the average seasonal crop water requirements. In this way, we defined three relevant states of the nature: “need water as usual”, “need more water than usual”, and “need less water than usual” (see Appendix A for more detail).

For the third point, we estimated a crop–water production function by running iteratively AQUACROP for each state of the nature for both soils with high WHC and soils with low WHC, gradually reducing the use of water for irrigation, following the methodology recently implemented by Linker et al. [46]. In such a way, we obtained the set of production functions reported in Appendix A.

For the fourth point, we assume that, in the absence of information, farmer’s expectation of crop irrigation requirements is conditioned by the probability of occurrence of each state of the nature and by its risk attitudes. Moreover, it is assumed that the farmer is not in the condition to differentiate irrigation practices based on the different characteristics of its field. According to our hypothesis on risk attitudes, states probabilities are the objective component of farmer’s prior probabilities, that is, farmer’s expectation about future events based on its previous experiences and with any additional information. The subjective component of farmer’s prior probabilities is a weighting factor that modifies farmer expectation about future events on the basis of its risk attitudes. Specifically, with such hypothesis farmer’s perceived uncertainty about states occurrence increase with increasing risk attitudes. Consequently, farmer’s actions tend to be more cautious, reducing its prior expectation on crop income. Thus, farmer’s prior probabilities range from 33% (equal probability attached by the farmer to the occurrence of each state under the hypothesis of maximum risk aversion) to the calculated objective probability of state occurrence,  $p_s$  (under the hypothesis of risk neutrality).

Now, the presence of information improves farmers’ expectations about future events, namely, farmers’ ability to predict weather condition and crop water requirements and to schedule irrigation intervention accordingly in the different regions of its field. In our simulation, we assumed the presence of an information service to schedule irrigation. This information service provides messages that could support farmers in predicting the state of the world they are going to face driving their irrigation management decision. The quality of information is then conditioned by both the probability of receiving messages and by the probability to correctly predict states (States posterior probabilities). If the probability of receiving messages differ from the probability of occurrence of the states predicted by messages (States prior probabilities), then, the information service will fail to correctly predict states for at least one state. A necessary, but not sufficient, condition to correctly predict states is that the probability of receiving messages equals the probability of occurrence of the states predicted by messages for each state. Thus, assuming that states prior probabilities equal the probabilities of receiving messages, the quality of information would be depending solely on posterior probabilities. In this respect, we carried out a sensitivity analysis introducing posterior probabilities which are increasingly informative with the aim to evaluate the relevant impact of an improvement in the quality of information.

We finally calculated the difference between expected “informed” profits and “uninformed” profits under different pricing condition (output and water prices), field quality characteristics and farmer’s prior expectation on states occurrence.

## 5. Empirical Analysis: Results

### 5.1. Stakeholder Consultation

Table 1 provides the main result of the Consultation process (Delphi method + workshop), i.e., a SWOT analysis of the main factors conditioning the adoption of PI, while Table 2 shows the Barriers limiting the diffusion of PI technologies and the main policy suggestions that might help to overcome such barriers.

**Table 1.** Strengths, Weaknesses, Opportunities and Threats (SWOT) analysis of the adoption of Precision Irrigation (PI).

Strengths	Weaknesses
<p><b>Energy saving:</b> the use of energy to irrigate is a key component for all types of irrigated crops, with particular reference to maize and potatoes.</p> <p><b>Water saving:</b> the possibility of increasing water productivity with PI is particularly evident for southern European regions (SR) as it limits the risk of water shortages and increases irrigation capacity.</p> <p><b>Optimizing fertigation:</b> increasing water productivity as an impact, including in reducing nutrient leaching (addressed by the respondents from North Europe—NR).</p>	<p><b>Investment costs:</b> these costs limit the adoption of PI, mainly for farmers with low financial capacity (addressed by most of the respondents from SR).</p> <p><b>Requirement of highly-skilled labor:</b> in Southern Europe, aging and low educational levels inhibit farmers’ attitudes to innovation (addressed by most of the respondents from SR).</p>
Opportunities	Threats
<p><b>Low water availability:</b> where water resources are limited, water productivity is important (addressed by SR).</p> <p><b>Low levels of soil water holding capacity:</b> increasing coarse soil texture increases the frequency of irrigation interventions and the opportunity to save water and energy using PI.</p> <p><b>High irregularity in field morphology:</b> irregular field morphology seems to foster the adoption of PI, as this technology should guarantee a better adaptation of water use.</p>	<p><b>Absence of, or inefficient, water pricing:</b> water pricing is not part of the debate in most European regions. Water pricing affects water uses only for a few regions where irrigation water is in demand.</p> <p><b>Reliance on Subsidies:</b> for SR respondents, subsidies highly impact the adoption of any innovation in due to financial constraints.</p> <p><b>Lack of compliance with rules:</b> low levels of regulatory clearing in some EU regions affect the effectiveness of policy initiatives to limit the misuse of water resources for irrigation.</p>

**Table 2.** Barriers and Policy suggestions influencing the adoption of PI.

Barriers	Policy Suggestions
Absence of incentives	Targeting specific policy measures that enhance the adoption of PI in those regions where the status of water bodies is compromised (combining direct/indirect subsidies, water pricing, rules of use, etc.).
Low PI usability	Investments in research aimed at increasing the ease of use of crop growth models and in-farm monitoring tools.
Low level of networking and absence of extension services	Development of advisory services for supporting farmers in using PI and promoting farmers’ networks (capacity building) to contrast farmer’s aversion to innovation.

By focusing on Strength and Opportunities in Table 1, all of the respondents agreed that the adoption of PI makes it possible to save water and energy, and optimize fertigation reducing nutrient leaching. The magnitude of such effects varies especially with field heterogeneity, with the frequencies of irrigation intervention and with the type of crop. From the members group experiences was revealed that most of the farmers actually applying PI practices are fruit growers as they are already accustomed to schedule irrigation, fertigation and pest control. Field heterogeneity is an important issue conditioning the application of PI practices for arable crops and vegetables production while

is not considered so important for fruit production, as in this case field heterogeneity is an issue a farmer should deal with through the design of the irrigation system rather than with the application of PI practices.

By focusing on Weaknesses and Threats, farmers' financial capacity and skills are considered to be the main limitations to adoption. Specifically, the group of experts agreed that age and education are considered the prerequisites conditioning the adoption of PI practices. Distrust and expected labor efforts are very important factors in limiting the adoption of PI practices. In addition, lack of funding and the absence of a clear regulatory framework further limit the diffusion of PI.

About barriers and policy suggestions (Table 2), the group of experts highlighted that the application of policy measures to face barriers and to favor the adoption of PI must be coherent to the priority of intervention settled by the regulator in a given region. Specifically, any policy intervention is justified if the adoption of PI practices make it possible to improve social benefits, but the priority of interest might vary between regions. For some regions, environmental issues, such as energy saving, water saving and pollutant abatements, might be considered the main priorities justifying the interest or not interest on PI. In this respect, PI might not be considered the right instruments to face water saving issues because of the above mention Jevon paradox. For some other regions, the motivational priority might be food security, that is, guaranteeing that irrigation covers crop water requirement. Under such condition, the Jevon paradox is no more an issue.

Besides setting the priority of intervention, the instruments considered most relevant by the members group to drive the adoption of PI are: (1) water saving practices required as a prerequisite to get access to subsidies; (2) subsidies for the adoption of water saving practices; (3) subsidies for the provision of advisory services. Instruments considered moderately important in driving the adoption of PI are: (4) subsidies for the equipment (i.e., water meters and sensors); (5) imposition of volumetric charges, and (6) discount on water charges for those farmers applying water saving irrigation practices.

Other relevant instruments included by experts are:

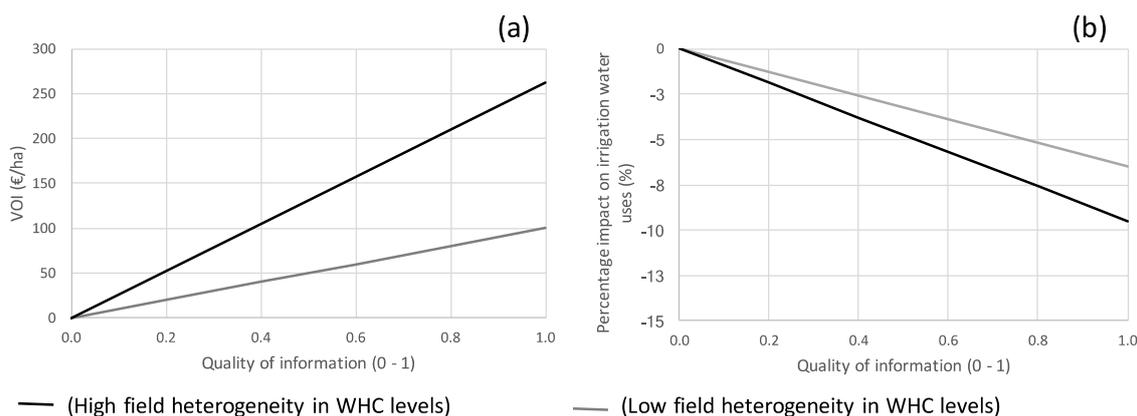
- Market driven incentives: Creation of quality standards associated to the correct implementation of PI practices (i.e., higher dry matter percentage; higher soluble solids content).
- Subsidies for dissemination: Workshops/classes to train/teach farmers about water–soil–plant–atmosphere interactions in general, and about PI techniques in particular.
- Subsidies to develop a local meteorological network: Web services to predict locally water requirement for the most important water demanding crops during the growing season.
- Cross compliance with other type of incentives to meet environmental goals (i.e., subsidies to develop more drought tolerant crops).

Despite the low desirability of the imposition of volumetric charges for irrigation, this instrument is considered the most practicable one, but in those rare circumstances where farmers are served on-demand and water for irrigation is metered. This is followed by subsidies for the equipment which are also not considered that much desirable. High desirability and high practicality was registered for the provision of advisory services, while High desirability and Low practicality was associated both for the inclusion of best irrigation practices in the conditionality requirements and for subsidies for the adoption of water saving practices. Thus, instruments considered practical in conditioning the adoption of PI practices are not necessarily considered desirable and vice versa. The combination of subsidies for the provision of advisory services with subsidies addressed to incentivize the adoption of water saving practices is considered a winning solution because advisors play the role to drive the adoption, supporting farmers in their investments and in the implementation of water saving practices, and whether possible PI. On the other hand, the imposition of volumetric charges is considered an instrument that should be implemented only when water availability is limited.

## 5.2. Pilot Economic Valuation

Results show how the variation of few key parameters (water use cost levels, yield price levels, farmer's risk attitudes levels, quality of information levels and land quality levels) may cause variation in the VOI generated with the transition to PI.

Figure 1a depicts the per hectare VOI, which we assume to correspond to the difference between farmer's income with and without PI, with increasing differences of the quality of information obtained with the compared information sources. We remind that the posterior probability  $p_{s|m}$  is the proxy used to assess the quality of information. The quality of information is set to 0 when posterior probabilities equals their prior,  $p_{s|m} = p_s$  and to 1 when posterior probabilities equals 1,  $p_{s|m} = 1$ .



**Figure 1.** VOI (a); and percentage variation in water uses (b) generated with the transition to PI for increasing differences of the quality of the information obtained through the comparing information sources (0—no difference between the comparing information sources; 1—maximum difference between the comparing information sources): example given for processing tomatoes cultivated on soils with high and low soil WHC levels.

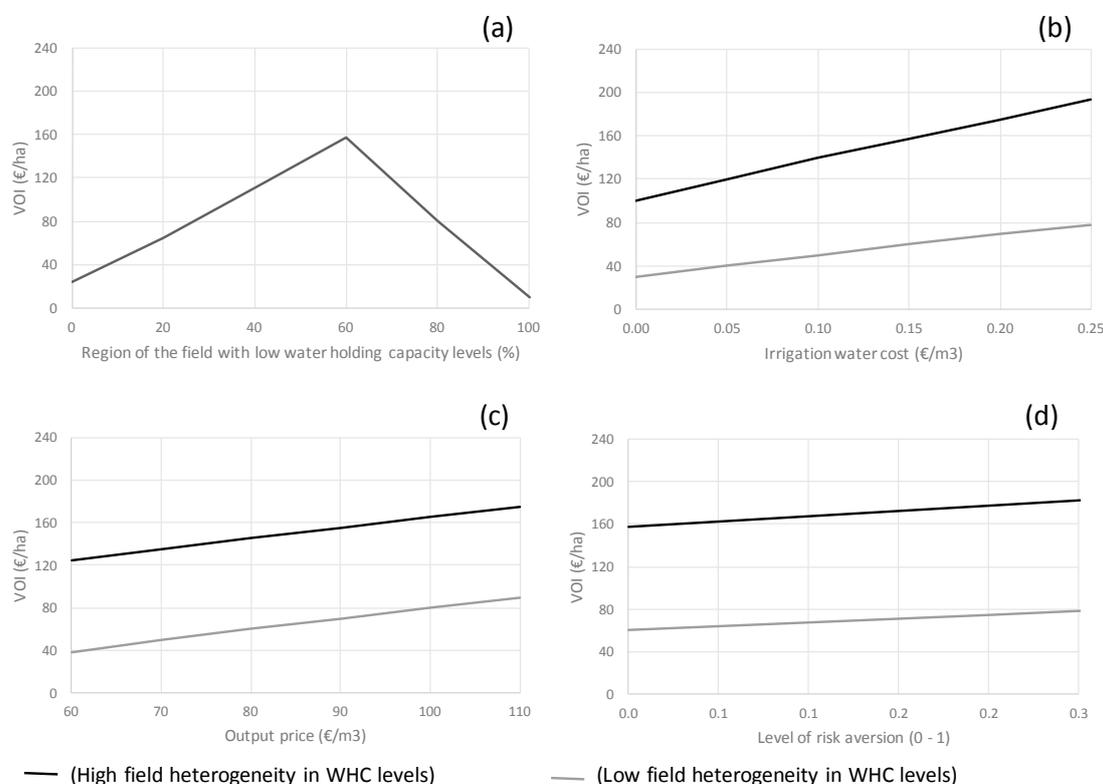
The VOI generated with the transition from traditional sources of information to PI increases with increasing differences of the quality of information obtained through the comparing sources of information. Moreover, with increasing quality of information increases also the difference in expected benefits between low and high soil WHC levels. The differences between the two trends are mainly attributable to differences in the consequences associated with the farmers' decisions whether or not to irrigate. For instance, "Wrong" decisions made for processing tomatoes cultivated in fields with homogeneous WHC do not significantly affect performance.

Considering the impact on irrigation water uses, the adoption of PI would enable farmers to save increasing amount of water with increasing quality of information and increasing field heterogeneity. Indeed, with increasing field heterogeneity the amount of saved water increases (Figure 1b).

Figure 2a shows expected benefits trends with the transition to PI for fields with increasing heterogeneity in WHC levels. The maximum heterogeneity with respect to field WHC is reached when the region of the field with low WHC levels reaches 50% of the field. Expected benefits increases as soil heterogeneity increases. The maximum VOI is obtained when the region of the field with low WHC levels reaches 60% of the field. The maximum VOI does not coincides to maximum field heterogeneity because of the differences in maximum production estimated under the comparing soil WHC conditions.

With the transition to PI, expected economic benefits may also increase with increasing yield prices (Figure 2c) and with increasing water use cost levels (Figure 2b), particularly for soils with high field heterogeneity. Finally, Figure 2d describes the VOI trends with respect to farmer's risk aversion attitudes. The figure highlights that, with increasing levels of uncertainty about farmer's state expectation before receiving the information (farmer's prior beliefs), it increases also the expected

values that the farmers associate to the improvement in the quality of information brought with any additional information. The level of risk aversion ranges from 0 to 1, where 0 correspond to risk neutrality (in our theoretical framework this is obtained when  $w_s h_s = h_s$  for each  $s$ ) and 1 to the maximum risk aversion (in our theoretical framework this is obtained when  $w_s h_s = 0.5$  for each  $s$ ).



**Figure 2.** Example given for processing tomatoes cultivated on soils with high and low soil WHC levels. VOI generated with the transition to PI for: (a) increasing region of the field with low WHC levels, assuming a +68% variation of the quality of information brought with the technology transition; (b) increasing costs of irrigation intervention; (c) increasing yield prices; and (d) increasing condition of uncertainty on farmer's prior beliefs.

The results confirm that, for a given crop and under given climatic conditions, the VOI generated with the transition to PI increase with increasing quality of information, with increasing yield prices and water use costs, and decrease with decreasing field heterogeneity. By comparing expected benefits with the costs for the adoption (equipment and licensing) it would be possible to assess under which circumstances, and for which degree of "informativeness", PI can be considered a valuable practice in terms of profit maximization.

Overall, the figures highlight that the activation of the message service affects farmers' beliefs and improve its ability to manage effectively irrigation and to correctly predict irrigation water requirement under the current climate scenario in the different regions of its field.

## 6. Discussion

Current literature about PI suffers of the absence of studies highlighting the conditions under which PI guarantees higher performance and water savings. The present study offers a methodology to partially fill this gap, using a combination of a stakeholder consultations and a simulation exercises that incorporates a crop growth model simulating yield responses to water uses within an economic model. The simulation confirms that expected benefits arising with the transition from traditional sources of information to PI varies with the quality of the additional information brought with PI,

with product prices and water use costs, as well as with soil heterogeneity and farmers' risk attitudes. All of these factors are considered relevant in conditioning expected benefits also for the qualitative analysis carried out through the Stakeholder consultation. The Stakeholder consultation further integrates the quantitative analysis highlighting the fact that the existence of favorable environmental and regulatory conditions to the adoption of PI may not guarantee its adoption due to cognitive or attitudinal constraints embedded in farmers' choices. Here, the whole group of stakeholders agreed that development of advisory services supporting farmers in using PI is a key policy issue to overcome farmer's aversion to the adoption of this innovation.

On the other hand, the quantitative analysis also shows levels of private benefits per hectare which are relevant but rather low compared with the overall values at stake. As a result, they may be easily overcome by general transaction costs, learning effort or personal attitudes, as well as risk attitudes. In addition, it should be considered that the decision space of farmers may not necessarily allow fully exploiting the information available (e.g., when farmers have to comply with irrigation turns).

One of the main limitations of this paper is the fact of not accounting explicitly for the public value generated by saving water resources and for the different economic, regulatory and environmental conditions that might affect the adoption of PI practices. So, while highlighting the potential of PI and the conditions that would affect such potential, it is not able to strike a balance of costs and benefits of PI adoption in different situations.

This is also connected to other limitations of the study, especially with the limited coverage of European contexts for the Stakeholder consultation, potentially resulting in biases in the generalizations here presented. Indeed, the regions considered in this study displayed very different endowments, infrastructures and rules. These differences affect the type and priorities of interventions aimed at improving irrigation efficiency and water savings in those contexts that should benefit from the diffusion of PI. Thus, a better coverage of European countries may enable to better qualify strength and weakness related to the intrinsic potentialities of the innovation here analyzed and to better qualify opportunities and threats related to the environmental and regulatory context that may condition the diffusion of PI. The same applies and is even more relevant for the quantitative exercise, that only concerns one single crop in a specific area.

In addition to this, the modelling part also suffers from the fact that the process of decision making is fully simulated and is not based on actual farmers' behavior. As a result, it is likely that benefits are overestimated with respect to reality.

Altogether, this study corroborates relevant factors already identified in closed fields of research related to irrigation technology and to information systems to support agricultural practices. It however allows validating these factors for the specific case of PI, as well as to identify some lessons learned, policy implications and avenues for further research.

## 7. Conclusions

PI represents a new technological frontier for optimizing the use of water resources in agriculture and this study constitutes a starting point for investigating the potential of PI in European irrigated agriculture. The theoretical studies discussed in this paper, together with the Stakeholder consultation, made it possible to carry out a SWOT analysis on PI adoption and to define a methodology for the assessment of the economic viability of the innovation. This was further tested through a pilot economic valuation.

The study highlights that the adoption of PI is strongly conditioned by the environmental, economic and regulatory framework of a region. Among other factors, soil conditions allow demonstrating the interplay between context variables and quality of information brought by the services in determining the benefits of PI. The main message from this exercise is to corroborate the idea that the profitability of adoption cannot be considered as generally given but has to be evaluated case by case.

To enhance the adoption of PI, the stakeholders participating in the consultation process emphasized the need to set up an advisory service that supports farmers in using PI. This concern is also confirmed in the literature with scholars reporting that farmers encounter significant problems in using current agricultural information management systems, notably in terms of functionality, interfaces and interfacing with the different parties involved [27,28,32]. An advantage of PI is that, unlike past irrigation innovations, it can be applied to any type of irrigation system and in any region of the world. Moreover, PI is considered to be a promising innovation for irrigated agriculture in Europe because it facilitates the accomplishment of current policy goals. Indeed, the new CAP reform explicitly addresses the need to improve water savings, dedicating funding to advisory weather services and training and supporting investments aimed at adapting farm structures and production methods [3]. This is subject to several conditions: (1) the existence of a River Basin Management plan (RBP); (2) the inclusion of specific measures dedicated to the agricultural sector in the RBP; and (3) the existence of water bodies in poor condition. These aspects concur to support the activation of specific CAP measures for targeting regions where the status of water bodies is undermined [33].

These potentially favorable conditions do not ensure however that net benefits from the use of PI are positive everywhere. In light of the upcoming policy context and relevant policy scenarios, further research is required to determine: (a) if and for which type of regions/areas the diffusion of PI could be considered a valuable instrument for the achievement of environmental goals; (b) for which type of users the adoption of PI is more likely to ensure economic benefits; and (c) which type of economic and regulatory instruments are more likely to guarantee the adoption of PI and the expected impact on the environment and the farm economy.

In addition, the development of methods for an improved economic evaluation of PI is also sought. A few pilot experimental sites around Europe would enable to better calibrate yield responses to irrigation water uses for different geographical regions and to compare the impact on both income and water uses of PI with traditional sources of information. Then, the integration of spatial data of crop land coverage and soil characteristics with historical series of climatic data for European geographical regions provides relevant information, although not sufficient, to estimate the potential value generated with the improvement of the quality of information brought with PI at a regional scale, identifying target regions to promote its adoption. In addition, the methodology presented in this study analyses the economic benefits generated with the transition to PI for single crops. However, most farms have multiple crops and the most profitable strategy will derive by the overall performance of PI for this bundle of crops, considering, e.g., common fixed costs. Finally, farmers with differing characteristics, belief and endowments may perceive differently the economic benefits generated with the transition to PI.

A major limitation of the assessment methodology provided with the present study is in the fact that the number of management zone is not determined as part of the optimization process. However, the possibility to differentiate management zones within the field is conditioned by the offset between the benefits generated by rationalizing the allocation of water within the field, which increase with increasing field heterogeneity, and the additional costs faced by the farmer to manage irrigation practices, which increase with increasing number of management zones [35]. Thus, a further development of the model presented in this study should be its extension to include management zones as part of the optimization process and its application on different crops at the farm level. Finally, a key issue to be further investigated is the role played by service providers in fostering the diffusion of PI, with particular reference to the strategies that they may use to induce farmers to undertake joint actions or coordinated investments in the use of this practice.

**Acknowledgments:** The research leading to these results has received funding from the European Community's Seventh Framework Programme under grant agreement No. KBBE-2012-311903 (FIGARO) (The objective of the FIGARO project is to create an innovative virtual platform able to combine and manage information from sensors, meteorological stations, and crop growth models to advise farmers when, and how much, to irrigate. In the context of FIGARO, real-time micro-weather stations, plant-based sensors (e.g., reflectance, infrared temperatures or video) and numerous real-time soil moisture and canopy cover sensors scattered around the field at critical

locations are coupled with a set of predictive models in a decision support system). 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 and Thrace (Greece) for having provided stakeholders contacts and for contributing to the survey.

**Author Contributions:** Davide Viaggi, Meri Raggi and Francesco Galioto conceived and designed the methodology; Francesco Galioto performed the empirical analysis; and Francesco Galioto wrote the paper with the contribution of Davide Viaggi.

**Conflicts of Interest:** The authors declare no conflict of interest.

## Appendix A

In the following, we provide the information used to implement the methodology developed in the present paper. The information provided in Tables A1–A3 was calculated by following the procedure described in Section 4.1.2. We recall that the assessment example is offered for processing tomatoes cultivated in Mirandola, northern Italy (Latitude: 44.8851500, Longitude: 11.0690200). Specifically, we run AQUACROP using available processing tomato crop parameters for that region [46] and local historical weather information calculating water requirements for a 20-year interval. With such information, we then computed a probability density function, assuming a normal distribution and we defined three state of the nature: “need less water than usual”, “need water as usual”, and “need more water than usual”. The probability associated to the first state of the nature is assumed to be:  $P(x \leq x_{low})$ , where  $x_{low}$  is for a lower bound of water requirement and  $\bar{x}$  for a average bound of water requirements. The probability associated to the third state of the nature is assumed to be:  $P(x \geq x_{up})$ , where  $x_{up}$  is for a higher bound of water requirement. Finally, the probability associated to the second state of the nature is assumed to be:  $P(x_{low} < \bar{x} < x_{up})$ . Results are reported in Table A1. For each state of the world, we then calculated relevant expected values obtaining the results reported in Table A2.

Once identified the reference crop water requirement values for each state of the world and field conditions, we implemented the methodology developed by Linker et al. [38] to calculate the relevant crop–water production functions. Specifically, for each state of the world and field characteristics combination, we estimated a second order production function:  $y = -ax^2 + bx + c$ , where,  $a$ ,  $b$ ,  $c$  are the function parameters,  $y$  is the production and  $x$  is the amount of irrigation water to be applied. The estimation of the crop–water production function parameters is reported in Table A3. Finally, to calculate profit functions, we used the information reported in Table A4.

**Table A1.** Probability of states occurrence calculated by running AQUACROP for processing tomatoes in northern Italy from 1993 to 2013.

Field Characteristics	States of the Nature		
	Need Less Water than Usual	Need Water as Usual	Need More Water Than Usual
High WHC	0.25	0.50	0.25
Low WHC	0.20	0.50	0.30

**Table A2.** Expected water requirement for each state of the nature calculated by running AQUACROP for processing tomatoes in northern Italy from 1993 to 2013.

Field Characteristics	States of the Nature		
	Need Less Water Than Usual	Need Water as Usual	Need More Water Than Usual
High WHC	250	320	430
Low WHC	320	410	510

**Table A3.** Crop water production functions estimated for each state of the nature and field conditions using the methodology developed by Linker et al. [38].

Field Characteristics	State of the Nature	Crop-Water Production Function Parameters		
		a	b	c
High WHC	Need less water than usual	0.0005	0.250	44.485
	Need water as usual	0.0005	0.319	19.485
	Need more water than usual	0.0004	0.344	11.485
Low WHC	Need less water than usual	0.0005	0.320	28.485
	Need water as usual	0.0004	0.328	19.485
	Need more water than usual	0.0005	0.510	0.000

**Table A4.** Water use cost and output prices for processing tomatoes published by Ghinassi and Zamarchi [48].

Parameter	Lower Values	Average Values	Upper Values
Output price (€/t)	76	93	96
Water use cost (€/m <sup>3</sup> )	0.09	0.13	0.15

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