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by

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Abstract

This paper aims to analyse the determinants of Italian farmers' adoption of sustainable irrigation technologies such as micro-irrigation (drip and sprinklers) and sub-irrigation technologies. To improve farmers' water management, climate variability adaptive behaviour should be incentivized. Italy, like other Mediterranean countries, has suffered the most for an increase in frequency and intensity of droughts, higher temperatures and fewer precipitations. Applying innovative irrigation systems, water scarcity and water stress may be overcome. Water conservation and saving technologies may help in supporting water-saving behaviour, increasing water conservation in the natural environment and reducing water stress to cultivations. However, accurate analyses of the determinants of adoption and intensity of these techniques are still scarce. This study fills this gap by using a micro-level approach which combines yearly Agricultural Accounting Information Network (RICA) datasets with climatic variables from the ERA-Interim dataset. Based on an unbalanced panel dataset for the period 2012-2016, the decision of a farmer whether to adopt an irrigation saving technology or not is estimated applying a logit and a probit model, while the intensity of adoption is estimated through a Tobit model. Our main findings confirm that crop typology, education, geography and climate are all relevant factors influencing the sustainable irrigation technology adoption choice as well as the adoption intensity given that most farmers adopt water-saving technologies only partially.

Keywords: Water conservation and saving technologies; Irrigation technologies; Technology adoption; Adaptation to climate change; Italian farmers

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1. Introduction

Water scarcity and sustainable water management describe two critical issues that humankind will be facing in the next future (Wheeler et al., 2015). Water scarcity is affecting about four billion people while water shortage is becoming the main socio-environmental detriment in the world (De Angelis et al., 2017; Hoekstra and Mekonnen, 2016). Numerous are the external causes - climate change, population growth, desertification and urbanization - which have put exceptional pressures on water resources, exacerbating water scarcity and depletion issues, principally in the arid and semi-arid regions. As a consequence, global food security (Alexandratos and Bruinsma, 2012), as well as the undernourishment and micronutrient deficiencies for which millions of people are already suffering, have been influenced negatively (FAO, IFAD and WFP, 2015). Since the world population will continue to expand (Undesa, 2018), the global agricultural sector will encounter important challenges in order to avoid famines, disorders and instabilities as well as all those difficulties related to water scarcity issues (FAO, 2011; FAO, 2012).

Human and economic activities may be directly or indirectly the main reason for water scarcity and depletion. Agriculture represents the sector which affects, the most, water resources. In fact, it is responsible for almost 70% of global freshwater withdrawals whose primary use is for intensive irrigation of crops characterized by low levels of efficiency. Moreover, the agricultural sector wastes water resources through many losses due to evaporation, percolation and runoff (FAO, 2011; MEA, 2005). Promoting the adoption of water conservation and saving technologies (WCSTs), within the environmental innovations, may highly contribute to reducing agricultural activity impacts on water resources in a context of water scarcity and water endowments variability (Green et al., 1996; Pfeiffer and Lin, 2014; Exposito and Berbel, 2019). Sustainable water management may be pursued through various strategies such as water demand reduction, water availability increase and water efficiency[2] improvement. Following this latter strategy generates fewer problems at both the social and environmental level (Alcon et al., 2011).

In this paper, we examine the drivers - restraints and incentives - for achieving widely accepted adoption of WCSTs, in Italy. More specifically, the adoption of new irrigation systems such as drip irrigation, low-pressure micro-sprinkling and sub-irrigation can optimize water requirements. The agricultural water demand has steeply enhanced during this last century, in all the world and Italy. In the developing countries, irrigation practices have been part of the so-called "Green Revolution"; and until now, only the 20% of the total world agricultural land is under irrigation whereas the vast majority is still rainfed (Wheeler et al., 2015). In the Mediterranean basin as well as in Italy, water demand steadily rises for irrigation in agriculture thanks also to the more erratic and inconstant climate.

As a negative consequence, global and European water reservoirs have declined steadily both in quantity and quality during this last century. The excessive withdrawals due to agricultural practice intensification may explain the majority of the pressure on water basins and of losses of biodiversity (AquaStat, 2018; Tilman et al., 2002; MEA, 2005; WHO, 1990). Furthermore, climate variability involving more frequent, extreme, and adverse climate conditions may exacerbate water shortages. This worsens agriculture and food production in several

[2] As underlined by Knox et al. (2012), the concept of efficient water uses presents differences by scientists, regulators and farmers. For farmers, water efficiency is more related to the maximization of input economic productivity and not to saving water practices as for scientists and regulators except for the case of inadequate allocated resources.

vulnerable arid zones, slackening food security and political stability (Saravia-Matus et al., 2012; Un, 2015). Crop production may be affected by climate variability directly through temperatures, precipitations, and extreme events as well as indirectly through biological changes, photosynthesis efficiency and water availability. Moreover, climate may influence cultivation and plant growth through the increase of evapotranspiration, higher losses of soil moistures and erosions and fertility losses of arid lands (Olsen and Bindi, 2002; Mestre-Sanchís and Feijóo-Bello, 2009; Huang et al., 2017). Therefore, water demand for agricultural products may dramatically increase because of climate variability, causing water requirement peaks and higher water use per hectares (Mestre-Sanchís and Feijóo-Bello, 2009; Olsen and Bindi, 2002). This, in turn, may affect water supply by reducing natural endowments, rising water withdrawals and increasing competition among alternative uses such as agricultural and civil services (Iglesias et al., 2009). Under scarcity conditions and climate change, substantial efforts should be devoted to improving water efficiency since greater crop production may be achieved with less water use through better water management (Chartzoulakisa and Bertaki, 2015).

The ratio between irrigation water requirements and withdrawals is in general very low, suggesting a scarce irrigation efficiency. By applying innovative irrigation technologies as WCSTs, water management improvements may be achieved (Frenken and Gillet, 2012; Chartzoulakisa and Bertaki, 2015) and the indispensable water for plant growth is poured directly on plant roots reducing water stress. To mitigate drought effects, the adoption of technically efficient irrigation systems allow maintaining water consumption of plants with reduced applications (Pereira, et al. 2002; Schuck et al., 2005; Dasberg and Or, 1999). In terms of water efficiency, the adoption of WCSTs compared to gravity irrigation systems (such as furrow, sprinkler and flooding) may reduce water losses and increase the rate of water consumed by plants. Hence, the vital water is reduced, and irrigation crop requirements better satisfy plant needs (Taylor and Zilberman, 2017; Wheeler et al., 2010). Rising irrigation efficiency by adopting WCSTs improves the optimization of fertilizers and reduces water evaporation from the soil as well as water losses due to percolation and run-offs. More specifically, irrigation efficiency may alleviate from crop diseases and rotting avoiding over-irrigation as well as resolve from salinity and weed growth issues (Skaggs, 2001; Alcon et al., 2019). Moreover, the implementation of WCSTs may ameliorate water productivity, measured as the gross value added per cubic meter of water used. This indicator allows for capturing the improvements in water productivity as the capability of producing more value with less water (Exposito and Berbel, 2019). Nevertheless, it is worth to note that to gain in terms of water efficiency and related economic benefits from such innovative technologies, a high and widespread level of knowledge and technological experience should be developed by farmers to adopt new irrigation technologies (Levidow et al., 2014).

The adoption of a defined innovative irrigation system derives from the interactions among institutions, scientists and farmers based on how much knowledge is widespread and on how much technology is available (Horst, 1998; Turral et al., 2010). According to production theory, farmers maximize their benefits choosing the right amount of production inputs on their future expectations. This means that farmers choices include the best adaptation strategies to climate variability. Thus, deciding to adopt new technology is mainly related to their expectations on the future outcome as well as perceptions and external information they may receive. Therefore, within different scenarios of climate change, farmers have the capability of achieving the sustainability path of growth lessening the exploitation of natural resources (Reidsma et al., 2010). Moreover, their decisions in terms of productive patterns and technology adoption may influence the result of the entire agricultural macro-regions as farmers are the main agents in the management of natural capital and natural resources. Promoting the knowledge of which are the main factors guiding the farmers' decision in adopting WCSTs represents a leading aim of agricultural water policy. Therefore, the interest in the determinants of farmers' choice in adopting sustainable water technologies may incentivise sustainable economic growth within the whole agricultural sector.

While a relevant stream of literature on irrigation systems is still present (Caswell and Zilberman, 1985), the WCSTs adoption literature has emerged in these last years (Shrestha and Gopalakrishnan 1993; Exposito and Berbel, 2019). Due to data availability, the econometric studies are based on single case-studies at the sub-regional scale in the developing countries (Skaggs, 2001; Shah et al. 2013; Getacher et al., 2014) or in the developed countries (Caswell and Zilberman, 1985; Exposito and Berbel, 2019….), or on cross-sectional analysis (Shrestha and Gopalakrishnan, 1993; Kondouri et al 2006). Collecting survey data for specific and homogeneous agricultural areas has the advantage of gathering highly comparable information on production, socio-economic conditions, climate and geographic factors and water endowments, but focusing on a specific agricultural area limit the external validity of the findings. Moreover, the use of econometric cross-sectional analysis do not allow in controlling for individual heterogeneity and endogeneity problems with the possibility of highly biased estimations (Greene, 2003).

Many previous studies focused primarily on the determinants of micro-irrigation systems such as socio-economic and geographical factors which may influence farmers' decisions on the irrigation system adoption. These determinants are selected on the basis of the economic theory or the researchers' perceptions (see Mango et al., 2018 for a review). Although it is acknowledged that adoption should be partial or incremental, few analyses consider the intensity of irrigation technology adoption as the area under innovative irrigation systems due to lack of detail in data. As a consequence, accurate analyses of the determinants of adoption and intensity of these irrigation techniques at farmer level within a country are still scarce.

This paper fills this gap by collecting detailed data at the farmer level for a well-developed country such as Italy belonging to the Mediterranean basin. So far, this analysis represents a first attempt of the WCSTs adoption, based on the extensive use of microdata within a whole country. Farm-level data are collected from the Italian database of Agricultural Accounting Information Network (Rete di Informazione Contabile Agricola - RICA) for the period 2012-2016 and are merged with climatic data. This combined dataset allows us to use panel data methodologies to control for unobserved heterogeneity and endogeneity. The point of deepening farmers' WCSTs adoption choice in Italy is mainly related to the diversified orographic and micro-climatic areas. Dissimilarities among farmers are principally due to geographical, socio-economic, productive, as well as climatic factors. These highly latitudinal diversities make Italy an important case-study within the Mediterranean countries which share similar climatic conditions and longitudinal positions.

The contribution of this analysis to the literature consists in analysing the driving forces of Italian farmers' adoption and intensity of sustainable irrigation technologies. How drip irrigation, micro-sprinkling and sub-irrigation systems may influence farmers' probability in adopting new and more efficient irrigation systems and farmers' adoption intensity in terms of hectares dedicated to WCSTs represent the two intertwined aims of this study. The first aim mainly regards the recognition of what may be the relevant factors among socio-economic, geographic, environmental and climatic characteristics that may have an impact on the decision of adopting low water consumption or water-saving technologies. The second aim, instead, is dedicated to the analysis of the factors which may affect the allocation of WCSTs over the total irrigated land. Applying two binary response models (logit and probit model) for the farmers' decision making and a Tobit model for the intensity use of irrigation system, the importance of human capital, physical capital, the typology of the soil as well as water sources are confirmed.

The paper is organized as follow. In Section 2 a focus on technology adoption of environmental innovations for irrigation is implemented. Section 3 develops the Italian irrigation context. In Section 4, the empirical framework and the data description are presented, while in Section 5 results are shown and discussed. Finally, in Section 6, some main conclusions with policy implications are organized.

2. Technology adoption of Environmental Innovations for Irrigation

Technological innovation can be considered as an improvement over past technologies and techniques used within a productive and socio-economic process with the aim of improving efficiency, effectiveness and higher values of outcomes. The innovation decision-process can be defined as a dynamic process (not an instantaneous action) where an economic agent (i.e. a farmer) pass through five steps (Knowledge, Persuasion, Decision, Implementation and Confirmation) (Rogers, 1971).

Starting from a disequilibrium in which the farmer does not efficiently use the available resources, a farmer searches information over new innovations to reach a new equilibrium. The final adoption in the long-run equilibrium is when the farmer decides to use definitively the new technology (or process) when he/she has full information on its use and its potentials (Feder et al., 1985).

A relevant literature in technology adoption has emerged since the sixties. Studies have explored the distinctive factors that may influence the decision of implementing innovations in general (Jaffe et al. 2002). A growing branch of this literature has focused on agricultural determinants of adopting innovation as agro-ecological constraints, farmers' characteristics, land features, seed supply constraints, risk preferences, or traditional values (Koundouri et al. 2006; Pannell et al, 2006; Arslan and Taylor, 2009; Asrlan et al., 2014). This topic has started to gain interest especially in developing country studies (among others Feder et al., 1985; Neupane et al., 2003; Sheikh et al., 2003 He et al., 2007; Arslan et al. 2014; Mango et al. 2018); where the focus was on the causes which determined success or failure of agricultural innovations such as improved fertilizers, ploughing techniques and pest control in developing countries (Feder and Umali, 1993; Baidu-Forson, 1999; Somda et al., 2002; Herath and Takeya, 2003).

Within the technology adoption literature, a specific branch is related to water technology adoption to improve water management and water conservation both with a theoretical and an empirical approach (Taylor and Zilberman, 2017). In the empirical analysis, the focus on the main factors, which may influence the adoption of WCSTs technologies, has been based on binary response models such as logit, probit and multinomial logit. These methodologies are run to understand the probability of adoption of a specific technology over a set of several technologies available. Other studies (Arslan et al., 2014; Pokhrel et al., 2018) used nested binary models, fractional methods or Tobit models in order to study the intensity of adoption in terms of land under a specific technology. In Table 1, the main studies on WCST adoption are summarized highlighting the method applied in the analysis.

Among the seminal works on this field, we may recall the analysis of Caswell and Zilberman (1985), Shresta and Gopalakrishnan (1993), Green et al. (1996) which focused mainly on farm productive characteristics (as crop type, field size, expected yields), geographic characteristics (as type of soil, acclivity) and water resources characteristics (as water source, water price and irrigated land size). Subsequently, Skaggs (2001), Moreno and Sunding (2005), Schuck et al. (2005) and Foltz (2003) introduced farmers' characteristics such as age, education, years of experience, in-farm and off-farm income, expectations on water availability, access to information and extension services. More recently, other studies, enlarging the initial framework, added further interesting factors such as electricity costs (Namara et al., 2007; Wheeler et al., 2010; Singh et al., 2015), farmers' risks measured as different moments of profit distribution (Kounduri, 2006), social factors – being part of farmers' organisations, the imitation in adopting WCSTs by other colleagues, social networks etc. – (Alcon, 2011; Salazar and Rand, 2016; Hunecke et al.) and mechanization levels within a farm (Mohammadzadeh et al., 2014). Financial aspects (Alcon, 2011), governmental incentives (Huang et al., 2017) and water measuring instrument use (Hunecke et al., 2017) have been also considered. All these above-mentioned studies substantially agree in confirming that the main determinants are socio-economic, technical, geographical and productive, even though results are contradictory for some factors (Kounduri et al., 2006).

Finally, further studies have introduced climatic variables as an effect on WCSTs adoption choice. Among the indicators used to capture climate effects, we may recall evapotranspiration, rainfall, temperature (Negri and Brooks, 1990; Huang et al., 2015), frost-free days (Negri and Brooks, 1990; Moreno and Sunding, 2005) and droughts aridity events (Schuck et al., 2005; Kondouri et al. 2006; Genius et al., 2014; Olen et al., 2015; Knapp and Huang, 2017). Moreover, Frisvold and Deva (2013) and Knapp and Huang (2017) focusing on climate and irrigation technology adoption used climatic variables considering different time span (from 5 to 40 years) and the variations and intensity of events.

The majority of the above-mentioned studies, with just a few exceptions, relies on one-year case-studies based on surveys related to case-specific productive agricultural areas. Using cross-sectional data limits the analysis to the explanation of why a farmer chooses to use new technology in that particular period considered. Moreover, this reduces the reliability of theoretical dynamic models which describe farmers' dynamic processes in choosing different adoption dates by excluding time-related elements such as learning by doing, observation and information collection, productive strategies changes, macroeconomic events and individual heterogeneity of farmers (Kounduri et al., 2006). The use of panel data models can improve substantially the results of the analysis controlling for a dynamic pattern either endogenous or exogenous reducing the effect of time-specific events and unobserved individual effects problems providing more robust and consistency estimates (Greene, 2003). Only a few studies used panel data developing either continuous, fractional, multi-choice or binary dependent variables model (Table 1). Moreover, most of the studies have been conducted in WCST adoption literature referred to countries and areas with important water problems such as Israel, Iran, Greece, Spain, India, Tunisia, Chile, African countries, United States and China (see Table 1 for references). At the best of our knowledge, even if Italy is a country relying importantly on irrigation for agricultural production no relevant studies are present in literature.

Table 1. Main studies on WCST adoption. Source Authors' elaboration

Authors	Year	Area	Country	Method
Caswell and Zilberman	1985	San Joaquim Valley (California)	United States	Multinomial logit
Shrestha and Gopalakirishnan	1993	Hawaii	United States	Probit model

Green et al.	1996	San Joaquim Valley (California)	United States	Multinomial logit
Skaggs	2001	New Mexico	United States	Logit model
Foltz	2003	Cap Bon	Tunisia	Probit model
Shuck	2005	Colorado	United States	Logit and multinomial logit
Moreno and Sunding	2005	Kern County (California)	United States	Nested logit model
Namara et al.	2007	Gujarat and Maharashtra regions	India	Logit model
Kounduri et al.	2007	Crete Island	Greece	Probit model
Wheeler et al.	2010	Alberta	Canada	Probit model
Alcon et al.	2011	Campo de Cartagena	Spain	Duration analysis
Mohammadzadeh et al.	2014	Urmia lake	Iran	Logit model and ordinal logistic model
Singh et al.	2015	Dahod district (Gujarat)	India	Logit model
Salazar and Rand	2016	All regions	Chile	Probit model with sample selection and Multinomial probit
Huang et al.	2017	Arkansas	United States	Logit and multinomial logit
Knapp and Huang	2017	Arkansas, Mississippi, Louisiana	United States	FE OLS regression
Hunecke et al.	2017	O'Higgins and Maule Regions	Chile	Partial Least Squares -SEM model
Mango et al.	2018	Chinyanja Triangle	Zambia, Malawi, Mozambique	Logistic model and OLS
Pokhrel et al.	2018	Various states	United States	Probit model and multivariate fractional regression model

3. Water use in the agriculture sector in Italy

The issuing of European environmental directives has improved the Italian environmental legislation and institutional framework on water quality and use (Massarutto, 1999). In 2000, the European Union issued the Water Framework Directive (WFD) n. 2000/60/EC which put the basis for Common sustainable water management within all the European members. The main objective of this directive consisted in improving the quality of European water basins and their use by 2015 (WFD, 2000). The WFD particularly pointed out the importance of water conservation in both quantitative and qualitative terms and supported water-saving policies in order to reach a sustainable use of water resources in the long run (Zucaro, 2011). The multidimensional approach used in WFD was based on the relevance of the ecosystem for the sustainable management of water (Berbel and Exposito, 2018).

Italian water policy is coherent with the Common legislation even if some delays in the development of an environmental policy put Italy well far behind (Massarutto, 1999). However, at the end of the timeframe scheduled, the year 2015, some European goals of WFD have been reached while others are still far behind. Relevant gaps must be filled in both for water pollution and water withdrawal. For example, in many Mediterranean countries, water extractions persist at a higher level with respect to their natural rate of renovation (WFD Report, 2015; Berbel and Exposito, 2018). In the next future, the lasting lack of a proper water management based on an efficient allocation of water endowments within the agricultural activities would cause the failing of national and supranational water policies in achieving European sustainable development goals (Sauer et al., 2010; FAO, 2017; Bazzani et al., 2005). Since the '70s, Italy has been organized that each region is responsible for water abstractions and water policies in general. When a basin belongs to more than two regions, a basin authority has been established as a competent authority. For water quality controls, Regional Environmental Agencies (ARPAs) have been in charge (Massarutto, 1999).

In Europe, differences in water use withdrawal and water availability are substantial among countries. Southern countries' water withdrawals are higher (60% of total water withdrawals) than those of northern countries which exploit water resources mainly for energy production (Eea, 2009). Moreover, southern European countries present higher levels of water scarcity because of climate variability. A forecasted increase in the frequency of drought spells and a reduction in precipitation frequency and intensity gathered with higher temperatures have risen negative impacts on agricultural yields (Eu, 2011; Euc, 2012). For this reason, the south of Europe represents an area exposed to climate variability where countries with similar geographical and pedoclimatic characteristics share akin problems and challenges in food production and water provisioning (Eea, 2018; AWRA, 2018; Milano et al., 2012). The Mediterranean basin is thus highly dependent on water irrigation for the agricultural production and climate variability will definitely affect the agricultural production pattern by influencing both supply and demand of food and increasing economic losses (Olsen and Bindi, 2002; Iglesias et al., 2009).

Italy, one of the major southern European countries, is heavily related to water demand for irrigation in agricultural production (Eurostat, 2019). Italian agriculture is the second in Europe, only after Spain, for the extension of irrigated surfaces with 2.4 millions of ha of irrigated lands and 11 million cubic meters of water used for irrigation and average water use of 4666 m3/ha (Istat, 2010). In Italy, the most water-intensive crop is rice (39.8% of total water used), followed by maize (27.9% of total water used), citrus and fruits (both 5.5% of total water used) and open fields horticultural crops (5.2% of total water used) (Istat, 2010). Italy is also characterized by highly disproportion volumes of water used between macro regions with the northern regions showing higher intensity use of irrigation compared to central and southern regions (6800 m3/ha against 3500 m2/ha) (Istat, 2010). This depends obviously by water consumption, but it reflects also important structural and historical differences of production patterns, irrigation systems and geographic conditions which make Italy a higher diversified agricultural water user (Zucaro et al., 2011). In the north of Italy, the more diffuse irrigation technique is the surface water as source of agricultural water mainly distributed through gravity by consortium water basins, whereas the central and the Southern areas of the country are characterized by the reliance on groundwater and pressurized distribution (Zucaro et al., 2011; Istat, 2010).

Regional differences emerge also in agricultural water efficiency in which the most water user regions (in terms of volume of water extracted) are the least efficient in terms of total production. The most evident example is for Lombardy and Piedmont which are the most agricultural water consumers, respectively 42.2% and 16.6% of the total water withdrawn, with a quite low share of the total amount of national crop production, respectively 4.4% and 2.9% of the total harvested production (Auci and Vignani, 2020).

The majority of water, distributed by Italian farmers, is with low efficient irrigation systems. The 62% of the total water withdrawn is used for traditional techniques of irrigation, of which 27.2% by furrow irrigation, 34.8% by flood irrigation, whereas sprinkling irrigation is used for the 27% of the total. In term of land, the inefficient irrigation practice accounts for totally 79.1% of the irrigated lands. Conversely, only 9.6% of the total water withdrawn is used with an efficient system (considering only drip irrigation). The land equipped with micro-irrigation systems is about 17.5% of the total lands, mostly distributed in the Centre and Southern macro-areas, especially along the Apennine mountains and the two islands Sicily and Sardinia (Istat, 2010).

Concerning the determinants of WCST adoption, the Mediterranean area, as well as Italy, has not been adequately investigated. Some exceptions are particular zones of the south-west area of Sardinia (Dono et al., 2011). Even though Italy faced in the last few years and will continue to face in the next future important negative consequences related to climate change, only the study of Bozzola (2014), Capitanio et al. (2015) and Pino et al. (2017) have considered Italy as an interesting case study.

While the former analyses the consequences of the individual producers' optimal use of inputs, in particular, irrigation water, taking into account risk preferences, the latter three studies consider farmers' encouragement in adopting irrigation water-saving measures. Moreover, in the first study of Bozzola (2014), the analysis is based on a very extended dataset at the farmer level - the Italian Farm Accountancy Data Network (FADN) – but it is more focused on climate-related risk perception when decisions of irrigation strategies should be taken. In the third study of Pino et al. (2017), the authors used the Theory of Planned Behaviour framework, mainly based on psychological studies to study WCSTs adoption propensity through survey data. The authors claimed that favourable attitudes towards water-saving measures, orientations of environmental associations and public bodies as well as farmers' innovativeness may influence positively the adoption of water-saving measures. Nevertheless, the study of Pino et al. (2017) lacked representability of the sample, due to the reduction of a large and highly capitalized farms taken from the AIDA database which is based on national companies obliged to present balance sheets, which does not represent the whole national farming system. In fact, the Italian farming framework is mainly characterized by small and unipersonal firms with only a few capitalized companies.

Finally, the work of Capitanio et al. (2015) was a long-term analysis considering the effect of climate change and irrigation decision over the Italian agriculture sector. Using a Ricardian model, the analysis considered as main variable of interest the value of land, as proxy of agricultural net farm income, regressed over climatic variables, other variables of interest (in this case irrigation) and additional control variables to estimate the effect of climate change on agricultural incomes (Capitanio et al., 2015). Their analysis within the economic climate change effects on agriculture literature was grounded over the works of Mendelsohn et al. (1994), Mendelsohn and Dinar (2003); Kurukulasuriya and Mendelsohn (2007), and Seo and Mendelsohn (2008). They use FADN data and a panel analysis with fixed effect (FE), finding that irrigation (compared to rainfed) is an important factor in creating agricultural income, whereas rainfall does not seem to be a crucial factor of income generation (Capitanio et al., 2015). Even if this study is worth of interest because of its depth of analysis it does not consider what are the determinants of irrigation decision. This objective has not been analysed in Italy at farm level yet.

4. Empirical strategy and Data description

4.1 The econometric models

Several studies (among others Skaggs, 2001; He et al., 2007; Wheeler et al., 2010; Afrankhteh, 2014; Singh et al., 2015; Namara et al., 2007; Foltz, 2003; Salazar and Rand, 2016; Trinh et al., 2018) modelled the optimal choice of adopting a new irrigation technology system as the probability of farmers on whether adopting or not. Using a binary discrete probability model, such as the probit and logit, the actual relationship between the farmers' observed choice and some explanatory variables, which include farmers' characteristics, as well as socio-economic, territorial and climatic factors, is verified.

The decision of adopting environmentally friendly technologies, choosing among various possible alternatives, has been analysed using cross-sectional data and binary or multinomial probability models (Moser and Barrett, 2006; Schuck et al., 2007; Huang et al., 2017; Pokhrel et al., 2018). As suggested by Feder et al. (1985), these two methodologies may capture only whether (or not) the adopting decision about the new irrigation technology is made, without considering the intensity of the phenomenon in terms of land hectares dedicated and allocated to the innovative technology under study. Among these studies, Pokhrel et al., (2018) also analyse the farmers' decision to adopt different proportions of land under different irrigation technology in a cross-section analysis, while Asrlan et al. (2014) using a panel data analysis identify the determinants affecting farmers' intensity use of the prevalent conservation farming practices in Zambia. For the farmer's decision of adopting a practice, the latent variable approach is used, and the conditional maximum likelihood approach is applied, whereas for the estimation of the intensity of adoption, a correlated random effects Tobit model and a pooled fractional probit model are used (Asrlan et al., 2014; Pokhrel et al., 2018).

Following these last studies, an analysis with two separated econometric models is proposed to capture: 1) the probability of adopting WCST by an Italian farmer by applying the logit and probit models (comparing a clustered population averaged with a traditional random effects probit and logit model beyond a correlated random effects model); and 2) the intensity of adopting the WCST technology (whether the technology was undertaken) by using the Tobit model (comparing a random effects model with correlated random effects model) in order to consider corner solutions.

4.1.1 Farmers' Decisions to Adopt WCSTs

The farmer's discrete choice whether to adopt a WCSTS or not is based on a latent variable approach. Under the hypothesis of rationality, as in Caswell and Zilberman (1985), a farmer adopts an innovation if and only if the expected utility from the new technology is higher than the expected utility of not having undertaken the adoption (Feder et al., 1985). The latent utility of a farmer may be defined as:

$$Y^*_{it} = X'_{it}\beta^* + v_i + \varepsilon^*_{it} \qquad (1)$$

where Y^*_{it} is the latent net utility of the *i-th* farmer at time *t*, X'_{it} is a vector of covariates which explicate the level of utility derived by the irrigation technology (socio-political, farmers', innovation and geographical and environmental characteristics), β^* is a vector of parameters of the explanatory variables to be estimated including an intercept, ε_{it}^* is a random error uncorrelated with the explanatory variables which follows a normal distribution with zero mean and fixed variance and v_{it} are time invariant unobserved effects (Cramer, 2003; Greene, 2003; Wooldridge, 2010, Ch. 15). A farmer will adopt the WCSTs technology when the expected utility difference of whether adopting WCSTs or not is positive (Huang et al., 2017).

However, the utility function is not easily and directly observable. One may only infer on the unobservable and latent utility function Y_{it}^* of the *i-th* farmer at time *t*, by modelling the *ex-post* response status on the adoption of WCSTs (Cramer, 2003). Using a binary choice model, the farmer's observable decision on innovation Y_{it} is represented by a dummy variable as follows:

$$
\begin{aligned}
Y_{it} &= 1 \quad \text{if} \quad Y_{it}^* > 0 \\
Y_{it} &= 0 \quad \text{if} \quad Y_{it}^* \leq 0
\end{aligned}
\tag{2}
$$

Therefore, we may predict the likelihood of adopting WCSTs as:

$$
Pr(Y_{it}=1|X_{it},v_i)=\phi(X_{it}\beta^*+v_i|X_{it},v_i) \tag{3}
$$

where $\phi(.\ )$ is the distribution function of ε_{it}^* and can be approximated by a logistic distribution or a normal distribution function. To estimate the parameters of interest, we focused on the unobserved effects logit or probit models. More specifically, random effect logit or probit models are preferred since the fixed effects logit or probit models are subject to incidental parameters problem in addition to computationally difficulties. Thus, the main assumptions required to estimate these models are the strict exogeneity of the observed covariates, the conditional independence assumption of the predicted variable and the normality assumption (Wooldridge, 2010). This last strong assumption implies the independence between v_i and X_i and that v_i has a normal distribution:

$$
v_i|X_i \sim N(0,\sigma_v^2) \tag{4}
$$

The conditional independence assumption of the predicted variable may be relaxed in two different way. First, when the heterogeneity is averaged out, a population average model is run where the responses are independent conditional on only X_i. Second, when a particular correlation structure between the unobserved effect and the explanatory variables is assumed, a correlated random effects probit model based on the full conditional maximum likelihood approach (CMLE) is applied.

Firstly, to avoid estimated coefficients' inconsistency due to underestimated standard errors, a population averaged clustered approach is applied by using the generalized estimating equation (GEE) approach (Neuhaus et al., 1991; Neuhaus, 1992). The population average estimation allows no-independence of observations among individuals thus dealing with autocorrelation and heteroscedasticity problems. The interpretation of the estimators is related to the change in the mean population outcome related to the change in the independent variables within the specific cluster of the *i-th* individual (Hubbard et al., 2010). For the estimation of the population average model, clustered-robust standard errors are computed in order to let vary the standard error within clusters and to allow autocorrelation across them, but not amongst them (Ullah and Gilles, 2011).

Secondly, when a particular correlation structure between the unobserved error and the explanatory variables is present, a Correlated Random Effect (CRE) model based on Mundlak (1978)'s devises is applied, and some drawbacks of the fixed and random effects models may be overcome. Fixed effects model is subject to incidental parameter problems which lead to inconsistency of the estimators and at the same time it does not allow the use of time-invariant variables. Conversely random effects estimation allows time-invariant estimators but is constrained to the very strong assumption of no-correlation between the error terms and the independent variables, which often is not the case leading to bias and inconsistency in the estimation results.

Using the Mundlak's approach, the heterogeneity problem is addressed by relaxing the strict assumption of random effects model ($Cov(X, \varepsilon) = 0$) and allowing unobservables to be correlated with some elements of X_{it} by assuming

$$v_i | X_i \sim N(\psi + \bar{X}_i \xi, \sigma_a^2) \tag{5}$$

where $\bar{X}_i$ is the average of X_{it} and σ_a^2 is the variance of a_i in the equation $v_i = \psi + \bar{X}_i \xi + a_i$

From this model, we can consistently estimate the partial effects of the elements of X_i on the response probability at the average value of v_i ($v_i = 0$). This allows comparing the betas with those of the population average model which represent the partial effects of X_i on the response probability at the average value of v_i. Testing the unconditional normality of v_i amounts to testing whether $\xi = 0$

4.1.2 Farmers' Intensity of adoption of WCSTs

Since farmers decides to adopt only partially the new technology, the intensity of WCSTs adoption is analysed determining the relevant drivers. In the presence of a censored dependent variable, as in our case, a Tobit model is preferred (Tobin, 1958). Since the intensity of adoption is represented by the amount of total irrigated land under WCSTs for each *i-th* farmer and is bounded in the range [0, 1], the dependent variable presents pileups at the corners and a continuous distribution in between (Asrlan et al., 2014). A two-limit Tobit model should be applied meaning that farmers may behave in three different ways: they may irrigate, not irrigate or irrigate only a fraction of their cultivated land with the WCSTs (Greene, 2003; Wooldridge, 2010; Wooldridge, 2013).

The censored dependent variable assumes the following form:

$$\begin{aligned} Y_{it} &= 0 \quad \text{if} \quad Y^*_{it} \leq 0 \\ Y_{it} &= Y^*_{it} \quad \text{if} \quad 0 < Y^*_{it} < 1 \\ Y_{it} &= 1 \quad \text{if} \quad Y^*_{it} \geq 1 \end{aligned} \tag{6}$$

Where the random effects Tobit model for panel data can be specified as

$$Y_{it} = X_{it}\beta + v_i + \varepsilon_{it} \text{ where } \varepsilon_{it} | X_i, v_i \sim N[0, \sigma_\varepsilon^2] \quad \text{when equation 6 is verified} \tag{7}$$

where Y_{it} is the logarithm of the amount of land irrigated with sustainable irrigation technologies of the *i-th* farmer in the *t-th* period with respect to the other typologies of irrigated lands, β are the coefficients to be estimated, X_{it} represents the vectors of explanatory variables such as social, economic, environmental, geographical and climatic

aspects, ν_i represent the unobserved effects considered as random, and ε_{it} is the error term with zero mean and constant variance σ^2.
Accounting for the unobserved heterogeneity issue, a two-limit Correlated Random Effect (CRE) Tobit model, as in Asrlan et al. (2014), is applied allowing the unobservables to be correlated with some elements of X_{it}. Introducing the Mundlak's devices, the mean in t of the explanatory variables, allows having unbiased and consistent estimations of the βcoefficients. The final specification of the two-limit CRE Tobit model is:

$$Y_{it} = X_{it}\beta + \psi + \bar{X}_i\xi + a_i + \varepsilon_{it}$$
$$\varepsilon_{it}|X_i,\ a_i \sim N[0,\ \sigma^2_{\varepsilon}]$$
$$a_i|X_i \sim N[0, \sigma^2_{a}] \qquad (8)$$

Additional analyses at the regional level of the all models examined (logit, probit and Tobit) have been realized for robustness checks. All the continuous covariates used in the analysis (except for Age) have been transformed in the logarithmic form in order to smooth the distribution reducing heteroscedasticity problems.

4.2 Data Description

The dataset used in this study is RICA which is at the basis of the European FADN (Farm Accountancy Data Network), the database whose data are collected randomly through the use of annual surveys over more than 10.000 farms. In this way a representative sample is created on the whole Italian agricultural sector. Within the RICA datasets, very precise and detailed information on farms' economic, productive, environmental, geographical and social factors may be found. All this information included in separate datasets have been merged for studying the relevant aspects of WCST adoption on farmers' decision. Moreover, yearly datasets have been further merged in order to obtain a unique unbalanced panel dataset of 13,592 farms for five years spanning from 2012 to 2016 for a comprehensive database of 45,837 observations.

To test whether climatic and weather conditions do influence sustainable irrigation technology adoptions, the assembled panel data from RICA have been combined with climatic data. These climatic data have been provided by the division of Impacts on Agriculture, Forests and Ecosystem Services (IAFES) of the Euro-Mediterranean Center for Climate Change with 0.5° x 0.5° grid cell spatial resolution (25 Km^2). Extracted from the ERA-Interim dataset of the European Centre for Medium-Range Weather Forecasts (ECMWF), this dataset includes seasonal values of reference evapotranspiration (ET_0) (FAO Irrigation and Drainage Paper N.56) accumulated precipitation (CPR), and maximum, minimum and average temperature (TEM). Finally, climatic data have been joined with the RICA dataset using the farms' georeferenced information included in this latter database.

Based on previous empirical studies on farmers' determinants of WCSTs adoption in developed and developing countries, a set of variables has been selected as explanatory variables for the econometric analysis and classified in Table 2. The explanatory variables have been grouped into five main characteristics: 1) Farms' characteristics, 2) Farmers' characteristics, 3) Financial and institutional characteristics 4) Water use characteristics and 5) Geographical and climatic characteristics.

Table 2: Description of the variables specified in the adoption and intensity model

Variable Acronym	Description	Measurement	Posited Sign	Supporting References
Dependent variable				
WCSTs dummy	Whether farmer adopted irrigation farming systems or not	Dummy (1 if yes, 0 if no)		Arslan et al. 2014; Pokherel et al., 2018
WCSTs intensity	Proportion of cultivated land that is under a given WCSTs practice	Variable is bounded by the [0,1] interval		Arslan et al. 2014; Pokherel et al., 2018
Explanatory variables				
Farms' characteristics				
Hours worked	It is the human capital within farm. It can be interpreted as a proxy of the economic dimension of the farm.	The logarithm of the total hours of work spent in the farm (either family or external work).	+	Boahene et al., 1996; He et al., 2007
Machine power	The propensity of adopting new technologies and intensity of capital. It is a proxy variable of the propensity to technology of the farmer.	The logarithm of the total machine power within the farms in kilowatts.	+	
Land extension	The extension of the farm can influence positively the adoption of WCST because higher economies of scale in technology investments.	UAA (Utilized Agricultural Area) in ha.	+	Trinh et al., 2018
Land value	The monetary value of land is a proxy of the value of the output product.	The logarithm of the market value of agricultural lands reported inside the balance sheet of the farm.	+	Moreno and Suning, 2005
Land Tenure	The amount of land used by the farmers but rented.	The logarithm of the size of land rented.	-	Alcon et al., 2019; Doss and Morris., 2001; Moreno and Suning, 2005; Pokherel et al., 2018
High-value crops Mixed production Livestock	The farms have been divided into high valued production (Olive-growing, Fruticulture, Viticulture, Horticulture and Floriculture), mixed farms (farms producing both livestock and vegetables production) and livestock production.	Dummy (1 if yes, 0 if no) for each category	+ high value, + mixed farms, - livestock	Green et al., 1996
Family Run	It indicates whether or not a farm was conducted prevalently by the farmer and his/her relatives.	Dummy (1 if yes, 0 if no)	+	Kounduri et al., 2006
Organic	The certification of organic products could contribute to decide in investing more in sustainable agricultural production activities meaning that a farmer has more environmentally friendly interests.	Dummy (1 if yes, 0 if no)	+	
Farmers' characteristics				
Female (head)	Gender can affect WCST adoption.	Dummy (1 if yes, 0 if no) for woman	+ or -	Asfaw et al., 2016; Somda et al., 2002
				Age (head) The age of the farmer. Years

	+ or -			Alcon et al., 2011; Alcon et al., 2019; Skaggs, 2001; Salazar and Rand, 2016
High education	Education level can influence propensity to innovate with WCST.	Dummy (1 if yes, 0 if no) indicating if the farmer has at least finished the high school.	+	Alcon et al., 2019, Moreno and Sunding, 2005; Salazar and Rand, 2016; Pokherel et al., 2018
External activities		Dummy (1 if yes, 0 if no) indicating if the farmer has an external work activity.	-	Skaggs (2001), Moreno and Sunding (2005), Schuck et al. (2005) and Foltz (2003)
Financial and Istitutional characteristics				

EU Funds	Funds directly received from EU through the CAP.	Log of funds received	+	
No-EU Funds	Funds received from other institutions different from EU, mostly National and Local governments.	Log of funds received	+	
ROI	ROI is a proxy of both the dimension of profits of the farm and the propensity of the farmer of investing within the farm.	the logarithm of the ratio of operating income over the total investments	+	
Leverage	It is an indicator of the debt rate of the farm and it can be interpreted as a proxy of both the access to capital and to indebtedness as a financial strategy of the farm.	The logarithm of the leverage of the farm calculated as the total of the investments over equity within the farm (the capital of the farm).	-	
Insurance	Insurance as a proxy of farmer's risk aversion	The logarithm of the amount spent in insurance by the farmer.	+	Kounduri, 2006
Water use characteristics				
Internal water source	Whether the water source is internal or not	Dummy (1 if yes, 0 if no)		Alcon et al., 2011; Moreno and Sunding, 2005; Salazar and Rand, 2016
Energy, electricity and water costs	The Cost of Energy, Electricity and Water can influence negatively WCST adoption.	Log of cost for water, energy and electricity within the farm.	+ for water - for energy and electricity	
Irrigated land	Higher irrigated area could influence higher adoption of WCST.	The logarithm of irrigated area.	+	Huang et al. (2017)
Geographic and Climatic characteristics				
Altitude avg.	The altitude of the farm can influence the production schemes and irrigation patterns.	The logarithm of the average altitude level of the farm.	-	Afrakhteh et al., 2015; Alcon et al., 2019; Green and Sunding, 1997; Negri and Brooks, 1990; Sherestha and Gopalakrishan, 1993
Field slope	The acclivity should contribute to the adoption of WCST such as drip irrigation.	The logarithm of the area with slope high acclivity within the farm.	+	
Sandy soil	Higher level of sandy soils within the farm can incentivize WCST adoption.	The logarithm of the area with sandy soil.	+	
Mixed soil	Higher level of sandy soils within the farm can discourage WCST adoption.	The logarithm of the area with loamy soil.	-	Afrakhteh et al., 2015; Green et al., 1996; Moreno and Sunfing, 2005; Sherestha and Gopalakrishan, 1993
Clay soil	Higher level of clay soils within the farm can discourage WCST adoption.	The logarithm of the area with clay soil.	-	
Aridity Index (AI)	Aridity is commonly quantified by comparing long-term average of water supply measure by seasonal accumulated precipitation (P) and long-term average of climatic water demand measured by seasonal reference evapotranspiration (ET0). $AI \geq 0.65$ indicates humidity areas, $AI < 0.65$ indicates arid areas.	The ratio between P and ET0. It is calculated considering the moving average of the last 5 years.	-	CGIAR, 2019

4.2.1 Farms' characteristics

Aspects related to farm productions are extremely important in WCSTs adoption. They are related to the farm size as well as to economic issues and size such as the intensity of labour and capital input used. The monetary value of the land can embed the value of the product output and the profitability of the agricultural activities which consequently can influence the intensity of land and the technology adopted for irrigation (Moreno and Suning, 2005). Whereas land tenure can influence WCSTs adoption since landowners are keener to invest in irrigation system (Alcon et al., 2019; Doss and Morris., 2001; Moreno and Suning, 2005; Pokherel et al., 2018). Also, the farm management typology, whether family farms or not, as well as the product specialization can influence WCST adoption, because the prevalent system of production can change substantially the pattern of water demand and water use between farms (Green et al., 1996). Therefore, dummy variables indicating the type of the organization (Family-run) and the prevalent production on the basis of RICA classification are constructed. In this last case farms are distinguished into: *High-value crops* farm (Olive-growing, Fruticulture, Viticulture, Horticulture and Floriculture), *Mixed production* farms (farms producing both livestock and vegetables production) and *Livestock* production. We have also considered the effect of the organic certification of products as organic farmers could have higher propensity for conservation and sustainable water management strategies than conventional farmers.

4.2.2. Farmers' characteristics

Demographic and social factors can strongly influence irrigation strategies and WCSTs adoption. Indeed, in various studies gender has been identified as an important driver for innovation, especially in developing countries (Asfaw et al., 2016; Somda et al., 2002), whereas in developed countries its effect is unclear. The age of the farmer is crucial, but there are still some doubts on its final effect in literature. Education is another element that can influence the choice and the propensity to innovation as well as the intensity of adoption. Several studies have highlighted that more educated farmers have higher propensity to invest in new technologies (Alcon et al., 2019, Moreno and Sunding, 2005; Salazar and Rand, 2016; Pokherel et al., 2018). The propensity to adopt new technologies can depend on the farmer's effort spent in terms of work within the farm. Some authors stated that external working activities can be a proxy for high risk aversion and that external working activities tend to reduce the choice of adoption of new technologies (Afrakhteh et al., 2015; He et al., 2007; Weeler et al., 2010). We have used dichotomous variable to describe whether the farmer has external working activity to the farm differently to other authors who use as a proxy in-farm and off-farm income (Skaggs, 2001; Moreno and Sunding, 2005, Schuck et al., 2005; Foltz, 2003).

4.2.5 Financial and Institutional characteristics

Farms' financial structure and socio-political and institutional aspects can substantially influence the propensity and intensity to adopt WCSTs. Important elements are economic incentives and policies related to technological innovations and agricultural development.

External funding can influence the adoption of technologies incentivizing behaviour that in absence of public help would not have been taken place (Rogers, 1971). In absence of specific indication of funding on

WCSTs the total amount of funding either from the European community or other sources of fund (in euros) have been considered as a proxy for the reliance of the farm on external funds. Two variables have been used for this purpose *EU Funds* (directly received from EU through the CAP) and *Non-EU funds* (funds received from other institutions different from EU, mostly National and Local governments).

Farms' financial aspects are highly related to WCSTs adoption, as credit access is not a problem in Italy, we have focused on the profitability of farms in terms of value generated. We have considered the Return on Investments (ROI) as a proxy for the profitability of a farm typical activity which can influence the propensity towards technology adoption of a farmer. Higher levels of profits could release higher income generation, therefore high level of Return on Investment (ROI) can represent the level of profit over the total investment made within the farm.

The dimension of debts in the farm can indicate both the availability of credit for the farmer and the dimension of external financial resources over the resource generated internally (Alcon et al., 2016; Boahene et al., 1996). We have used leverage (the total of the investments over equity) as a proxy of both the access to capital and to indebtedness as a financial strategy of the farm.

Another important aspect is the aversion to risk and its perception can influence the decision of a farmer on whether investing or not in a WCSTs. As stated by several study in irrigation technology the individual attitude towards risk in undertaking new techniques and the propensity to innovate are strictly linked (Rogers, 1971; Kounduri et al., 2006). We have used the amount spent in insurance by the farmer has been used as proxy of the farmer's propensity to risk. The higher is the variable the higher is the risk aversion of the farmer, so whether the explanatory variable is relevant or not it may influence positively the adoption of WCSTs.

4.2.4 Water use characteristics

All the factors related to water use are strictly influencing the irrigation strategies and the technology used such as the extension of irrigated land can influence the type of irrigation method used within a farm. The cost of water can directly and highly influence the amount of water demand and used within a farm, energy and electricity occurred in the farm in logarithmic form. Cost of energy and electricity can influence negatively the adoption of WCSTs which are typically higher energy intense than traditional irrigation systems (furrow and fload). In absence of specific water prices and tariff, it has been used as proxy the total cost for water, energy and electricity has been used even it could release to dull results because of the opposite effect within it (positive for water costs and negative for electricity and energy).

The type of water source used also can highly influence the availability of water and the technology of irrigation used in the farm because of pressure, cleanliness, difference in height between source and user which can highly affect the adoption of WCSTs (Alcon et al., 2011; Moreno and Sunding, 2005; Salazar and Rand, 2016). Moreover, the source of the water, which influence the quantity available, its price and quality, can change substantially all the pattern of irrigation and the technology used for it. We considered water source as internal or external considering the latter taken from outside the farmer property, either as a service from water authority or pumped from a superficial water body out of the farm. We used for considering water source a dummy variable indicating if water was diverted from an internal source as Pit, Artificial Ponds and Water Tanks within the farm.

4.2.3 Geographic and Climatic characteristics

The physical and biological aspects exogenously related to the farm such as altitude and the acclivity (slope) can directly influence irrigation systems strategies. One of the main aspects influencing WCSTs adoption is soil type. The level of sand and clay in the soil can condition importantly the availability of water in the surface layers and influencing consequently the water needs of crops (Afrakhteh et al., 2015; Green et al., 1996; Moreno and Sunfing, 2005; Sherestha and Gopalakrishan, 1993). If a land was mainly sandy it should positively increase the probability of WCSTs decision because of the reduced efficiency and effectiveness of other irrigation systems (such as flooding or furrow), conversely a clay land should reduce the probability of adopting WCSTs because of higher water soil retention. We used a set of variables for considering this aspect as the logarithm of the farm area with soil, clay soil and mixed soil (loamy).

Climate and weather are also key factor in influencing WCSTs adoption. The perception of the farmer over climate change and adverse climatic conditions rely on their ability and memory related to how weather conditions are perceived in terms of changed and worsened water scarcity and water needs. Different studies consider climate and weather into the decision pattern of farmers, but many of them take climatic or weather values only as yearly average or the global average of the time frame considered (e.g. Asfaw et al., 2016; Huang et al., 2017; Knapp and Huang; 2017).

As main climatic variable we used the aridity index (AI) compute as the ratio of the value of the accumulated precipitation (AccumPricip in mm) of a specific season and potential evapotranspiration[3] (ET0 in mm) (CGIAR, 2019). AI is a unit less measure which indicates how much water needs of crops have been satisfied by precipitations occurred:

$AI_{season} = AccumPricip / ET0$

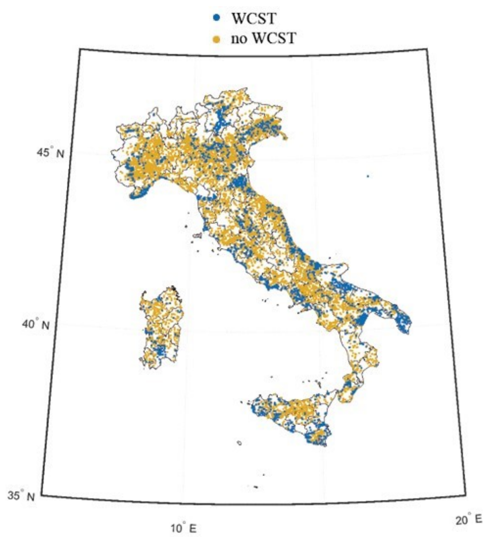
Values higher than 1 indicate that precipitations for that season satisfied crop water needs. Conversely, values lower than 1 indicate that rains do not cover the crop water needs for a specific season. Following Mendelsohn et al. (1994), Bozzola et al. (2017), Van Passel at al. (2017), seasonal data for winter (January, February, March), spring (April, May, June), summer (July, August, September), autumn (October, November, December) have been considered on the basis of each ERA-Coordinates which are related to the real geographic coordinates of the observed farms.

[3] Reference Evapotranspiration (known also as Potential Evapotranspiration) (ET_0) is the evaporative demand of the atmosphere independently of crop type, crop development and management practices; its value is independent from the water abundance of the location to which is referred, it is only affected by climatic parameters and it is comparable to other ET_0 in different time and space (Allen et al., 1998). It is measured in mm*day^{-1}. ET_0 indicates the evaporating power of the atmosphere in both a specific area and time without considering crop and soil characteristics, its value represents the amount of water lost by evaporation and plant transpiration and it is a proxy of the water requirement of crops to compensate natural water losses (Allen et al., 1998; Villalobos and Fereres, 2016). ET_0 is calculated through the Penman-Monteith method using a hypothetical grass reference crop of specific height, soil resistance in shadow and water standard condition (Allen et al., 1998). The standard ET_0 computation considers solar radiation (sunshine), air temperature, humidity and wind speed from data of standard climatological records, therefore it can be considered a comprehensive index of weather condition for plant water requirements (Allen et al., 1998).

In order to consider short past weather conditions, different moving average have been used to test how much the recent weather conditions do influence water technology strategies. Based on the study of Woodill and Roberts (2018) a five years back moving averages have been used. The time frame of the climatic data considered is 2007-2016. The moving average for each season of the year have been used for the following climatic variables. Therefore, our final indicator is a five-year moving average of the seasonal AI of each observed unit.

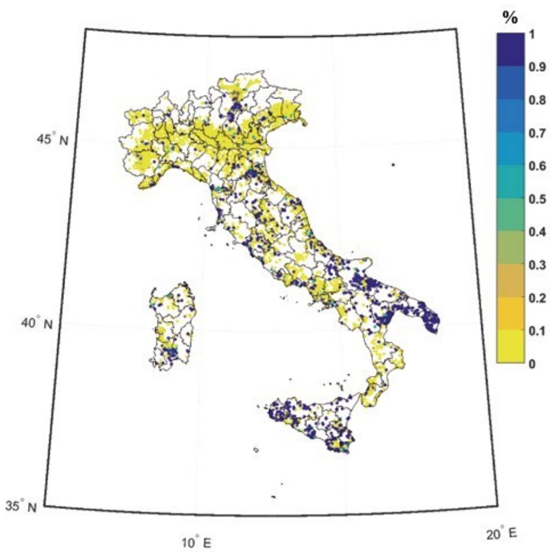
In Table 3, descriptive statistics of the main variables used in the study are reported. Figure 1 and 2 show the geographical distribution of the WCSTs choice and the proportion of area irrigated under the use of WCSTs respectively.

Figure 1: Number of WCST (red) and traditional irrigation technology (blue) total irrigated land for each farm from 2012 to 2012.



Source: Our own elaboration

Figure 2: Area under WCST on proportion over the total irrigated land for each farm from 2012 to 2012.



Source: Our own elaboration

Table 3: Descriptive statistics

Variable	mean	p50	min	max	N
Farms' characteristics					
Hours worked	8.08	7.99	4.09	12.41	45826
Land extension	4.04	3.87	3.51	7.06	45830
Family-run	0.86	1	0	1	45830
High-value crops	0.40	0	0	1	45830
Mixed production	0.09	0	0	1	45830
Livestock	0.24	0	0	1	45830
Organic	0.05	0	0	1	45830
Machine power	4.79	4.82	0	8.13	44285
Land tenure	3.14	2.79	2.74	6.65	45830
Land value	13.19	13.01	12.73	17.16	45830
Farmers' characteristics					
Age (head)	55	54	16	97	45830
Female head	0.22	0	0	1	45830
External activities	0.26	0	0	1	45830
Higher education	0.30	0	0	1	45830
Financial and institutional characteristics					
Insurance	7.78	7.55	7.38	13.00	45830
ROI	11.97	11.97	11.93	12.66	45625
Leverage	7.72	7.72	7.59	8.41	45786

EU Funds	9.89	9.71	9.43	14.52	45830
No-EU Funds	8.37	8.00	8.00	13.57	45830
Water use characteristics					
Internal water source	0.99	0.76	0.76	6.04	45823
Energy, electricity and water costs	8.66	8.43	8.24	13.59	45830
Irrigated land	2.61	2.25	2.23	6.91	45632
Geographical and climatic characteristics					
Altitude avg.	4.99	5.34	0	7.61	45830
Field slope	2.06	1.84	1.84	7.28	45830
Sandy soil	1.83	1.63	1.63	7.26	45830
Mixed soil	3.82	3.65	3.32	7.64	45830
Clay soil	1.37	1.17	1.17	6.63	45830
AIJFM	0.86	0.79	0.19	2.67	271354
AIAMJ	0.39	0.36	0.03	1.45	271354
AIJAS	0.35	0.27	0.03	1.88	271354
AIOND	1.44	1.40	0.29	4.43	271354

5. Main Results and Discussion

We estimated the probability of adopting and the intensity of adoption of innovating irrigation systems based on WCSTs. Based on the methodologies described, results on the whole sample and on the macro-area of Italy[4] are described and discussed in more details in the following sections.

5.1 Results of the probability of adoption of WCSTs (Logit, Probit and CRE Probit)

Table 4 presents the results of the probability of adopting micro-irrigation technologies based on population average and random effects logit model as well as population average and correlated random effects probit model. These binary response models are estimated on the whole sample of the Italian farmers (13,054 farms) accounting for serial correlation across time by computing robust White-Huber standard errors. In the last two columns of Table 4, the odds ratios of logit models are presented.

The statistical significance of the explanatory variables' coefficients remains high and stable across all the different estimated models. The signs of all the coefficients seem to be reasonable and conform to our expectation that the Italian farmers characterized mainly by being small, family-run and climatic risk adverse are more likely to adopt WSCTs.

As regards farms' and farmers' characteristics, the findings show that neither *Machine power* nor *Higher education* are significant in determining the adoption of WSCTs for all the models. However, since Italian farms

[4] Italy is usually split in four macro-areas: North-west, North-east, Centre, South and Islands.

are prevalently dominated by small, family-run farms, our results, based on logit models, provide evidence for managing constraints. As in Kondouri et al. (2006), a family-run farm is less likely to adopt new irrigation technologies suggesting that to invest resources in WCSTs is relevant human skills as well as information access. The size of a farm measured by both *Hours worked* and *Land extension* presents diverging results. While the coefficient of the workforce is highly statistically significant with a positive sign, the coefficient of land extension, expressed in UAA, is statistically significant but with a negative effect. Thus, an increase in the probability of WCSTs adoption when rising the time spent on a farm is counterbalanced by a reduction in the probability of adopting WCSTs when land extension rises. An additional hectare of UAA in the farm negatively influences the probability of adoption of WCSTs. New irrigation systems are more likely to be observed on small and labour-intensive farms. This result is partly in contrast with some results of the literature on irrigation technology adoption for which the size of the farm matters positively on WCSTs adoption decisions (e.g. Green et al., 1996; Huang et al., 2017). However, the study of Knapp and Huang (2017), finding a positive relationship between size and traditional irrigation methods, but no-effects with WCSTs, may be very close to our results.

As expected, among the three crop type variables, the coefficient signs are statistically significant in all the models estimated. Both the *High-value crops* (olives, fruits, viticulture, horticulture) variable and the *Mixed production* (animal and crop production together) variable positively influence the probability of adopting WCSTs, while the *Livestock* variable, meaning a farm specialized in cattle rearing (bovines and others herbivorous animals), are less likely to adopt WCSTs. Livestock farms are less inclined to adopt new irrigation systems. In terms of odds ratio, comparing crops with and without a high value (farming productions mixed or not), with the other variables being the same, the odds of adopting WCSTs for high-value crops (for mixed productions) is estimated to be about 14 times (4 times) as high as the odds of adopting innovative irrigation systems for crops with low value (for no-mixed productions). Farms dedicated to crop production and that receive the organic product certification (*Organic*) are more likely to adopt WCSTs. However, the coefficient sign statistically is significant only for the random effects logit and the correlated random effects probit model. This confirms that a farmer who produces organic products is more environmentally friendly.

The propensity towards adopting technology measured by the total machine power used within the farm (*Machine power*) shows the statistical irrelevance in all the models estimated. Similar to Pokhrel et al. (2018) which captured technology ability through computer use, we find that the stock of technological capital, already owned by the farmer, does not influence the adoption of sustainable irrigation technologies.

As Moreno and Sunding (2005) and Salazar and Rand (2016), our results confirm a negative relationship between the *Land tenure* variable and the probability of WSCTs adoption suggesting that sustainable irrigation systems are more likely to be observed when land is owned with respect to rented. Owner-farmers, in fact, are more likely to adopt new irrigation technologies that provide further benefits over the longer term (Soule et al., 2000; Salazar and Rand, 2016). Since future profits from yields are incorporated in the monetary value of land, *Land value* variable should rise the propensity of adopting new irrigation technologies. This relationship is not confirmed by our results where three out of four estimations show statistically significantly negative sign. This implies the higher is the value of the land the less likely the field will be irrigated with WCSTs.

Farmers' own characteristics are also relevant in the choice of adopting WCSTs. Younger and male farmers are more likely to adopt new irrigation technologies (Alcon et al. 2011; Asfaw et al., 2016) while doing external activities are not statistically significant for the choice of new irrigation system (Alcon et al. 2011; Asfaw et al., 2016; Salazar and Rand, 2016).

As regards financial and institutional characteristics, it is worth to note that the farms' debt (*Leverage*) and the capability to generate an adequate return on investment (the *ROI* index) are irrelevant for the choice of which is the best irrigation system to adopt. The estimated coefficient of the insurance variable as a proxy for farmers' perceived risk is positive and statistically significant at 1%, suggesting that farmers are risk adverse and covering from the risks is essential issue for choosing WCSTs as in Kounduri et al. (2007) and Bozzola (2014). The EU Funds and non-EU funds may affect in a different way the probability of adopting new irrigation technologies. More specifically, the negative and statistically significant sign of non-EU funds and the positive and statistically significant sign of EU funds seem to confirm a strong influence of national and local governments with respect to EU common agricultural policy. A similar result was obtained by Huang et al. (2017) for the use of sprinkler irrigation system in Arkansas. This could depend on the fact that fruits and horticulture, which use higher levels of WCST, are less sustained by the EU Common Agricultural Policy funds than cereals and other arable crop productions which conversely use conventional irrigation methods.

Among the water use characteristics, the coefficients of the *Internal water source* (tank, wells and ponds) and *Irrigated land* variables show positive and statistically significant signs while the *Energy, electricity and water costs* variable is not significant in determining the adoption of WCSTs. As in the theoretical results of Caswell and Zilberman (1986), and the empirical findings of Green et al. (1996), Alcon et al. (2011), Moreno and Sunding (2005), Salazar and Rand (2016) and Huang et al. (2017), an internal source of water as the groundwater source and an increasing proportion of irrigated area rise the likelihood of adopting WCSTs. Farmers with water endowments within its own property have higher probability of adopting WCSTs than those relying only on external sources. The higher is the hectares irrigate of the farmer's field the higher is the benefit in terms of scale economy.

The last relevant characteristics – geographical and climatic – are also significant drivers of the probability of adopting sustainable irrigation technologies. A higher altitude as well as a mixed soil reduce water requirements while the aridity indexes present diversified signs depending on the season considered. Differently from the literature (Moreno and Sunding 2005; Afrakhteh et al., 2015; Alcon et al., 2019), the slope of the field is irrelevant for the irrigation system choice. As regards the quality of the soil, Moreno and Sunding (2005) and Caswell and Zilberman (1986) underlined that drip technologies are soil-quality augmenting. Our results confirm that a mixed soil which is not water intensive, is less likely that requires the adoption of WCSTs (Kondouri et al. 2006).

From Sherestha and Gopalakrishan, 1993, one of the first studies of climate impacts on the probability of adopting irrigation techniques to the more recent ones (Kondouri et al 2006; Bozzola, 2014; Asfaw et al., 2016; Salazar and Rand, 2016; Huang et al., 2017; Knapp and Huang; 2017), the effects of climate variables on the probability of adopting new irrigation systems are largely confirmed. Similar to Kondouri et al. (2006), climate effects are captured by an aridity index, but differently, we compare the long-term average of water supply to the long-term average of climatic water demand. Following Mendelsohn et al. (1994), the aridity index is computed for all the four seasons to better estimate the climate effects in the different phases of crop growth. In Figure 3, the trends of the four seasonal aridity indexes – winter season *AIJFM* (January, February and March), spring season *AIAMJ* (April, May and June) summer season *AIJAS* (July, August and September) and autumn season *AIOND* (October, November and December) – are shown. Focusing on the coefficient signs, it is worth to note that these are statistically significant across all the models. While for the growing season (*AIAMJ*) and summertime (*AIJAS*) the findings present unexpected positive signs, for the winter and autumn periods the signs are negative as expected. Although to a superficial consideration, this may appear puzzling, because the higher is the level of the

AI, the less is the deficit of water for plant necessities[5] and the less should be the water requirements, in reality, this is in line with what the literature supposes. Looking deeply at Figure 3, we note that in spring and summertime the aridity indexes remain stable with low variability and below the threshold 0.5, meaning that lands may be defined as semi-arid areas. On the contrary, during winter and autumn, the aridity indexes are well above the threshold 0.65 and lands may be classified as non-drylands. Thus, the low levels of spring and summer aridity indexes show positive effects on the probability of adopting new irrigation systems. More specifically, spring and summer periods characterized by higher aridity are more likely to require more water for crops to reduce the production risk due to adverse climatic conditions as droughts (Kondouri et al. 2006). The opposite occurs for the more humid periods (winter and autumn) where the probability of WCSTs adoption is less.

For robustness purpose, we carried out the same analysis running only the correlated random effects probit model distinguishing for each Italian macro areas: North-west, North-east, Centre, South and Islands (see Table 6 of Appendix). Results confirm more or less the overall findings in terms of signs though the significance sometimes is lacking.

Table 4: Probability of adoption of WCSTs

VARIABLES	(1) PA Logit Model	(2) RE Logit Model	(4) PA Probit Model	(5) CRE Probit Model	(7) Logit Model PA Odds Ratio	(8) RE Logit Model Odds Ratio
Farms' characteristics						
Hours worked	0.505***	1.579***	0.311***	0.398***	1.657***	4.850***
	(11.57)	(11.02)	(10.83)	(3.144)	(11.57)	(11.02)
Land extension	-1.488***	-5.151***	-0.894***	-0.297	0.226***	0.00579***
	(-5.243)	(-4.965)	(-5.098)	(-0.373)	(-5.243)	(-4.965)
Family-run	-0.131*	-0.704***	-0.0642	-0.246	0.877*	0.495***
	(-1.824)	(-3.322)	(-1.461)	(-1.609)	(-1.824)	(-3.322)
High-value crops	0.917***	2.608***	0.630***	1.269***	2.502***	13.57***
	(14.13)	(12.41)	(16.19)	(10.26)	(14.13)	(12.41)
Mixed production	0.482***	1.344***	0.413***	0.522***	1.620***	3.833***
	(5.775)	(5.051)	(8.651)	(3.215)	(5.775)	(5.051)
Livestock	-1.956***	-6.200***	-0.918***	-3.208***	0.141***	0.00203***
	(-12.66)	(-9.444)	(-11.16)	(-6.721)	(-12.66)	(-9.444)
Organic	0.123	0.580**	0.0341	0.324*	1.131	1.787**
	(1.295)	(2.033)	(0.532)	(1.661)	(1.295)	(2.033)
Machine power	0.000138	0.0392	-0.0200	0.254	1.000	1.040
	(0.00389)	(0.362)	(-0.952)	(1.367)	(0.00389)	(0.362)
Land tenure	-0.280***	-0.307	-0.128**	-0.352	0.756***	0.735
	(-2.709)	(-1.020)	(-2.052)	(-0.865)	(-2.709)	(-1.020)
Land value	-0.181**	-0.429*	-0.142***	1.861***	0.835**	0.651*
	(-2.092)	(-1.815)	(-2.859)	(2.808)	(-2.092)	(-1.815)
Farmers' characteristics						
Age (head)	-0.00796***	-0.0212***	-0.00435***	-0.00744*	0.992***	0.979***
	(-3.868)	(-3.619)	(-3.535)	(-1.867)	(-3.868)	(-3.619)
Female head	-0.101*	-0.309**	-0.0681**	-0.108	0.904*	0.734**
	(-1.828)	(-1.988)	(-1.986)	(-1.071)	(-1.828)	(-1.988)
External activities	-0.0693	-0.405**	-0.0511	-0.150	0.933	0.667**
	(-1.175)	(-2.335)	(-1.374)	(-1.298)	(-1.175)	(-2.335)
Higher education	0.00303	-0.0950	-0.0176	0.0711	1.003	0.909
	(0.0515)	(-0.583)	(-0.511)	(0.630)	(0.0515)	(-0.583)
Financial and institutional characteristics						
Insurance	0.145***	0.475***	0.0558**	0.229***	1.156***	1.608***
	(3.821)	(4.057)	(1.972)	(2.870)	(3.821)	(4.057)

[5] This means that the need of water is covered by precipitation reducing the perception of aridity.

ROI	0.547	2.513	0.336	0.166	1.728	12.34
	(0.664)	(0.894)	(0.455)	(0.0898)	(0.664)	(0.894)
Leverage	1.729	6.593	0.835	12.41	5.635	730.0
	(1.467)	(1.080)	(0.908)	(1.459)	(1.467)	(1.080)
EU Funds	-0.212***	-0.808***	-0.0434	-0.290*	0.809***	0.446***
	(-2.872)	(-3.658)	(-0.902)	(-1.765)	(-2.872)	(-3.658)
No-EU Funds	0.131***	0.344***	0.107***	0.157**	1.140***	1.411***
	(3.649)	(3.170)	(4.072)	(2.078)	(3.649)	(3.170)
Water use characteristics						
Internal water source	0.416***	1.276***	0.291***	0.250**	1.517***	3.582***
	(10.47)	(8.304)	(12.58)	(2.296)	(10.47)	(8.304)
Energy, electricity and water costs	0.0236	0.0467	0.0257	-0.0210	1.024	1.048
	(0.500)	(0.323)	(0.873)	(-0.163)	(0.500)	(0.323)
Irrigated land	1.399***	4.390***	0.739***	1.804***	4.050***	80.61***
	(17.33)	(14.69)	(14.77)	(7.926)	(17.33)	(14.69)
Geographical and climatic characteristics						
Altitude avg.	-0.339***	-1.295***	-0.189***	0.0213	0.712***	0.274***
	(-13.08)	(-15.47)	(-12.49)	(0.0640)	(-13.08)	(-15.47)
Field slope	-0.0525	0.0917	-0.0125	0.329	0.949	1.096
	(-0.488)	(0.330)	(-0.206)	(0.527)	(-0.488)	(0.330)
Sandy soil	-0.00823	0.0259	0.0221	0.390	0.992	1.026
	(-0.0863)	(0.0862)	(0.386)	(0.933)	(-0.0863)	(0.0862)
Mixed soil	-0.604***	-1.293*	-0.252**	-0.139	0.547***	0.275*
	(-2.849)	(-1.840)	(-2.037)	(-0.249)	(-2.849)	(-1.840)
Clay soil	-0.121	-0.333	-0.0551	-0.0506	0.886	0.717
	(-1.508)	(-1.268)	(-1.173)	(-0.115)	(-1.508)	(-1.268)
AIJFM	-0.288**	-0.662	-0.290***	0.387	0.750**	0.516
	(-2.231)	(-1.526)	(-3.329)	(1.230)	(-2.231)	(-1.526)
AIAMJ	1.608***	4.136***	1.571***	1.732	4.994***	62.58***
	(3.742)	(3.037)	(5.327)	(1.574)	(3.742)	(3.037)
AIJAS	0.746**	2.897***	0.0125	0.978	2.109**	18.13***
	(2.027)	(2.620)	(0.0505)	(0.941)	(2.027)	(2.620)
AIOND	-0.498***	-1.300***	-0.384***	-0.369*	0.608***	0.272***
	(-5.609)	(-4.379)	(-5.574)	(-1.809)	(-5.609)	(-4.379)
Regional dummies	Yes	Yes	Yes	Yes	Yes	Yes
Time-dummies	Yes	Yes	Yes	Yes	Yes	Yes
Mundlak's devices				Yes		
Constant	-17.01	-74.58	-9.564	252.5	0.000	0.000
	(-1.201)	(-1.214)	(-0.816)	(0.811)	(-1.201)	(-1.214)
Observations	43,917	43,917	43,917	43,917	43,917	43,917
Number of ID	13,054	13,054	13,054	13,054	13,054	13,054

*Note: z-statistics with robust adjustment are reported in parentheses, * p-value <0.10; ** p-value <0.05; *** p-value <0.01*

5.2 Results of the Tobit model for the intensity of WCST adoption (Tobit random effects and CRE Tobit)

In the intensity of adoption analysis, the land percentage of WCSTs adoption is considered. This allows capturing how much extensive is the innovation in irrigation in farmers' lands (Asrlan et al., 2014). In this case, the measure is based on how much of the irrigated land is dedicated to WCSTs by a farmer who decides to adopt WCSTs. In Table 5 we report the coefficient estimations of the adoption intensity of WCSTs on the whole sample of Italian farmers, while in Table 7 we replicate the analysis for each macro-areas of Italy. In first table, the random effects Tobit and the correlated random effects Tobit models are shown while in the second only the correlated random effects Tobit model is reported.

Most of the drivers considered are statistically significant and respect the same sign as in the case of determining adoption decision on WCSTs. The main difference regards the typology of soil. Although the *Sandy soil* variable was not significant in the WCSTs adoption choice, it increases the intensity of adoption in all models in line with Kondouri et al. (2006). This type of soil, in fact, is an water-intensive soil as it easily absorbs water.

Another difference is the cost of energy, electricity and water. This variable was not significant in the estimation of WCSTs adoption choice and presented a positive sign, while in the intensity of adoption random effects Tobit estimation the coefficient is statistically significant, and the sign is negative. The higher the energy, electricity and water costs in a farm the lower proportion of land is dedicated to new irrigation systems. This could depend on the high intensity of energy needed by WCST which affect the size of land dedicated to WCSTs.

As in Pokhrel et al. (2018), irrigated land and own holding the land increases adoption intensity of WCSTs. As in the case of WCSTs adoption choice, the two more arid periods (spring and summer) represent a stimulus in intensifying irrigation using drip or sprinkler systems.

The Tobit random effects model has also been used to analyse the effects on the intensity of adoption on land of WCST irrigation for the Italian macro-areas (North-west, North-east, Centre, South and Islands). The overall results respect more or less the above findings for the whole sample just described above. Some differences are related to some specific areas. For example, the *Land tenure* variable becomes positive for the North-east area suggesting that even if the land is rented may affect the intensity of WCSTs adoption

Table 5: Adoption intensity of WCSTs

VARIABLES	(1) RE Tobit Model	(3) CRE Tobit Model
Farms' characteristics		
Hours worked	0.439***	0.180***
	(13.19)	(4.428)
Land extension	-1.570***	-0.100
	(-8.680)	(-0.360)
Family-run	-0.296***	-0.152**
	(-4.572)	(-2.274)
High-value crops	0.813***	0.703***
	(17.81)	(15.24)
Mixed production	0.377***	0.325***
	(6.592)	(5.676)
Livestock	-1.806***	-1.624***
	(-18.21)	(-16.28)
Organic	0.197**	0.148*
	(2.444)	(1.812)
Machine power	0.0542*	0.0873
	(1.697)	(1.537)
Land tenure	-0.131*	-0.273*
	(-1.693)	(-1.904)
Land value	-0.156**	0.349*
	(-2.262)	(1.827)
Farmers' characteristics		
Age (head)	- 0.00647***	-0.00354*
	(-3.324)	(-1.774)
Female head	-0.0907*	-0.0473
	(-1.809)	(-0.935)
External activities	-0.0811	-0.0192
	(-1.447)	(-0.336)

Higher education	-0.0178	0.0448
	(-0.317)	(0.784)
Financial and institutional characteristics		
Insurance	0.141***	0.0876***
	(5.563)	(3.199)
ROI	-0.0492	-0.665
	(-0.0620)	(-0.800)
Leverage	2.475	2.460
	(0.887)	(0.775)
EU Funds	-0.275***	-0.105
	(-4.897)	(-1.466)
No-EU Funds	0.0761***	0.0563**
	(2.952)	(2.029)
Water use characteristics		
Internal water source	0.391***	0.170***
	(14.55)	(5.127)
Energy, electricity and water costs	-0.0666*	-0.0432
	(-1.823)	(-0.968)
Irrigated land	1.844***	1.741***
	(35.09)	(26.24)
Geographical and climatic characteristics		
Altitude avg.	-0.364***	-0.0577
	(-14.74)	(-0.501)
Field slope	0.00685	0.0631
	(0.0911)	(0.341)
Sandy soil	0.118*	0.284**
	(1.776)	(2.385)
Mixed soil	-0.220	0.239
	(-1.585)	(1.207)
Clay soil	-0.0381	0.0537
	(-0.632)	(0.329)
AIJFM	-0.141	0.145
	(-1.308)	(1.248)
AIAMJ	1.549***	1.421***
	(4.439)	(3.328)
AIJAS	1.120***	1.023***
	(3.729)	(2.668)
AIOND	-0.463***	-0.308***
	(-5.610)	(-3.514)
Regional dummies	Yes	Yes
Time-dummies	Yes	Yes
Mundlak's devices		Yes
Constant	-17.31	-54.18
	(-0.738)	(-0.433)
Observations	43,917	43,917
Number of ID	13,054	13,054

*Note: z-statistics with robust adjustment are reported in parentheses, * p-value <0.10; ** p-value <0.05; *** p-value <0.01*

6. Conclusions

This study is the first on the determinants of decision on sustainable irrigation technology adoption and on the intensity of adoption in Italy. Combining social, economic, productive, geographical and climatic data and using a representative dataset in order to control both for time and individuals, the analysis has been conducted at national and at macro-areas levels. The latitudinal extension makes Italy an important case-study because results may be generalized and applied to other similar countries especially the Mediterranean ones which suffer for the same water scarcity problem and management.

Water use in agricultural activities is a topic extremely crucial for sustainable development challenges and this study contributes to the literature in this direction. The main contribution of this analysis is identifying what are the principal factors influencing the adoption as well as the intention of sustainable technologies in agricultural water management at national level. This issue will be crucial in the next future for Italian agriculture when properly suited policies would be implemented in order to improve the efficiency of water use in water scarce areas.

The results of this study can give important information to policy makers in order to incentivize the use of WCSTs and to identify the best profile of farmers who are willing to change their irrigation strategies toward more sustainable ones. The average farmer with high probability to adopt WCSTs is male and he is the direct owner of the land, which is of small extension relying to internal water resources for water access. The education level and age of him are not influencing the adoption of WCSTs. The farm is situated in the south of Italy or in the Islands and it is located at low altitudes. The agricultural activities are conducted at commercial level (not familiar), they are specialized in high value crops and they are carried out with a high intensity of working hours (both from family and outside). The farmer has no external economic activities, he is risk averse (his insurance costs are high) and he does not receive EU funds. The average farmer who adopts WCSTs is more sensitive to the effects of past seasonal weather conditions related to autumn and winter more than in warmer seasons.

Generally, the climatic characteristics have highlighted that short past time weather condition do influence the strategic decision patterns of the farmer determining the adoption of WCSTs. The most important seasons in conditioning the probability of adoption seem to be spring and summer in which precipitations and evapotranspiration influence negatively. AI seems to be a good synthesis of weather conditions and related to water use in agriculture, which combine ET_0 and precipitation. AI estimated coefficients shown high statistical significance in determining the adoption of WCSTs, therefore it indicates the influence of past climatic conditions on the farmers' decisional schemes of adoption.

The study has both internal and external validity and it can be easily replicated in other countries if extended datasets would be available. This study puts the base for next analyses on the determinants of sustainable technology adoption in irrigation in Italy and in the Mediterranean basin, which may strongly help to cope with the important challenges of the Italian and Mediterranean agricultural sector due to Climate Change and water resource scarcity that could occur in the next future.

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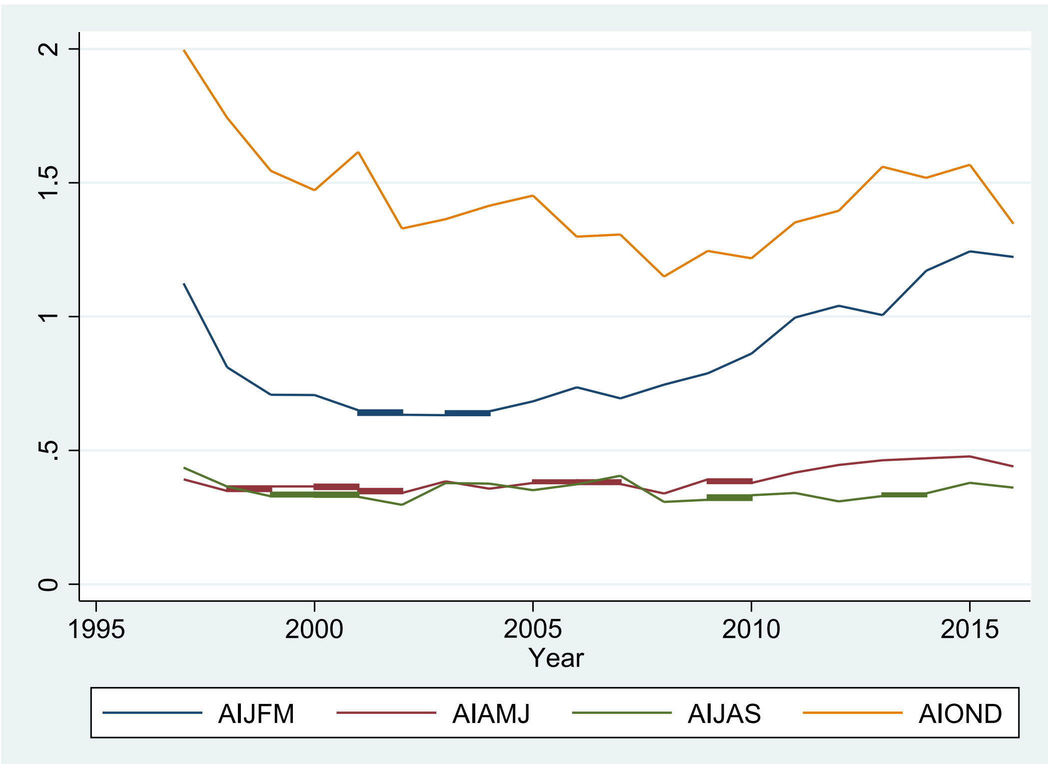
Appendix

Figure 3: Tendencies of the seasonal aridity indexes



Source: our elaboration

Table 6: Probability of adoption of WCSTs for macro-areas

VARIABLES	(1) CRE Probit Model North-west	(2) CRE Probit Model North-East	(3) CRE Probit Model Centre	(4) CRE Probit Model South and Islands
Farms' characteristics				
Hours worked	-0.0988	0.0593	0.490*	0.929
	(-0.416)	(0.243)	(1.868)	(0.108)
Land extension	-0.354	-0.0216	-1.104	-0.988
	(-0.202)	(-0.0156)	(-0.556)	
Family-run	-0.918***	0.260	0.349	-0.163
	(-2.682)	(0.536)	(1.313)	(-0.0141)
High-value crops	1.695***	1.753***	0.631***	0.988
	(5.635)	(5.277)	(3.455)	(0.0278)
Mixed production	0.580	1.123***	-0.0772	0.682
	(1.409)	(3.312)	(-0.297)	(0.0506)
Livestock	-1.898***	-2.115**	-2.883***	-5.069
	(-2.740)	(-2.164)	(-5.623)	
Organic	1.158**	-0.559	0.630**	0.241
	(2.411)	(-0.754)	(1.962)	(0.0139)
Machine power	0.615**	-0.618*	1.364***	0.246
	(2.265)	(-1.651)	(3.425)	(0.0247)

Land tenure	-1.211	0.488	-0.473	0.605
	(-1.233)	(0.723)	(-0.464)	(0.0319)
Land value	-0.601	2.830***	2.720	5.433
	(-0.595)	(2.736)	(1.251)	(0.135)
Farmers' characteristics				
Age (head)	-0.0157**	-0.0249**	-0.000453	-0.00707
	(-2.091)	(-2.174)	(-0.0696)	(-0.00960)
Female head	0.275	-0.509**	-0.159	0.0723
	(1.449)	(-2.044)	(-1.031)	(0.0110)
External activities	0.126	0.253	-0.488**	-0.319
	(0.575)	(0.940)	(-2.449)	(-0.0205)
Higher education	-0.200	-0.0401	-0.000162	-0.207
	(-0.875)	(-0.128)	(-0.000926)	(-0.00768)
Financial and institutional characteristics				
Insurance	0.498***	0.203*	0.00919	0.105
	(2.870)	(1.757)	(0.0481)	(0.0324)
ROI	-2.546	2.905	5.868	-6.220
	(-0.638)	(0.675)	(0.912)	
Leverage	18.06	-13.28	41.56**	36.69
	(1.431)	(-0.291)	(2.003)	
EU Funds	0.213	-0.369	0.269	-0.301
	(0.525)	(-1.574)	(0.832)	(-0.00357)
No-EU Funds	0.683***	0.306**	0.127	-0.108
	(3.459)	(2.232)	(0.917)	(-0.0285)
Water use characteristics				
Internal water source	0.466	-0.101	0.238	0.811
	(1.534)	(-0.527)	(1.388)	(0.0194)
Energy, electricity and water costs	0.303	-0.0628	-0.268	0.160
	(1.239)	(-0.241)	(-1.161)	(0.00224)
Irrigated land	0.463	2.186***	1.711***	2.611
	(0.934)	(6.501)	(4.276)	(0.0668)
Geographical and climatic characteristics				
Altitude avg.	0.322	0.702	-0.0212	-1.323
	(0.585)	(1.156)	(-0.0163)	(-0.0509)
Field slope	-1.660**	-0.399	-0.593	1.524
	(-2.521)	(-0.274)	(-0.812)	(0.0149)
Sandy soil	2.002***	-1.174	1.338	0.200
	(2.830)	(-1.185)	(1.575)	(0.0115)
Mixed soil	0.875	-0.508	0.590	-1.413
	(1.025)	(-0.485)	(0.549)	(-0.0252)
Clay soil	1.677**	-1.358	-1.732**	-0.143
	(2.198)	(-1.125)	(-2.083)	(-0.0177)
AIJFM	-2.280**	-1.376	-0.938	3.787
	(-2.166)	(-1.459)	(-1.292)	(0.0473)
AIAMJ	0.386	1.320	-8.508**	9.097
	(0.170)	(0.327)	(-2.361)	
AIJAS	0.891	-0.802	8.665**	1.821
	(0.342)	(-0.443)	(2.358)	(0.178)
AIOND	-2.053***	0.334	-0.716	1.807
	(-3.017)	(0.414)	(-1.068)	(0.0192)
Regional dummies	Yes	Yes	Yes	Yes
Time-dummies	Yes	Yes	Yes	Yes
Mundlak's devices	Yes	Yes	Yes	Yes
Constant	876.6*	-562.4**	-2.553	1,349
	(1.847)	(-2.107)	(-0.00857)	(0.00001)
Observations	9,955	9,903	9,877	14,182
Number of ID	2,645	2,874	3,260	4,275

*Note: z-statistics with robust adjustment are reported in parentheses, * p-value <0.10; ** p-value <0.05; *** p-value <0.01*

Table 7: Adoption intensity of WCSTs for macro-areas

VARIABLES	(1) CRE Tobit Model North-west	(3) CRE Tobit Model North-East	(5) CRE Tobit Model Centre	(7) CRE Tobit Model South and Islands
Farms' characteristics				
Hours worked	-0.0400	0.0973	0.348**	0.158***
	(-0.277)	(1.088)	(2.425)	(3.772)
Land extension	0.946	-0.211	-1.294	-0.0862
	(0.846)	(-0.407)	(-1.020)	(-0.286)
Family-run	-0.594**	0.0832	0.272	-0.110
	(-2.439)	(0.441)	(1.400)	(-1.606)
High-value crops	1.353***	0.956***	0.525***	0.396***
	(8.453)	(9.011)	(4.294)	(7.605)
Mixed production	0.537**	0.609***	-0.0212	0.276***
	(2.543)	(4.947)	(-0.135)	(4.281)
Livestock	-1.193***	-1.064***	-2.171***	-1.661***
	(-4.561)	(-4.647)	(-7.659)	(-11.91)
Organic	0.806**	-0.221	0.442*	0.0885
	(2.327)	(-0.888)	(1.843)	(1.123)
Machine power	0.234	-0.184*	0.982***	-0.0405
	(1.467)	(-1.759)	(4.069)	(-0.604)
Land tenure	-1.335**	0.557**	-0.173	-0.291*
	(-2.537)	(1.973)	(-0.278)	(-1.830)
Land value	-0.617	0.588**	1.993	0.512
	(-1.260)	(2.201)	(1.435)	(1.501)
Farmers' characteristics				
Age (head)	-0.00663	-0.0122**	-0.00289	-0.000922
	(-1.145)	(-2.527)	(-0.557)	(-0.390)
Female head	0.176	-0.0852	-0.0949	-0.0421
	(1.234)	(-0.764)	(-0.691)	(-0.692)
External activities	0.0508	0.0869	-0.264	-0.0508
	(0.317)	(0.709)	(-1.628)	(-0.735)
Higher education	-0.136	-0.0671	0.00121	0.0125
	(-0.850)	(-0.497)	(0.00851)	(0.173)
Financial and institutional characteristics				
Insurance	0.293***	0.0680	-0.0171	0.00232
	(3.656)	(1.584)	(-0.145)	(0.0604)
ROI	-1.198	-0.384	6.750	-1.229*
	(-0.344)	(-0.146)	(1.577)	(-1.761)
Leverage	-0.877	-27.62	8.236	5.635
	(-0.0510)	(-1.365)	(0.985)	(1.033)
EU Funds	0.528**	-0.173	0.0184	-0.0169
	(2.085)	(-1.488)	(0.0654)	(-0.189)
No-EU Funds	0.242**	0.176***	0.0580	-0.0217
	(2.477)	(3.190)	(0.573)	(-0.726)
Water use characteristics				
Internal water source	0.376***	-0.0163	0.143	0.298***
	(3.276)	(-0.283)	(1.459)	(6.556)
Energy, electricity and water costs	0.236*	0.0144	-0.261*	-0.00862
	(1.701)	(0.163)	(-1.923)	(-0.158)
Irrigated land	0.750***	1.764***	1.890***	1.950***
	(2.761)	(15.23)	(9.252)	(23.38)
Geographical and climatic characteristics				
Altitude avg.	0.138	0.0196	0.132	-0.0955
	(0.360)	(0.109)	(0.204)	(-0.690)
Field slope	-1.326*	0.153	-0.510	0.415**
	(-1.888)	(0.324)	(-0.435)	(2.478)
Sandy soil	1.360**	-0.582**	1.244***	0.0666
	(2.254)	(-2.055)	(3.067)	(0.546)
Mixed soil	0.796	-0.0333	1.269*	-0.145

	(1.362)	(-0.0864)	(1.655)	(-0.613)
Clay soil	1.507**	-0.618	-0.661	-0.0201
	(2.024)	(-1.388)	(-0.784)	(-0.132)
AIJFM	-0.0121	-1.326***	-1.003*	1.055***
	(-0.0184)	(-3.158)	(-1.950)	(2.683)
AIAMJ	3.306**	1.318	-3.336	3.347***
	(2.433)	(0.774)	(-1.475)	(3.445)
AIJAS	-0.643	-0.0552	7.559***	1.688**
	(-0.465)	(-0.0769)	(2.848)	(2.194)
AIOND	-1.214***	-0.511	-0.875*	0.390
	(-2.611)	(-1.637)	(-1.715)	(1.557)
Regional dummies	Yes	Yes	Yes	Yes
Time-dummies	Yes	Yes	Yes	Yes
Mundlak's devices	Yes	Yes	Yes	Yes
Constant	92.33	-507.3	5.435	-55.97
	(0.273)	(-1.155)	(0.0205)	(-0.173)
Observations	9,955	9,903	9,877	14,182
Number of ID	2,645	2,874	3,260	4,275

*Note: z-statistics with robust adjustment are reported in parentheses, * p-value <0.10; ** p-value <0.05; *** p-value <0.01*