What are the factors driving the adoption of sustainable irrigation technologies in Italy?

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Abstract

The Mediterranean basin is one of the main critical areas in terms of water scarcity and water stress. Southern European countries show high levels of water scarcity because of a forecasted increase in frequency and negative impacts of droughts and changes in precipitation frequency and intensity. One of the main drivers to overcome this condition is irrigation system within the agricultural activities. In this context, innovations and water saving technologies can highly help the reduction of the impacts of agricultural activities on water resources. One of the main questions for achieving sustainability in water management in agriculture is to understand what important factors are driving the decision of farmers in adopting water saving technologies in their irrigation schemes.

In this paper, the analysis focuses mainly on what are the principal determinants of Italian farmers' adoption of sustainable irrigation technologies. Micro-irrigation (drip and sprinklers) and sub-irrigation technologies are considered sustainable technologies for water management. These irrigation systems may help in water saving increasing water conservation in the natural environment through the reduction of water stress. Social, economic, productive, and geographical and climatic aspects are considered as relevant factors in influencing a farmer decision on the adoption of irrigation technologies. Using the Agricultural Accounting Information Network (RICA) dataset on Italian farmers, this study is based on a micro level approach which fills the gap in the agrarian and environmental economics literature.

On the decision of a farmer whether to adopt an irrigation saving technology or not, the logit and probit models are applied. Moreover, to investigate the intensity of adoption a Tobit model is estimated. In both cases, an unbalanced panel data on Italian farmers combined with climatic data from Euro-Mediterranean Center for Climate Change from 2012 to 2016 is used. Our findings confirm that production, education, geography and climate are all relevant factors influencing the choice of whether to adopt sustainable irrigation technology or not as well as intensity of adoption given that most farmers adopt water saving technologies only partially.

1.Introduction

Water scarcity and sustainable water management is one of the most important issues that human kind is facing in the next future (Wheeler et al., 2015). Water scarcity is affecting around four billion people in the world and water shortages is becoming one of the main socio-environmental problem in every part of the world (De Angelis et al., 2017; Hoekstra and Mekonnen, 2016). Several causes such as climate change, population growth, desertification and urbanization are putting extraordinary pressures on water resources exacerbating water scarcity issues especially in arid and semi-arid regions.

Moreover, water scarcity and water depletion represent one of the main constrains to global food security (Alexandratos and Bruinsma, 2012). Nowadays, almost 800 million people are undernourished and 2 billion suffer micronutrient deficiencies (FAO, IFAD and WFP, 2015). The world population will be 9.7 billion people following the projections of the United Nation Department of Economic and Social Affairs (Undesa, 2018). Therefore, it is clear that the global agricultural sector will face important challenges in order to avoid famines, disorders and instabilities and those difficulties could be intensified by water scarcity problems (FAO, 2011; FAO, 2012).

The main drivers of water depletion and water pollution are directly or indirectly due to anthropic stresses related mostly to economic activities both on consumption and production side. One of the main sectors affecting water resources is agriculture which is responsible for almost 70% of global freshwater withdrawal whose primary use is for intensive irrigation of crops characterized by low levels of efficiency and water losses due to evaporation, percolation and runoff (FAO, 2011; MEA, 2005).

Agricultural water demand increased steeply in the last century as irrigation practices were part of the "Green Revolution" occurred in developing countries around the '60's, even if 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). Global water reservoirs declined steadily both in quality and quantity during the last century and one of the most important causes was the excessive withdrawal as well as water pollution due to agricultural practices intensification all over the world (AquaStat, 2018). Pressures on water basins and externalities of agricultural activity are endangering many ecosystems with important losses of biodiversity and ecosystem services in rivers basins, humid areas and estuaries all over the world with impacts on public health (Tilman et al., 2002; MEA, 2005; WHO, 1990).

Furthermore, climate change with the consequence of more frequent, extreme, and adverse weather conditions and serious water shortages is worsening agriculture and food production in several vulnerable arid zones especially in poor countries affecting food security and political stability (Saravia-Matus et al., 2012; Un, 2015). Climate change in fact may affect crop production directly as well as indirectly through temperatures, precipitations, biological changes, photosynthesis efficiency and water availability but also through evaporation, losses of soil moistures and land drying with erosions and fertility losses (Mestre-Sanchís and Feijóo-Bello, 2009; Olsen and Bindi, 2002). Therefore, water demand for agricultural products may dramatically increase due to the rising evapotranspiration which causes water requirements peaks and higher water use per hectares (Mestre-Sanchís and Feijóo-Bello, 2009; Olsen and Bindi, 2002). This in turn can affect water supply through less endowments, excessive reservoirs withdrawals, and greater competition between agricultural and civil services uses (Iglesias et al., 2009).

Irrigation efficiency, which can be defined as the ratio between irrigation water requirement and the amount of water withdrawn for irrigation, is low in most of the world (Frenken and Gillet, 2012) indicating as the agricultural sector is characterized by high potential for adjustment and correction in water using (FAO, 2011).

Sustainable water management may be pursued through various strategies such as water demand reduction, water availability increase and water efficiency improvement. Following this latter strategy generates less problems at both social and environmental level (Alcon et al., 2011). In this context, innovations and in particular water conservation and saving technologies (WCST) may highly contribute to reduce agricultural activity impacts on water resources in a context of water scarcity and water endowments variability (Exposito and Berbel, 2019).

WCST such as drip irrigation, low pressure micro-sprinkling and sub-irrigation can optimize the application of water directly to plants root reducing water stress through a high frequency water application which decreases the difference between evapotranspiration and the plant extraction of water (Pereira, et al. 2002; Schuck et al., 2007; Dasberg and Or, 1999). In terms of input used efficiency, the adoption of WCST compared to traditional irrigation method (such as furrow, sprinkler and flooding) can increase the rate of water consumed by the plants at a given level of water application both reducing the total use of water and satisfying irrigation crop requirements (Taylor and Zilberman, 2017; Wheeler et al., 2010). WCST also increase irrigation efficiency improving the optimization of fertilizers and through the reduction of water evaporation from soil, water losses due to percolation and run-offs, crop diseases and rotting due to over-irrigation, salinity problems and finally weed growth (Skaggs, 2001; Alcon et al., 2019). Moreover, the use of WCST can improve the water productivity considered as the biomass output per unit of water used which can represent an economic valuation of agricultural water if the price of crop over the amount of water used is considered (Exposito and Berbel, 2019). Anyway, it has to be noted that the gained efficiency and related economic benefits of such technologies are conditioned to a high level of both technological and technical knowledge over the new technology adopted (Levidow et al., 2014).

Irrigation is a socio-technical process, in which institutions, available technology, local conditions and farmers should be incentivized in creating more interactions for driving the adaptation of both irrigation service systems and more efficient irrigation technologies (Horst, 1998; Turral et al., 2010). On the base of their future expectations and productive needs, farmers are the main actors in making choices for applying adaptation strategies to climate and productive conditions. They may decide to adopt a new technology considering several factors directly related to their expectations on the future outcome, as well as the perceptions and the external information they may receive. Therefore, farmers have an important role in reaching the sustainability path considering different scenarios of climate change events (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 one of the main agents in the direct management of natural capital and natural resources.

An important literature emerged in WCST adoption in the last years focusing principally on socio-economic and geographical factor influencing the adoption of this technology by farmers. These studies adopt mainly econometric analysis on single case studies mostly at sub-regional scale, providing important empirical improvements on this topic. The strategy of cross-sectional analysis is most of the time driven by data scarcity constraining the analyst at survey collecting data methods considering specific and homogeneous agricultural areas with low diversity of farms on various aspects: production, socio-economic conditions, climate and geographic factors and water endowments.

This paper intends to fill the gap through the overcoming of these limitations. The approach is based on data at farmer level which are distributed on the entire country: Italy. So far, there have been no previous studies focused on WCST adoption with an extensive use of micro data elaborated on all over the country. In this paper, farm level data are used, collected from the Italian database of Agricultural Accounting Information Network (Rete di Informazione Contabile Agricola - RICA). The importance of deepening farmers' choices of WCST adoption in Italy is mainly related to the diversified orographic and micro-climatic areas which the country presents. Therefore, dissimilarities among farmers are principally due to geographical, socio-economic, productive, as well as climatic factors. The highly latitudinal diversity in climatic, orographic, and geographical conditions makes Italy an important case-study within the Mediterranean countries which share similar climatic conditions and longitudinal positions.

This paper wants to contribute to the relevant and growing literature by testing what are the principal determinants of Italian farmers' adoption of sustainable irrigation technologies, which are considered as: drip irrigation, micro-sprinkling and sub-irrigation technologies. How sustainable irrigation technologies, such as drip, micro-sprinkling and sub-irrigation technologies within the WCST, may influence farmers' probability in adopting new and more efficient irrigation systems and farmers' adoption intensity in terms of hectares of irrigated areas under WCST, 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 in taking the decision of adopting low water consumption or water saving technologies.

The second aim, instead, is dedicated to the analysis of the factors, within the same collected characteristics, which may have an influence on the allocation of WCST over the total irrigated land. It has been used two binary response models (logit and probit model) for the farmers' decision making and a Tobit model for the intensity use of irrigation, 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 and 3, the Italian irrigation context and the main literature on WCST adoption are presented. In Section 4, data, the empirical framework and the methodology are described, while in Section 5 results and a discussion of them are presented. Finally, in Section 6, some main conclusions are reported by deriving some policy recommendations.

2. Water use in the agriculture sector in Italy

In 2000, the European Union issued the Water Framework Directive (WFD) with which put the base for a sustainable water management within all the Union members. The objective of this directive was that of improving the quality of European water basins and water 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 have a sustainable use of water resources in the long run (Zucaro, 2011). The multidimensional approach used in WFD considered as relevant the ecosystem-based objectives for the sustainable management of water (Berbel and Exposito, 2017). Moreover, WFD recognized agricultural activities as an important driver of pressures on water resources inserting enforcement measure of the WFD within the Common Agricultural Policy (Groundwater Framework Directive, 2006). At the end of timeframe scheduled, the end of 2015, even if some goals have been reached under WFD, the main results are still far behind and important gaps must be filled in terms of water pollution and water withdrawal. For example, the water extraction remains higher than its natural rate of renovation especially in many Mediterranean countries (WFD Report, 2015; Berbel and Exposito, 2017). In the next future, lack of a proper water management based on an efficient allocation of water endowments in the agricultural activities (techniques and crops) could cause failing national and supranational water policies in addressing European sustainable development strategies (Sauer et al., 2010; FAO, 2017; Bazzani et al., 2005).

In Europe, there are considerable differences among countries in water use withdrawal composition and water availability. Southern countries withdrawal water more for irrigation agriculture (60% of water withdrawal) than northern countries which use water mostly for energy production (Eea, 2009). Southern European countries show high levels of water scarcity because of a forecasted increase in frequency and negative impacts of droughts and changes in precipitation frequency and intensity (Eu, 2011; Euc, 2012). Southern Europe is one of the main areas exposed to climate change in which several 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 highly dependent on water irrigation for agricultural production and climate change will definitely affect the agricultural production pattern influencing both supply and demand of food with high economic losses (Olsen and Bindi, 2002; Iglesias et al., 2009).

Italy is one of the major countries using irrigation for agricultural activities in Europe (Eurostat, 2019). Italian agriculture is second in Europe, only after Spain, for the extension of irrigated surfaces with 2.4 million of ha of irrigated lands and 11 million cubic meters of water used for irrigation and an average water use of 4666 mc^2/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 northern regions showing higher intensity use of irrigation compared to central and southern regions (6800 mc^2/ha against 3500 mc^2/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 total amount of national crop production, respectively 4.4% and 2.9% of the total harvested production (Auci and Vignani, 2014).

The majority of water, distributed by Italian farmers, is with low efficiency 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 account for totally the 79.1% of the irrigated lands. Conversely, only the 9.6% of the total water withdrawn is used with efficient system (considering only drip irrigation). The land equipped with micro-irrigation systems is the 17.5% of the total lands, mostly distributed in the Center and Southern macro-areas, especially along the Apennine mountains and the two islands Sicily and Sardinia (Istat, 2010).

3.Technology adoption of Environmental Innovations for Irrigation

3.1 Adoption of Environmental Innovations in agriculture

The adoption of innovation as a mean of economic evolution has been used by farmers since the emergence of the first agricultural communities in the Neolithic as a way of recombining productive factors and agricultural processes in order to obtain efficiency, improvement in food production and food security (Perret and Stevens, 2006).

An important literature in technology adoption has emerged since the sixties, exploring specific factors which may influence the decision of implementing innovations. A growing branch of this literature has focused on agriculture both theoretically and empirically. The topic started to gain interests in development studies in order to analyze what were the causes determining success or failure of basic agricultural innovations such as improved fertilizers, ploughing techniques and pest control in developing countries (Feder and Umali, 1993).

A technological innovation can be considered as an improvement over past technologies and techniques used, within a productive process or a socio-economic process, with the aim of improving them gaining efficiency (resources used over results obtained), effectiveness (objective over results) and higher values of outcomes. The introduction of a new technology can follow three phases: 1) invention or the creation of a model for improving technology; 2) innovation or the real implementation of invention on product or process; 3) diffusion or technological innovation spread over the market through the adoption by the other economic agents (Rennings, 2000, Jaffe et al., 2002).

The innovation decision-process can be defined as a dynamic process (not an instantaneous action) through which an economic agent (i.e. farmer) pass through being aware of the presence of an innovation to the real and stable adoption of it (Rogers, 1971). This process can be divided in five steps: after being aware of the possibility of undertake the innovation (a. Knowledge), the economic agent collects information on the innovation (b. Persuasion), then he/she decides whether to adopt or not the innovation (c. Decision), afterwards he/she effectively introduces the innovation in he/her economic process (d. Implementation), and at the end he/she decides whether or not continue using it after a real trail of the innovation (e. Confirmation) (Rogers, 1971). The innovation process starts in a situation of disequilibrium in which the farmer does not efficiently use the available resources, thus, he/she starts looking for information over new innovations and leading experiments until a new equilibrium is obtained (Feder et al., 1985). 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).

The decision of undertaking an innovation depends on the expected value of farmers' benefits after the adoption. So, the adoption process should be considered concluded only when the expected profits, obtained with the implementation of the new technology, are maximum (Feder, 1982; Feder et al., 1985; Shresta and Gopalakrishnan, 1993). Anyway, considering only profits as single driver of decision can be limiting, because farmers do not consider only profit maximization elements of the economic theory in their adoption choices, but also a bundle of different factors which may influence all together the utility function of the farmer (Rogers, 1971; Foster and Rosenzweig, 2010). The interaction among all these factors may affect benefits and costs, which, even if they might be observable or not directly from the outside, are definitely perceived by the farmer who is the only one able to rank each option, confronting it with the other possible alternatives (other technologies or the old the technology) and creating a final ranking of all the alternatives. This process is well-described in the neoclassical economic theory where the final decision is based on the comparison of several alternatives with different levels of expected utility depending on intrinsic and extrinsic characteristics (Somda et al., 2002; Baidu-Forson; 1999). If for example the compared alternatives are A and B, with an expected utility of UA and UB respectively, the farmer chooses the one which gives the higher utility between the two, this means A if UA is higher than the UB, or vice versa B if UA is less than UB, otherwise he/she is indifferent between the two alternatives since they both give the same expected utility A≡B if UA≡UB. Therefore, the final choice, based on the comparison among the two alternatives, depends on the utilities a farmer may obtain and on the main characteristics possessed (Somda et al., 2002).

These elements influencing the expected utility of the decision maker can be classified following Neupane et al. (2002), Foltz (2003), Sheikh et al. (2003), Boahene et al. (1999) and adapting the findings of Wisdom et al. (2014) as:

- *Socio-political and external environment characteristics*, which can depend on governmental regulations, incentives from the governments, social norms and social networks, credit availability;
- *Organizational (Individual) characteristics*, which can depend on absorptive capacity, awareness, knowledge, skills, competence, social position, current practice adopted, demographic factors, past experiences, age, tendency to be innovators, land tenure, family size, type of crop, connections

(direct or indirect) with experts and innovation developers, norms and values, culture, size and structure of the farm, previous training, risk aversion and readiness to change;

- *Innovation characteristics*, which can depend on complexity, price, relative advantage, observability, cost-efficacy, feasibility, ease in implementation, compatibility with existing practice, facilitating procedures (training courses), fitting with local norms and values and intrinsic risks.
- *Geographic and Climate characteristics*, which can depend on seasonal temperature, rainfall, evapotranspiration, aridity, soil type, soil quality, source of water used, altitude and slope.

The above characteristics may be mixed, objective and subjective, from the point of view of the farmer and even if both can be observed or not from an external analyst, all of them contribute to the probability of adopting the innovation (Fig.1).

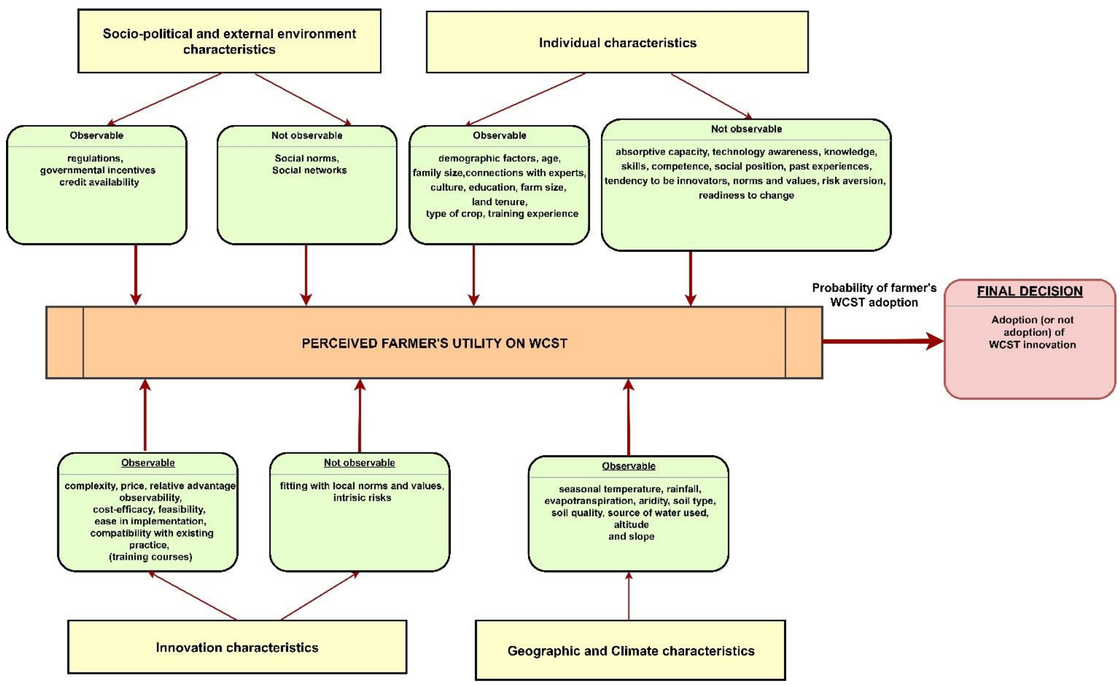


Figure 1. Observable and not observable characteristics which influence the farmer's decision of WCST adoption.

An environmental innovation (EI) can be defined as a new or modified technology, technique or process which may reduce the negative impact on the environment and the pressure on natural resources (Horbach, 2008), whether this effect is intended or not (Kesidou and Demirel, 2012). The incentive in adopting EI is not only related to environmental sustainability, but also to the incremental economic benefits due to savings or extra profit obtainable with it (Kesidou and Demirel, 2012). Moreover, EI adoption is characterized by additional positive spillovers thanks to internalization of negative externalities related to environmental damage which can augment EI embedded value considering the effect on the society as a whole (Horbach, 2008; Barbieri et al., 2016). EI have potential win-win solutions that attracted the interest of policy makers for sustainable development strategies because of the double benefits deriving from economic growth and environmental benefits which can lead to long term structural changes toward a greener economy (Barbieri et al., 2016; Mazzanti, 2018). Therefore, to understand the potential sustainable growth of a sector, it is worth to note the importance of all the drivers of adopting EI (Antonioli et al., 2017; Horbach, 2008).

3.2 Literature on WCST adoption

In considering a sustainable agriculture, one of the main issues in achieving sustainability is to understand what are the main factors driving the decision of farmers in adopting EI. Specifically, in agricultural water management, we can consider the adoption of WCST in farmer's irrigation schemes as EI, so what affect their decisions in adopting sustainable technologies in water use can be worth of interest for the sustainable economic growth of the whole agricultural sector.

Within the technology adoption literature, developed during the last decades, 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). One of the first and main works in this direction was that of Caswell and Zilberman (1985) which, applying a multinomial logit as an econometric model, studied the determinants of the choice of alternative irrigation technology adoption (furrow, sprinklers and drip) among California famers. They found that cost saving considerations, spatial distance, the use of groundwater and price water policies are important factors for innovative WCST adoption (Caswell and Zilberman, 1985). Shresta and Gopalakrishnan (1993), Green et al. (1996) and Moreno and Sunding (2005) confirmed their results expanding the variable of interest including also the relevance of soil properties, specific locations, technical (crop choices) and informational factors as crucial in the process of farmers' decision of WCST adoption. Skaggs (2001) added at the analysis on WCST adoption the farmers' expectations of their perception over the future related to their economic activities and over both water prices increases and water rights losses, but without statistical evidence of their importance in the WCST adoption process. Other studies such as Schuck et al. (2005), Wheeler et al. (2010) and Alcon et al. (2011) confirmed the main results of previous studies with little differences due to the methods applied and the different case studies. From the point of view of economics literature, researches on WCST had focused principally on socio-demographic, productive, geographical and technical determinants which may influence innovation adoption decision, but results are contradictory for some factors (Kounduri et al., 2006). Anyway, principally all the studies agree in confirming that the main determinants are strictly socio-economic, technical and productive.

Few other studies diversified the line of the main literature concentrating on some specific issues of the problem. For instance, Kounduri et al. (2006) focusing on risk aversion of farmers in adopting WCST found that risk perception is one of the main factor in influencing the process decision, whereas Hunecke et al. (2017) analyzed the importance of social capital in the adoption process confirming the main role of the trust in water institutions, the social norms and the social network both formal and informal. Other studies have inserted climatic variables to analyze their effect on WCST adoption such as Negri and Brooks (1990) who used evapotranspiration, rainfall, temperature in the growing season and frost free days, Negri et al. (2005) focused on maximum temperature and high intensity or low intensity of precipitations, finding that either extreme peak of temperature or fall in rainfall are crucial for WCST farmers' adoption. While Genius et al. (2014) introduced the aridity index as a synthesis of average annual temperature over total annual precipitation, Olen et al. (2015) added extreme climate conditions proxy variables as droughts, heats, and frost; however, both studies find those variables as important drivers for adoption and diffusion of WCST. Frisvold and Deva (2013), using a long span of period (40 years) of seasonal mean temperature and the number of months below a threshold temperature of the long period mean as well as a measure of soil erosion due to excessive precipitations, found that only the last variable is a key determinant in farmers' choice over WCST. Knapp and Huang (2017) focused on climate variables using a different set of time period (5, 10, 20 and 30 years) for calculating the classical mean variables and their coefficient of variation (CV) influencing WCST adoption (mean temperature and total precipitations in the growing season) and adding indexes for severe droughts (Palmer index) and intense rainfall (rainfall higher than 25.4mm threshold). They found that both long and short run climate events do affect farmers' decision on WCST adoption, but that average climate conditions and occurrences of extreme events are more statistically significant than the CV values. Huang et al. (2017) used method of moments to analyze the risk related to climate conditions in the decision of adopting WCST and the Palmer Index as a measure of intense drought, finding that both are significant in irrigation decisions.

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 (Table 1). Using cross-sectional data limits the analysis to the explanation of why a farmer chooses to use a 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). Panel data model can improve substantially the results of the analysis controlling for dynamic pattern either endogenous or exogenous reducing the effect of time specific events and unobserved individual effects problems providing more robust and consistence estimates (Greene, 2003). Only few studies used panel data developing either continuous, fractional, multi-choice or binary dependent variables model. The principal method used is binary choice model, with probit and logit models, these models can capture the probability of adoption of the WCST innovation. Other extensively used methods based on multi-choice dependent variable applying multinomial logit models. These methodologies are run to understand the probability of adoption of a specific technology over a set of several technologies available. Other studies (as Arslan et al., 2014) 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.

Most of the studies 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).

Among the Mediterranean area, Italy has not been adequately analyzed as a whole with the only exception of some particular zones as for example 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 analyzes the consequences of the individual producers' optimal use of inputs, in particular irrigation water, taking into account risk preferences, the latter considers farmers' encouragement in adopting irrigation water saving measures. Moreover, in the first study, even if the analysis is based on a very extended dataset at farmer level - the Italian Farm Accountancy Data Network (FADN) -, it is more focused on climate-related risk perception when decisions of irrigation strategies should be taken. In the third study, the authors used the Theory of Planned Behavior framework, mainly based on psychological studies to study WCST adoption propensity through survey data. The authors claimed that favorable 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 (Pino et al., 2017). Nevertheless, the study of Pino et al. (2017) lacked of 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, 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 a 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 topic has not been analyzed for all territories of Italy at farm level until now.

4.Theoretical Framework, Empirical strategy and Data description

4.1 Econometric model

In literature, several studies (among others Skaggs, 2001; Wheeler et al., 2010; Afrankhteh, 2014; Singh et al., 2015; Namara et al., 2007; Foltz, 2003; Salazar and Rand, 2016) have analyzed irrigation technologies adoption in agriculture defining the probability of farmers in undertaking the decision of adoption with respect to the choice of no-adoption. Using binary discrete probability models such as probit and logit models, they verify the effective relationship between the qualitative status observed in the data and several explanatory variables which includes farmers' characteristics as well as socio-economic territorial factors.

The decision of adopting environmentally friendly technologies, choosing among various possible alternatives, has been analyzed on the basis of cross-sectional data using multinomial probability models such as multi probit and logit models (among the most recent studies Schuck et al., 2007; Pokhrel et al.; 2018) or mixed methods (among the most recent studies Huang et al., 2017; Moser and Barrett, 2006). As suggested by Feder et al. (1985), these two methodologies used 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. Asrlan et al. (2014) is a first example of identifying the determinants which may affect farmers' adoption choice and intensity use of the prevalent conservation farming practices in Zambia. They capture the farmer decision of adopting a practice using the latent variable approach based on the conditional maximum likelihood approach, whereas they estimate the intensity of adoption using both a correlated random effects tobit model and a pooled fractional probit model (Asrlan et al., 2014).

Following Asrlan et al. (2014), an analysis with two separated econometric models is proposed to capture both: 1) the probability of adopting WCST by an Italian farmer; and 2) the intensity of adopting the WCST technology (whether the technology was undertaken). Respectively, the two models used for achieving these two aims are a logit/probit model (comparing population averaged clustered with the random effects for logit model and a random effects probit model with a correlated random effects model) and the Tobit model (comparing a random effects model with correlated random effects model) in order to consider corner solutions.

A regard the first model, the analysis is based on individual's discrete choice where the dependent variable is binary. Assuming that a farmer is rationale as in Caswell and Zilberman (1985), the decision of adopting an innovation is made if the expected utility outcome after new technology adoption is higher than the utility of not having undertaken the adoption (Feder et al., 1985). Since the utility function is not easily and directly observable, using a binary choice model one may predict only indirectly the likelihood of undertaking the decision of WCST adoption. In other words, one may infer the ex-post response status on the adoption of WCST related to the unobservable and latent utility function Y* of the i_{th} farmer (Cramer, 2003). The binary variable related to the adoption is Y with Y=1 meaning adopting WCST and with Y=0 meaning not adopting WCST. The latent utility of the farmer may be defined as:

$$Y_{i,t}^{*} = X_{i,t}^{T}\beta^{*} + \varepsilon^{*} \qquad (1)$$

where $Y_{i,t}^{*}$ is the latent net utility of the farmer related to irrigation technology, $X_{i,t}^{T}$ is a vector of covariates which explicate the level of utility derived by the irrigation technology (social, productive, economic, geographical and environmental factors), β^{*} is a vector of parameters of the explanatory variables to be estimated including an intercept and ε^{*} is a random error uncorrelated with the explanatory variables with zero mean, a symmetrical distribution around zero and fixed variance (Cramer, 2003; Greene, 2003). The farmer will adopt the WCST technology if his expectations of the difference between utility expectations of adopting WCST ($Y_{i,t}^{*}\ when\ Y = 1$) and not adopting WCST ($Y_{i,t}^{*}\ when\ Y = 0$) is positive (Huang et al., 2017). Since the utility of the farmer i_{th} $Y_{i,t}^{*}$ is not directly observed, one may infer it through the decision undertaken by the farmer from the observable outcome of adoption which is a dummy variable as follows:

$$Y = 1\ if\ Y_{i,t}^{*} > 0$$
$$Y = 0\ if\ Y_{i,t}^{*} \leq 0$$

Therefore, the probability that a farmer will adopt WCST is:

$$Pr\left(Y_{i,t} = 1\right) = P\left(X_{i,t}\right) = P\left(\varepsilon_{i} > X_{i,t}\,\beta^{*}\right) = 1 - \mathrm{F}(X_{i,t}\,\beta^{*}) \quad (2)$$

Where $F(.)$is the distribution function of ε^{*}which can be well approximated by a logistic distribution (or a normal distribution function) (Cramer, 2003). Therefore, the probability that a farmer will adopt WCST assume the form of the logit model (or a probit in case of considering the normal distribution function), which has been extensively used in the literature on farmers' technology adoption (He et al., 2007; Trinh et al., 2018), transforming the probability of adopting WCST (Y=1) in:

$$P_{r}(Y_{i,t} = 1) = E\left(Y_{i,t} = 1|X_{i,t}\right) = \frac{e^{X\beta}}{1+e^{X\beta}} \qquad (3)$$

Where $P_{i,t}$ is the probability of undertaking the adoption of WCST technologies for the i-th farmer in the t-th year if the binary dependent variable takes the value of *1* , $\beta_{i,t}$ is the vector of parameters to be estimated, $X_{i,t}$ is the vector of a several set of variables related to socio-economic, geographical, policies, environmental and climatic factors (Greene, 2003). Conversely (1- *Pr* $(Y_{i,t}=0)$ is the probability of not adopting WCST (Cramer, 2003; He et al., 2007; Wooldridge, 2010).

Considering the odds rather than the probability of adopting WCST means to take the ratio of the probability of success over the probability of failure (Greene, 2003; Skaggs, 2001):

$$\left(\frac{P_{i,t}}{1-P_{i,t}}\right) = \frac{1+e^{X\beta}}{1+e^{-X\beta}} = e^{X\beta} \quad (4)$$

Taking the logarithms of the odds, a logit model is obtained where a linear relationship between the response variable and the coefficients is present:

$$L_{i,t} = ln\left(\frac{P_{i,t}}{1-P_{i,t}}\right) = ln\left(e^{X\beta_{it}}\right) = z_i = \beta_0 + \beta_1 X_{i,t} + u_{i,t} \qquad (5)$$

where u_i is the stochastic error term, β are the coefficients of the regression. Using the maximum likelihood method, the values of $Pr(Y_{i,t}=1)$ are obtained through the transformation of (5) in terms of exponentials (Skaggs, 2001).

Heteroscedasticity and autocorrelation are very common in binary panel models. As suggested by Drukker (2003), the Wooldridge test for serial correlation in panel data (Wooldridge, 2010) should be carried out in order to test for autocorrelation among the same individuals i_{th}. Whenever data reveal the presence of serial correlation, this leads to inconsistency problem within the estimated model. Moreover, the presence of heteroscedasticity may produce underestimated standard errors with the possibility of over-rejection of coefficients using standard hypothesis tests.

In order to avoid inconsistency of the estimated coefficients due to underestimated standard errors, it has been used a population averaged clustered approach (PA) calculated with the generalized estimating equation (GEE) approach (Neuhaus et al., 1991; Neuhaus, 1992). The PA estimation allows non-independence of observations among clusters dealing with autocorrelation and heteroscedasticity problems giving robust estimations, conversely the interpretation of the estimators and odds ratios are related to the change in the mean population outcome related to the change in the independent variables within the specific cluster of the individual i_{th} (Hubbard et al., 2010). For the estimation of the PA model, clustered-robust standard errors have been 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).

In order to have more robustness of the results a probit model have also been applied, in this case it is not possible to obtain the odds ratios. The probit model works mainly as the logit model with the latent equations in (1), whereas only the underline distribution of the function (a normal distribution function instead of the logistic distribution function) changes. Moreover, a Correlated Random Effect (CRE) was used to solve the problems related to FE and RE. In fact, in a binary response model such as logit and probit, the choice between a fixed effect and random effect (RE) estimation presents specification problems with panel data (Greene, 2003). FE is subject to incidental parameter problems which lead to inconsistency of the estimators, at the same time it does not allow the use of time-invariant variables. Conversely RE allows time-invariant estimators, but it is constrained to the very strong assumption of not correlation between the error terms and the independent variables, which in reality is very difficult to be respected leading to bias and inconsistency in the results (Greene, 2003).

In order to cope with the problems of FE and RE models the solution could be in the middle between the two methods using the Mundlak's approach (Mundlak, 1978), which projects the effects of the group mean by calculating the mean value of the time varying variables that can absorb the heterogeneity problem due to correlation between the estimators and the error terms relaxing the strict assumption of RE ($Cov(X, \varepsilon) = 0$), in order to use a Correlated Random Effect (CRE) model (Greene, 2003, Wooldridge, 2013).

In this case, following Greene (2003), using the Mundlak's approach in binary choice model the equation 1 and the probability of Y=1 becomes:

$$Y_{i,t}^{*} = \alpha_i + X_{i,t}^{T}\beta^{*} + \varepsilon^{*} \quad (6)$$

$$Pr\left(Y_{i,t} = 1 | X_{i,t}\right) = \mathrm{F}(\alpha_i + X_{i,t}\,\beta^{*}) \quad (7)$$

with:

$$\alpha_i = \alpha + \delta\bar{x}_{i,t}^{T} + u_i \quad (8)$$

so that:

$$Y_{i,t}^{*} = \alpha + \delta\bar{x}_{i,t}^{T} + X_{i,t}^{T}\beta^{*} + u_i + \varepsilon^{*} \quad (9)$$

and

$$Pr\left(Y_{i,t} = 1 | X_{i,t}\right) = \mathrm{F}(\alpha_i + \delta\bar{x}_{i,t}^{T} + X_{i,t}\,\beta^{*} + u_i) \quad (10)$$

Where α_i in equation 6 is the individual unobserved heterogeneity and $\bar{x}_{i,t}^{T}$ in equation 8 is the group mean (individual time mean of X_i^T) of the time-varying variables (Greene, 2003). Then, the model is transformed in the CRE equation as in 9 with the probability of success expresses in equation 10. In the CRE model, the use of the time mean reduces the problems of the RE assumption. Applying this model specification with time-varying and time invariant variables, estimations obtained are robust and consistence (Greene, 2003, Wooldridge, 2013).

The second econometric model - the Tobit model - allows analyzing the intensity of WCST adoption since farmers decides to adopt only partially the new technology and not always in the whole irrigated land, combining different irrigation methods. For intensity of adoption, the dependent variable is represented by the amount of total irrigated land under WCST for each i*th* farmer (Asrlan et al., 2014). The Tobit model (Tobin, 1958) is used in presence of censored dependent variable as in this case, in which a significant fraction of the observation is limited at 0. For all the farmers who do not adopt WCST, who are the majority, a corner solution model should be applied. Specifically, the Tobit model allows for a corner solution model in which the dependent variable is always observed with positive values, but it assumes the value of 0 for a relevant part of the sample (Greene, 2003; Wooldridge, 2010; Wooldridge, 2013). The censored dependent variable assumes the form:

$$Y_{i,t} = 0 \; if \; y^{*} \leq 0 \quad (11)$$

$$Y_{i,t} = y^{*} \; \; if \; y^{*} > 0 \quad (12)$$

In this case the regression with the classical OLS is inconsistent, a possible solution is the use of the Tobit model (Tobin, 1958; Greene, 2003) regressing the latent variable y^{*}.

The Tobit model can be specified as:

$Y_{i,t}^{*} = X_{i,t}^{T}\beta + \varepsilon \sim N[0, \sigma^2]$ when conditions in equations 11 and 12 are verified.

where $Y_{i,t}$ 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, $\beta_{i,t}$ are the coefficients to be estimated, $X_{i,t}$ represents the vectors of explanatory variables such as social, economic, environmental, geographical and climatic aspects, and $\varepsilon_{i,t}$ is the error term with zero mean and constant variance σ^2.

The difference between the corner solution model, as in this case, and a classical censored model is the interpretation of the coefficient estimators of the Tobit model which in the former case is not any longer explaining the marginal effects of the regressors over the dependent variables (Wooldridge, 2010). In this case, coefficients must be transformed using the inverse mills ratio $\lambda = \frac{\phi(\frac{\beta}{\sigma})}{\Phi(\frac{\beta}{\sigma})}$ in order to consider the marginal effects of each independent variables (Wooldridge, 2010). In order to consider the unobserved heterogeneity problem, the model adopt the Mundlak's approach transforming the model in a Correlated Random Effect Tobit model as Asrlan et al. (2014) applied, using the mean of the time variant independent variables as in equation (9) for the logit model. This allows having unbiased and consistent estimations of the β coefficients (Asrlan et al., 2014). The final specification of the CRE Tobit model is:

$$Y_{i,t}^{*} = X_{i,t}^{T}\beta + \delta\bar{x}_{i,t}^{T} + u_i + \varepsilon_{i,t} \sim N[0,\sigma^2]$$

Additional analysis at regional level of the all models (logit, probit and tobit) have been realized in order to have robust results. All the continuous covariates used in the analysis (but not Age) have been transformed in their logarithmic form in order to smooth their distribution reducing heteroscedasticity problems.
To the best of our knowledge, until now only Asrlan et al. (2014) have analyzed the intensity of adoption of conservative farming in Zambia applying a similar methodology related to the specific definition of the dependent variable.

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 related to farmers' determinants factors in technology adoption both in western and developing countries there have been identified different sets of variables for describing the determinants of WCST adoption to be used as explanatory variables in the two econometric models. The explanatory variables have been divided into six groups of characteristics which are described in the following: 1)

Farm characteristics, 2) Farmer characteristics, 3) Geographic characteristics, 4) Water use characteristics, 5) Financial characteristics and 6) Climate characteristics.

Descriptive statistics of the main variables used in the study are reported in Table 7 and in Table 8 Climatic variables are shown in appendix. In Figure 1 and 2 it is shown respectively the geographical distribution of WCST and the proportion of area irrigated under the use of WCST.

4.2.1 Farm characteristics

4.2.1.1 Total work (LogHwork)

An element highly influencing the adoption of sustainable technologies is represented by the human capital in the farm (Boahene et al., 1996; He et al., 2007) measured by the logarithm of the total hours of work spent in the farm (either family or external work). It can be interpreted as a proxy of the economic dimension of the farm.

4.2.1.2 Type of production (Crop Type)

The prevalent system of production can change substantially the pattern of water demand and water use between farms (Green et al., 1996), therefore it has been taken into consideration using dummy variables indicating the prevalent type of production using the indication of RICA classification dividing farms into type of production: Olive-growing, Fruticulture, Viticulture, Horticulture and Floriculture, Cereals production, Granivore (Pigs and Poultry), Herbivorous, Oilseed production and Mixed production (cultivation and breeding). 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.

4.2.1.3 Value of land (Value Land)

The monetary value of land can embed the value of the output product and the profitability of the agricultural activity which consequently can influence the intensity of land using and the technology adopted for irrigation (Moreno and Sunfing, 2005). To consider this, it has been used as explanatory variable the logarithm of the market value of agricultural lands reported inside the balance sheet of the farm.

4.2.1.4 Land Size (Log UAA)

The extension of the farm can influence positively the adoption of WCST because higher economies of scale in terms of farm land may influence technology investments (Trinh et al., 2018). To consider this aspect, it has been used the UAA (Utilized Agricultural Area) in ha.

4.2.1.5 Land Tenure (Log Land Rented)

Various precedent studies highlighted the importance of land tenure on technology adoption (Alcon et al., 2019; Doss and Morris., 2001; Moreno and Sunfing, 2005; Pokherel et al., 2018) the investment in WCST seems to be higher in land owned farms. The logarithm of the size of rented land has been used to capture this factor.

4.2.1.6 Family Farming (Family Farm)

A dummy variable has been created to indicate whether or not a farm was conducted prevalently by the farm.er and his/her relatives.

4.2.17 Organic Farming (Organic)

The certification of organic products could contribute to decide in investing more in sustainable agricultural production activities meaning that a farmer has a more environmentally friendly interest. A dummy variable has been created to indicate when a farm is cultivating certified organic products.

4.2.1.8 Technology (Kw Machine)

The propensity of adopting new technologies can be influenced by the interest in technology by the farmer. This element has been captured creating a proxy variable of the propensity to technology of the farmer with the logarithm of the total machine power within the farms in kilowatts.

4.2.2. Farmer characteristics

4.2.2.1 Gender (Female)

Various studies have highlighted the importance of gender in technology adoption, especially in developing countries (Asfaw et al., 2016; Somda et al., 2002), whereas in developed countries gender is not so influencing in sustainable technology adoption choices (..). To consider this factor a dummy variable was used to indicate whether the farmer is a female.

4.2.2.2 Age (Age and Age^2)

Many studies indicate that younger farmers are more willing to adopt new and sustainable technologies (Alcon et al., 2019; Skaggs, 2001; Somda et al., 2002), whereas other studies highlight that older farmers are more inclined in adopting new technologies because of higher experiences (Jianjun et al., 2016). The age of the farmer in has been considered in order to test this assumption and to verify how much age is important in influencing the decision of WCST adoption in marginal terms the same variable in quadratic form is been considered as well (Afrakhteh et al., 2015; Doss and Morris., 2001; Salazar and Rand, 2016).

4.2.2.3 Education (High Educ)

Several studies have highlighted that more educated farmers with more schooling years have higher propensity to invest in new technologies (Alcon et al., 2019, Moreno and Sunding, 2005; Salazar and Rand, 2016; Pokherel et al., 2018). A dummy variable has been created to indicate if the farmer has at least finished the high school.

4.2.2.4 External activity (Extra)

Various studies on technology adoption indicate that if the farmer has external working activities tend less in adopt new technologies because the risk adverse behaviour tends to reduce the willingness to undertake risks (Afrakhteh et al., 2015; He et al., 2007; Weeler et al., 2010). A dummy variable has been created to indicate if the farmer had an external economic activity.

4.2.2.5 Risk Propensity (Insurance)

The aversion to risk and its perception can influence the decision of a farmer on whether investing or not in a WCST. As stated by several study in irrigation technology the individual attitude towards risk in undertaking new techniques and the sensitivity to technology progress among farmers are very difficult elements and to consider (Rogers, 1971; Kounduri et al., 2006). In order to include this important factor, the logarithm of 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 it would influence (positively or negatively) the adoption of WCST.

4.2.3 Geographic characteristics

4.2.3.1 Altitude (Avg Altitude)

The altitude of the farm can influence the production schemes and irrigation patterns, therefore WCST adoption can be influenced by the altitude level, so the logarithm of the average altitude level of the farm has been used to consider this fact.

4.2.3.2 Acclivity (Sloped Area)

The slope of the agricultural lands within a farm can influence the adoption of WCST, as other studies have considered this element has been included into the analysis using the logarithm of the area with slope high acclivity within the farm (Afrakhteh et al., 2015; Alcon et al., 2019; Green and Sunding, 1997; Negri and Brooks, 1990; Sherestha and Gopalakrishan, 1993).

4.2.3.3 Soil Type (Soil Sandy, Soil mixed, Soil Clay)

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 WCST 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 WCST because of higher water soil retention. This aspect which is quite important in irrigation technology decision has been considered using three explanatory variables indicating the area of the farm with sand soil, clay soil and mixed soil in logarithmic form.

4.2.4 Water use characteristics

4.2.4.1 Cost of Energy, Electricity and Water (Log Cost Water Energy Electricity)
The cost of water can directly and highly influence the amount of water demand and used within a farm, in absence of specific water prices and tariff it has been used as proxy the total cost for water, energy and electricity occurred in the farm in logarithmic form.

4.2.4.2 The area of land under irrigation (Irrigated Land)
The extension of irrigated land can influence the type of irrigation method used within a farm, therefore the logarithm of irrigated area has been used as explanatory variable.

4.2.4.3 Internal water source (LogInternalWater)
The type of water source used 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 WCST (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. In this paper water source have been considered 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. The variable used in the econometric model considers the extension of irrigated land served by an internal source of water (considered as Pit, Artificial Ponds and Water Tanks within the farm) in logarithmic form.

4.2.5 Financial characteristics

4.2.5.1 Return on Investments (ROI)
The profitability of typical activity of the farm can influence the inclination in technology adoption of the 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. ROI is a proxy of both the dimension of profits of the farm and the propensity of the farmer of investing within the farm, therefore to consider this in the analysis an explanatory variable as the ratio of the operating income over the total investments in logarithm terms has been included. The expectations are that it is relevant for WCST adoption and the higher is the ROI the higher is the investments in WCST.

4.2.5.2 Leverage (Leverage)
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). The Leverage 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. In order to consider the aspect of debt and access to capital it has been used 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).

4.2.5.3 Fundings (Eu Funds; Non-EU funds)
External funding can influence the adoption of technologies incentivizing behavior that in absence of public help would not have been taken place (Rogers, 1971). In absence of specific indication of funding on WCST the total amount of funding either from the European community or other sources of fund (in euros) have been considered as a proxy of the reliance of the farm on external funds. Two variables have been used for this purpose Eu Funds

(directly received from EU throughthe CAP) and Non-EU funds (funds received from other institutions different from EU, mostly National and Local governments).

4.2.6 Climate characteristics

Climate and weather are key variables in influencing WCST 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). 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. 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), three moving averages have been used: 5 years back, 4 years back considering also the current year and 3 years back. 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.

4.2.6.1 Maximum Temperature (Max Temp)

Temperature peaks are detrimental for crop growth and in several studies have been used as a proxy of extreme weather conditions which can lead the farmer in changing their way of water use for crop production (Huang et al., 2017; Knapp and Huang; 2017). Perceived higher level of maximum temperature should push farmers to consider higher risks of droughts and periods of water scarcity so incentivize a higher rate of adoption of WCST.

4.2.6.2 Minimum Temperature (Min Temp)

Low levels of temperature can be used as a proxy of climate change. The raising level of the minimum seasonal mean may be especially representative for cold period. As above the perception of higher minimum temperature could lead to WCST in order to cope with water risks due to hotter seasons.

4.2.6.3 Average Temperature (Avg Temp)

Average temperature are usually used in similar studies for their immediateness and simplicity in their interpretation even if they can hide peaks and extreme conditions (Asfaw et al., 2016). In this paper also the average temperatures have been tested among the other weather variables, the concept is the same as above for Min Temp and Max Temp.

4.2.6.4 Cumulative Precipitation (Cum Precip)

The total precipitation occurred in one season can influence substantially soil moisture and the need for water of the crops. The higher is the total cumulative precipitation the wetter is the soil; therefore, water needs should be reduced. Theoretically, rational farmers should implement WCST at higher level when cumulated precipitations are less.

4.2.6.5 Reference Evapotranspiration (ET_0)

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). Therefore, considering the difference of cumulated precipitations and ET_0, or their rate (Cumulated Precipitation / ET_0) can be used as an indicator of crop water requirements. 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 comprensive index of weather condition for plant water requirements (Allen et al., 1998).

4.2.6.6 Aridity Index (AI)

This index is made by the ratio of the value of the Cumulative Precipitation of a specific season and the Potential Evapotranspiration in the same season (CGIAR, 2019). It indicates how much water needs of crops have been satisfied by precipitations occurred in a specific season, so it is an indicator of how much Accumulated Precipitation covers Evapotranspiration in terms of water:

For each season: $AI_{season} = Cum\ Pricip/\ ET0$

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.

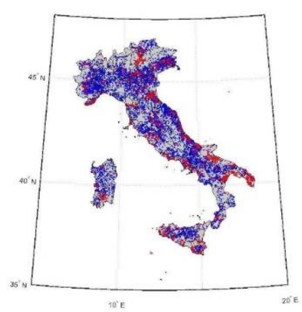
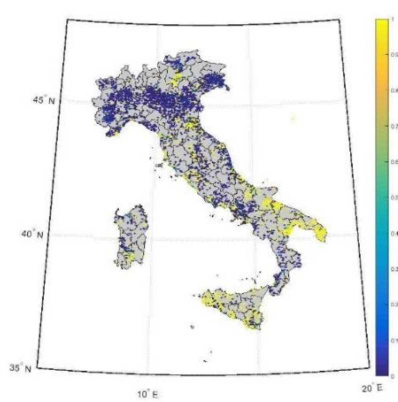


Fig 1. Number of WCST (red) and traditional irrigation technology (blue) total irrigated land for each farm from 2012 to 2012. (Our own elaboration)

Fig 2. Area under WCST on proportion over the total irrigated land for each farm from 2012 to 2012. (Our own elaboration)



5.Main Results and Discussion

All the results of the binary response models logit, probit (Robust, Population average and CRE) and Tobit run at national level are reported in Table 1 with estimated coefficient of binary response models with standard errors, in Table 2 the Odds ratios of the logit models and in Table 3 the estimated coefficient and the standard errors of the Tobit model. In appendix in Table 4,5 and 6 (in appendix) are presented the same analysis at regional level, distinguishing between all the Italian farmers and the macro-areas of Italy (North-west, North-east, Centre, South and Islands).

In preliminary analysis different models have been compared in terms of weather variables and different length of moving averages in order to have wide information over the most representative and explicative variables for climatic and weather conditions. The most robust of the climatic variables has been the AI which include precipitation and temperature within it, therefore in the model estimations only the AI has been inserted among the covariates. The best moving average for the seasonal climatic variables has been calculated considering five years back without the current year. For instance, in order to calculate the seasonal moving average for AI in spring (April, May and June) for the year 2014, AI has been calculated considering the average value of AI for the same season in the years from 2013 to 2009.

All the coefficients of the two estimations within the different models present approximately constant magnitudes and the same signs for the variables included indicating that both the binary response models and intensity analysis (Tobit) are robust. In both models all the set of variables on farms' and farmers' socio-economic, geographical, financial, and water use characteristics are significant and present the expected sign, only the climatic variables appear to be not so intuitive to be interpreted even if highly significant.

Below, results are discussed for each estimation and model in more details.

5.1 Results of the binary response models (Logit, Probit and CRE Probit)

Table 1 present the micro-irrigation technologies adoption based on population averaged, random effects and fixed effect logit model with robust standard errors or White-Huber standard errors, in order to cope with heteroscedasticity and autocorrelation issues. Moreover, in the same table, are presented results of the population averaged, random effects and CRE probit model, for the latter with and without robust standard errors, whereas for the former two both robust standard errors have been considered. The estimation is over the all sample considering all Italian farms with 13,054 farms and 43,917 observations.

All the models at national level shows highly significant explanatory variables (more than thirty over forty) among the socio-economic and geographical characteristics, with most of them presenting the expected signs.

As expected crop type variables are highly statistically significant, both the high value crops (olives, fruits, viticulture, horticulture) and mixed production (animal and crop production together) positively influence the probability of adopting WCST. Conversely, the crop type variable indicating that farm is specialized in livestock (breeding bovines and others) is also significant, but with a negative impact on the probability of WCST adoption which indicate that livestock farms have less probability to adopt WCST.

The amount of work force available within the farm do matter, in fact the variable Total work (LogHwork) is highly significant with positive sign indicating that increasing time of work spent in the farm (either internal or external) influence positively the probability of WCST adoption.

Unexpectedly, the total machine power used within the farm (Kw Machine) is not significant meaning that the stock of technological capital, already owned by the farmer, does not influence the adoption of sustainable irrigation technologies. This last variable is a proxy of capital intensity used in the farm, our results indicate that the high capitalized farms have higher propensity to adopt WCST.

The size of the farm in terms of land extension expressed in UAA is significant, but with negative effect indicating that an additional hectare of UAA in the farm negatively influences the probability of adoption of WCST. This result is partly in contrast with a part of the literature on irrigation technology adoption which suggests that the size of the farm matters positively in WCST adoption decisions (e.g. Green et al., 1996; Huang et al., 2017), however, this result is in line with the study of Knapp and Huang (2017) which has found a positive relation with size and traditional irrigation methods, but not for WCST.

Conversely the size of irrigated land is highly significant with positive coefficient indicating that higher size of irrigated land in the farm influence positively the adoption of WCST. This might depend on economy of scale obtainable with WCST irrigation related to the use of sophisticated technologies, in fact WSCT imply substitution of labour by capital and energy with reduction of labour required for irrigation with traditional technologies which is very important for the farmer.

Land tenure is relevant, because the amount of rented land influence negatively the probability of the adoption of WCST. This result is intuitive and in line with Moreno and Sunding (2005), as the investment in WCST are usually made with higher probability by farmers which own the land with respect to who rents it. Therefore, the higher is the size of not directly owned land the lower is the probability of adoption. Unexpectedly the market value of agricultural lands (Value Land) owned by the farmer has not significant influence in defining the WCST adoption decision. This finding is in contrast with the study of Salazar and Rand (2016) for Chilean vineyards in which land value is a key factor in explaining WCST adoption. This could be explained by the endogenous differences in the two areas of study (Chile and Italy) which are quite diversified. Overall the results on land may indicate that market value is not a key element in WCST adopting decisions, but this is not true for rented land as a proportion over the whole utilized agricultural land.

The results show that the type of conduction of the farm is important, highlighting that commercial and business farms have higher propensity to adopt WCST, in fact the variable Family Farm is highly significant, but with negative coefficient revealing that if a farm is conducted principally by the sole farmer, or more generally at familiar level, this may reduce the probability of WCST adoption. This finding is similar to Mango et al. (2018) and it can be read in the sense that a farm run at family level is detrimental in terms of investing in WCST since the adoption depends on how intensively works the main family component and the level of initial capital necessary for the investment. This is consistent with previous results highlighting that WCST rely on time available, human skills and labor and not only size, therefore only farms with a business structure and with external labour force can afford to invest time and resources in WCST. Our results highlight who at Italian level the intensity of labour used within the farm influence WCST higher than the intensity of capital.

As regards the farmers’ characteristics, the estimated coefficient of Female, Organic, and Extra are not significant, suggesting that those elements are not essential for influencing the adoption of WCST. Besides, the Age variable is not significant meaning that this element does not influence the probability of adoption WCST, this results is in line with Alcon et al. (2019), Mango et al. (2018), Namara et al. (2007) and Huang et al. (2017). Unexpectedly the estimated coefficient of the variable indicating the level of education (High Education) is not significant, giving not answer over the question whether or not high levels of education influence the adoption of WCST.

The risk aversion of the farmer seems to influence positively the decision of adoption, in fact the proxy variable insurance is both significant and positive indicating that higher amount spent in protecting to risks increase the probability of adopting WCST.

For the financial characteristics of the farm, only external fundings are significant, but with counterintuitive signs, in fact the estimated coefficients of Non-Eu Funds are positive whereas the coefficients for the variable Eu Funds are negative. This may indicate that depending on the institution which offers funds national or European, may modify the attitude towards the probability of adopting WCST. If funds come from EU, the probability of adoption decreases whereas increases if funds from other national institutions. 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. As regards for the last two variables which describe the financial situations of Italian farms, ROI and Leverage, they show not significant coefficient, meaning that farmers' decision of WCST adoption is not related to the farm indebtedness and to the capability to generate an adequate return on investments.

The coefficients of the geographical variables are less intuitive even if easily comprehensible. Slope and sandy texture of soil are unexpectedly not significant, whereas average altitude, mixed and clay soil textures are significant with negative sign. This means that if soils are characterized by a water retaining texture then the probability of adopting WCST decreases. Since average altitude is highly significant with negative sign, the farms located at higher altitude have less probability of adopting WCST because of higher moisture environment.

The variable related to internal water (tank, wells and ponds) source is highly significant with positive sign, indicating that for farm with water endowments within its own property the probability of WCST adoption is higher than that for the farm relying on external sources. Conversely to what expected water costs (considering also energy and electricity costs) is not significant in most of the model used, whereas the Cost of Energy, Electricity and Water are significant and influencing positively the probability for a farmer to adopt WCST only for the population average probit model (at 5% of significance level).

The variables indicating geographical macro-areas confirm the actual situation in which the WCST is asymmetrically distributed on the Italian territory. In fact, the dummy variables reinforce the fact that farms in the south or in islands part are the ones which suffer the most for the lack of water. They have already adopted WCST systems and continue to show a higher propensity in adopting the micro-irrigation technology due to a positive and significant sign. On the contrary, farms located in the northern part of the country (both west and east side) show a negative estimated coefficient meaning that for a farm located in those regions the availability of adopting WCST is reduced.

As regards to the climate explanatory variables, in preliminary analysis in which various combinations of the climatic variables (Temperature, precipitation and ET0) have been used, all the estimated coefficients were for all the different moving averages considered and for most of the seasons. The only variable with low significance was the minimum average temperature both if it is considered in terms of season and in terms of different moving average. However, some of them present counterintuitive signs especially for spring and summer. In fact, the estimated coefficients of the warm seasons assume opposite signs than the expected ones (negative for temperature in spring and positive for precipitation in summer), whereas for autumn and winter the signs are correct and highly significant. Apart from the difficulties in understanding and explaining why summer and spring present an opposite relationship i.e. the probability of adopting reduces when temperature increase and precipitations is scarce, the case of autumn and winter may indicate that warmer conditions in those seasons occurred in the past years can increase the probability of adopting WCST. This suggests that an average farmer may be more sensitive to climate change effects, in deciding of adopting a WCST system when colder seasons are more warm than when the warm seasons get hotter. For example, our results are highlighting that warmer and drier conditions in winter and autumn in the past years (in this case 5 five years) can influence the decision of the farmer of adopt WCST due to perceptions of change in climatic average conditions.

The final estimation using AI released more stable results overcoming many problems of instability of the estimation, but with counterintuitive signs continue for spring season. Highly significance of the coefficient of AI is shown in all the binary response models for Winter season (January, February and March), Spring season (April, May and June) and Autumn season (October, November and December), whereas the AI coefficients are significant for Summer season (July, August and September) only in the fixed effects logit model and for the population average probit model.

AI is highly significant for all the seasons (apart for summer) for the 5 years moving average, but either in this case the signs of spring season are opposite to what expected (positive) whose explanation is not so easy, but it is comforting that is confirmed the importance of autumn and winter for taking the decision by farmer. In this case, a negative sign indicates that higher levels of the aridity index reduce the probability of WCST adoption. This is because high levels AI, calculated as the rate between cumulative precipitation and evapotranspiration, mean that precipitation had covered part of the water needs for the development of crops reducing the perception of aridity and reducing the probability of WCST adoption. Conversely the positive sign of AI in spring season means that increasing the level of water need satisfied by precipitation reduce the probability of WCST, which should not be rationale for a farmer. A possible answer is that farmers' perceptions over past climatic average conditions are highly sensitive to changes occurred during cold season (autumn and winter) than in warm season (spring and summer) not considering the latter in their decisional schemes for WCST adoption. Therefore, farmers are not completely aware about climatic conditions because of distorted perception mechanisms. Following our findings, farmers seem to do not completely consider past warm season in their decisional scheme because they can be accustomed to temperature peaks or droughts periods, whereas they are more sensitive to changes in temperature and rain during the cold seasons which could be perceived more anomalous and dangerous for agricultural productions. Another possible answer is that farmers are not rational agent in taking climatic information in their technology adoption schemes.

5.1.1 The Odds ratio of the logit models

The odds-ratios indicate that the elasticity of each explanatory variables over the probability of the average farmer to adopt WCST, meaning how much the 1% change in the explanatory variable may influence the probability to adopt WCST for the average farmer. The odds-ratios are available only for logit models (Population average, Random Effects, Fixed Effects). They indicate the likelihood of adopting WCST due to the covariate and they must be interpreted considering the sign of the coefficient. The resulting odd-ratio are shown in Table 2. They have to be interpreted as increase of one unit in the independent variable increase the probability of the dependent variable by the number expressed in the odds-ratio. For instance, for internal water sources, each hectares of land served by internal water source increase the probability of adoption by 1.5%

To be noticed are the values higher than one for a subset of variables, which seems to be the more relevant in explaining WCST adoption. Those are: Total working, high value crops, mixed crops, internal water source, size of irrigated land, No-EU funds, Risk propensity and the macro-regional dummy for farms in the south and in the islands. For climatic variables the highest odds-ratio are for AI in spring time. All other odds-ratio related to the estimated coefficients are between 0 and 1.

5.1.2 Regional models

It has been carried out an analysis at macro-area level running five different probit models (both population averaged and Random Effects) for each Italian macro areas: north-east, north west, center, south and islands. The aim was to give consistency to the results obtained in the national model, while considering regional differences because of the high variety of geographical, socio-economical and productive factors characterizing Italian farms. This analysis has been conducted in order to consider if a different decision pattern among the different macro areas in Italy arises, in both estimations the coefficients are reported. Estimations are shown in table 4 and 5 in the appendix.

The results are very similar to the general model and they not show many differences arising between macro areas. The main differences are that organic (positive), extra work of the farmer out of the farm (positive in north-west, negative in the center) and the intensity of capital (positive in the south, negative in the center and islands) gain statistical significance in the regional models (apart for the Center area), suggesting that within macro areas those socio-economic factors seem to influence WCST adoption. Conversely, the land value becomes significant with positive sign for central regions, meaning that for that area the value of land does affect positively WCST adoption. Moreover, the variable Age becomes significant only in the south, indicating that at regional level older farmers have less probability to adopt WCST than younger farmers in line with various previous work (Alcon et al., 2019; Mango et al., 2018; Namara et al., 2007; and Huang et al., 2017). Financial variables become significant ROI negative for the islands and Leverage positive for the center and the south.

Regarding the geographical variables acclivity becomes significant (negative in the center, positive in the islands) and all variables related to soil type become significant: clay soil texture (negative in the north-west and islands), sandy soil texture (negative in the north-east, positive in the south) and soil mixed texture (negative in the north regions).

Water cost and Energetic costs become significant with a positive effect on the WCST adoption in the north-west and south macro-region, reflecting the importance of the local water authorities in water management in these areas which most of the time apply water tariffs. This highlights that for these regions a positive water price elasticity of farmers, who could use WCST as a strategy to reduce water costs.

All other variables are significant as in the general model following the same pattern, suggesting consistency with the findings at national level. Also for the climatic variables the pattern is similar to the general model, but some changes in the controversial warm season in which for north-east, center and south macro areas the sign of AI become correct (negative). Conversely for north-west and center macro areas the sign of the estimated AI coefficient changes for cold seasons, becoming positive with not an apparent intuitive scheme for those macro areas.

Table 1. Estimated coefficient of the binary response models.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	1 Logit Model Pop AVG	2 Logit Model Random Effects	3 Logit Model Fixed Effects	4 Probit Pop AVG	5 Probit Random Effects	7 Probit Correlated Random Effects con robust	9 Probit Correlated Random Effects NO robust
Log_Htot_working	0.341***	1.371***	0.652***	0.200***	0.780***	0.466***	0.466***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
crop_alto_valore	0.929***	2.937***		0.664***	1.511***	1.443***	1.443***
	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)	(0.000)
crop_type_mixed	0.468***	1.543***		0.390***	0.659***	0.642***	0.642***
	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)	(0.000)
livestock	-1.754***	-7.343***		-0.837***	-3.569***	-3.685***	-3.685***
	(0.000)	(0.000)		(0.000)	(0.000)	(0.001)	(0.000)
Log_terreni_agricoli	-0.073	-0.348		-0.100**	-0.129	-0.221	-0.221
	(0.348)	(0.210)		(0.027)	(0.444)	(0.360)	(0.104)
Log_SAU	-1.150***	-4.415***		-0.614***	-2.290***	-2.243***	-2.243***
	(0.000)	(0.000)		(0.001)	(0.000)	(0.002)	(0.000)
Log_SAU_Affitto	-0.306***	-0.709**		-0.171***	-0.352*	-0.392*	-0.392**
	(0.002)	(0.035)		(0.003)	(0.067)	(0.062)	(0.015)
eta	0.010	0.052		0.005	0.027	0.027	0.027
	(0.349)	(0.149)		(0.404)	(0.203)	(0.226)	(0.201)
eta2	-0.000**	-0.001***		-0.000**	-0.000**	-0.000**	-0.000**
	(0.036)	(0.009)		(0.049)	(0.016)	(0.021)	(0.020)
Log_KWMacchine	-0.032	-0.016	0.490**	-0.032*	-0.010	-0.062	-0.062
	(0.318)	(0.887)	(0.044)	(0.082)	(0.883)	(0.549)	(0.303)
Female	-0.042	-0.209		-0.039	-0.120	-0.108	-0.108
	(0.411)	(0.210)		(0.213)	(0.220)	(0.304)	(0.275)
family_farm	-0.249***	-1.215***		-0.126***	-0.740***	-0.635***	-0.635***
	(0.000)	(0.000)		(0.002)	(0.000)	(0.000)	(0.000)
extra	0.043	0.037	0.307	0.025	0.025	0.093	0.093
	(0.423)	(0.843)	(0.521)	(0.467)	(0.820)	(0.433)	(0.412)
organic	0.010	0.086		-0.049	0.081	0.080	0.080
	(0.900)	(0.776)		(0.390)	(0.673)	(0.715)	(0.649)
edu_sup_laurea	0.035	-0.099		-0.002	-0.040	-0.041	-0.041
	(0.515)	(0.592)		(0.952)	(0.718)	(0.723)	(0.703)
Log_alt_med	-0.349***	-1.475***		-0.191***	-0.814***	-0.826***	-0.826***

	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)	(0.000)
Log_area_inclinata	-0.074	0.236		-0.031	0.037	0.029	0.029
	(0.509)	(0.438)		(0.657)	(0.832)	(0.873)	(0.842)
Log_tess_sciolto	0.012	0.290		0.043	0.178	0.156	0.156
	(0.897)	(0.366)		(0.458)	(0.385)	(0.579)	(0.233)
Log_tess_medio	-0.509**	-1.178		-0.200	-0.733*	-0.870*	-0.870***
	(0.014)	(0.103)		(0.129)	(0.091)	(0.072)	(0.002)
Log_tess_argilla	-0.100	-0.292		-0.035	-0.183	-0.216	-0.216*
	(0.201)	(0.295)		(0.465)	(0.259)	(0.221)	(0.076)
Ln_fonte_interna	0.403***	1.595***	0.400***	0.280***	0.781***	0.768***	0.768***
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Log_aiuti_EU	-0.364***	-1.458***	-0.375	-0.170***	-0.768***	-0.789***	-0.789***
	(0.000)	(0.000)	(0.219)	(0.000)	(0.000)	(0.000)	(0.000)
Log_aiuti_nonEU	0.094***	0.299***	0.205	0.071***	0.175***	0.184**	0.184***
	(0.003)	(0.007)	(0.118)	(0.002)	(0.006)	(0.015)	(0.009)
Log_costoAEC	0.064	0.174	-0.175	0.058**	0.074	-0.019	-0.019
	(0.136)	(0.244)	(0.353)	(0.026)	(0.441)	(0.897)	(0.803)
Log_assicurazioni	0.160***	0.628***	0.400***	0.088***	0.332***	0.242***	0.242***
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.003)	(0.001)
nord_ovest	-0.761***	-2.965***		-0.497***	-1.679***	-1.622***	-1.622***
	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)	(0.000)
nord_est	-0.858***	-3.895***		-0.383***	-2.114***	-2.132***	-2.132***
	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)	(0.000)
sud	0.490***	2.374***		0.233***	1.288***	1.318***	1.318***
	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)	(0.000)
isole	1.132***	5.111***		0.527***	2.843***	2.935***	2.935***
	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)	(0.000)
Log_ROI	0.077	1.815	-1.816	-0.055	1.097	0.542	0.542
	(0.919)	(0.499)	(0.762)	(0.933)	(0.511)	(0.763)	(0.807)
Log_Leverage	1.328	7.874	54.439	0.578	4.696	10.208	10.208
	(0.213)	(0.231)	(0.100)	(0.466)	(0.316)	(0.420)	(0.299)
AIJFM_ma5lag	-0.656***	-1.759***	1.322***	-0.598***	-0.930***	-0.940**	-0.940***
	(0.000)	(0.000)	(0.001)	(0.000)	(0.002)	(0.040)	(0.000)
AIAMJ_ma5lag	2.864***	9.368***	0.968	2.736***	5.066***	4.888**	4.888***
	(0.000)	(0.000)	(0.588)	(0.000)	(0.000)	(0.011)	(0.000)
AIJAS_ma5lag	0.148	1.218	4.041***	-0.609***	0.721	0.726	0.726
	(0.534)	(0.261)	(0.009)	(0.000)	(0.442)	(0.722)	(0.130)

AIOND_ma5lag	-0.633***	-2.083***	-0.743**	-0.500***	-1.102***	-1.090***	-1.090***
	(0.000)	(0.000)	(0.026)	(0.000)	(0.000)	(0.003)	(0.000)
Anno_2013	0.127***	0.454***		0.088***	0.242***	0.248***	0.248***
	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)	(0.000)
Anno_2014	0.203***	0.691***		0.155***	0.361***	0.374***	0.374***
	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)	(0.000)
Anno_2015	0.355***	1.247***		0.283***	0.665***	0.679***	0.679***
	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)	(0.000)
Anno_2016	0.383***	1.473***		0.285***	0.786***	0.792***	0.792***
	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)	(0.000)
Log_sup_irr	1.132***	4.123***	2.444***	0.602***	2.174***	2.163***	2.163***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
mean_Log_Htot_working						0.667***	0.667***
						(0.000)	(0.000)
mean_Log_aiuti_nonEU						-0.050	-0.050
						(0.754)	(0.720)
mean_Log_assicurazioni						0.333	0.333**
						(0.327)	(0.013)
mean_Log_ROI						2.512	2.512
						(0.586)	(0.572)
mean_Log_Leverage						-40.775	-40.775
						(0.632)	(0.464)
Constant	-7.491	-72.829		-2.086	-45.030	202.236	202.236
	(0.561)	(0.250)		(0.838)	(0.297)	(0.714)	(0.583)
Observations	43,917	43,917	3,260	43,917	43,917	43,917	43,917
Number of ID	13,054	13,054	846	13,054	13,054	13,054	13,054
chi2	2461	2702	309.1	2571	2146	2200	2200
p	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Table 2. Odds-ratio of the Logit models (Population average, Random Effects and Fixed effects).

	(1)	**(2)**	**(3)**
VARIABLES	**1 Logit Model Pop AVG Odds Ratio**	**2 Logit Model Random Effects Odds Ratio**	**3 Logit Model Fixed Effects Odds Ratio**
Log_Htot_working	1.406***	3.941***	1.919***
	(0.000)	(0.000)	(0.000)
crop_alto_valore	2.533***	18.857***	

	(0.000)	(0.000)	
crop_type_mixed	1.596***	4.677***	
	(0.000)	(0.000)	
livestock	0.173***	0.001***	
	(0.000)	(0.000)	
Log_terreni_agricoli	0.929	0.706	
	(0.348)	(0.210)	
Log_SAU	0.317***	0.012***	
	(0.000)	(0.000)	
Log_SAU_Affitto	0.737***	0.492**	
	(0.002)	(0.035)	
eta	1.010	1.053	
	(0.349)	(0.149)	
eta2	1.000**	0.999***	
	(0.036)	(0.009)	
Log_KWMacchine	0.969	0.984	1.632**
	(0.318)	(0.887)	(0.044)
Female	0.959	0.812	
	(0.411)	(0.210)	
family_farm	0.780***	0.297***	
	(0.000)	(0.000)	
extra	1.044	1.038	1.359
	(0.423)	(0.843)	(0.521)
organic	1.010	1.090	
	(0.900)	(0.776)	
edu_sup_laurea	1.036	0.906	
	(0.515)	(0.592)	
Log_alt_med	0.705***	0.229***	
	(0.000)	(0.000)	
Log_area_inclinata	0.929	1.266	
	(0.509)	(0.438)	
Log_tess_sciolto	1.012	1.336	
	(0.897)	(0.366)	
Log_tess_medio	0.601**	0.308	
	(0.014)	(0.103)	
Log_tess_argilla	0.905	0.746	
	(0.201)	(0.295)	

Ln_fonte_interna	1.496***	4.930***	1.492***
	(0.000)	(0.000)	(0.001)
Log_aiuti_EU	0.695***	0.233***	0.687
	(0.000)	(0.000)	(0.219)
Log_aiuti_nonEU	1.098***	1.349***	1.227
	(0.003)	(0.007)	(0.118)
Log_costoAEC	1.066	1.190	0.839
	(0.136)	(0.244)	(0.353)
Log_assicurazioni	1.173***	1.874***	1.491***
	(0.000)	(0.000)	(0.001)
nord_ovest	0.467***	0.052***	
	(0.000)	(0.000)	
nord_est	0.424***	0.020***	
	(0.000)	(0.000)	
sud	1.632***	10.737***	
	(0.000)	(0.000)	
isole	3.101***	165.864***	
	(0.000)	(0.000)	
Log_ROI	1.081	6.144	0.163
	(0.919)	(0.499)	(0.762)
Log_Leverage	3.773	2,627.417	4.392e+23
	(0.213)	(0.231)	(0.100)
AIJFM_ma5lag	0.519***	0.172***	3.751***
	(0.000)	(0.000)	(0.001)
AIAMJ_ma5lag	17.528***	11,708.151***	2.632
	(0.000)	(0.000)	(0.588)
AIJAS_ma5lag	1.159	3.380	56.892***
	(0.534)	(0.261)	(0.009)
AIOND_ma5lag	0.531***	0.125***	0.476**
	(0.000)	(0.000)	(0.026)
Anno_2013	1.135***	1.575***	
	(0.000)	(0.000)	
Anno_2014	1.225***	1.996***	
	(0.000)	(0.000)	
Anno_2015	1.426***	3.480***	
	(0.000)	(0.000)	
Anno_2016	1.466***	4.363***	

	(0.000)	(0.000)	
Log_sup_irr	3.100***	61.720***	11.519***
	(0.000)	(0.000)	(0.000)
Constant	0.001	0.000	
	(0.561)	(0.250)	
Observations	43,917	43,917	3,260
Number of ID	13,054	13,054	846
chi2	2461	2702	309.1
p	0	0	0

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

The second model focuses more on the intensity of adoption in the sub-sample of the farmer adopting WCST, considering technology adoption not only a binary process (adopt or not), but a measure of how much a farmer decide to adopt in terms of land under the innovation employed (Asrlan et al., 2014). In this case it has been measured how much irrigated land, by a farmer who decide to adopt WCST, is dedicated to WCST.

Considering a censored distribution, in which an important part of the observation is lower bounded, one can consider the coefficients estimated using a Tobit model as marginal effect of the covariates over a continuous dependent variable (Greene, 2003). Using the logarithmic form of both the dependent and the continuous independent variables it is possible to obtain an interpretation of the coefficients in terms of elasticity. Therefore, the estimated coefficient represents the change in land under WCST by 1% change of the explanatory variables (Greene, 2003). In other words, the Tobit model (both Tobit random effects and CRE Tobit) indicates the incremental extension of lands under WCST depending by a change of each analyzed covariates, considering all the other variable as fixed. The analysis of intensity has been performed over 8.228 uncensored observations, which have values of irrigated land under WCST higher than zero, whereas 35.689 left-censored observations have been excluded by the modelling system. The results of the models are shown in Table 3 and 4.

The significant estimated coefficients for the intensity analysis at national level are completely the same of the ones for the binary response model with the same sign, which indicate consistency of the overall results. But in this last case the answer the coefficients give is different. For example, in this case the coefficient of the size of the farm (which is -1.328 for the random effects and -1.340 for the CRE) indicates that a change of 1% in the size of the farm reduce by -1.3% the size of irrigated land with WCST. For dummy variables the meaning is the same, but the effect is related to a change from a state of existence or not existence of the dummy condition. For example, being a high value crop farm indicates that the adoption of high value crop for a farm (compared to not adopting it) increase the level of land under WCST by 0.87%.

The only difference from the previous analysis is that in the case of intensity the area of mixed type of soil reduce the quantity of land under WCST by -0.29% (CRE Probit) for each unitary increase in that variable. Another difference is for the cost of energy and water which reduces the size of land under WCST by -0.096% (CRE Probit), for each additional percent unitary increment of energy and water costs. This last result could depend on the high intensity of energy needed by WCST which affect the size of land dedicated to WCST.

The Tobit random effects model has also been used to analyze the effects on the intensity of adoption on land of WCST irrigation for the Italian macro-areas (as before north-west, north-east, center, south and islands). The overall results follow the scheme of the national analysis just described above. The only differences are for: the value of agricultural land (negative sign -0.5% for the north-west), organic farming (positive sign 0.8% for north-west and 0.5% for center), high education (negative sign -0.3% for the north-east), acclivity (negative for the north-east -0.5% and positive for the islands 0.4%), mixed soil type (negative for north-east and islands -0.6% and -0.5% respectively, positive for south 0.4%), cost of water of energy (positive for north-east 0.3%) and leverage (positive for the south 19%).

For climatic variables the effects are similar to the national results, but with negative values AI also for warm seasons (spring for center and summer for north-east, south and islands), which release clear information over the negative effect of AI on WCST adoption at regional level. Counterintuitive signs of AI coefficient are just for winter in north-west regions and autumn in central regions.

Table 3. Intensity analysis the estimation of the Tobit model at national level (both random effects Tobit and Correlated Random Effects).

VARIABLES	**(1)**	**(3)**
	1 Tobit Model Aridity Index	**3 Tobit Model CRE**
Log_Htot_working	0.391***	0.243***
	(0.000)	(0.000)
crop_alto_valore	0.869***	0.830***
	(0.000)	(0.000)
crop_type_mixed	0.402***	0.388***
	(0.000)	(0.000)
livestock	-1.817***	-1.846***
	(0.000)	(0.000)
Log_terreni_agricoli	-0.105	-0.168**
	(0.135)	(0.019)
Log_SAU	-1.328***	-1.340***
	(0.000)	(0.000)
Log_SAU_Affitto	-0.223***	-0.241***
	(0.006)	(0.003)
eta	0.008	0.007
	(0.441)	(0.481)
eta2	-0.000*	-0.000*
	(0.062)	(0.081)
Log_KWMacchine	0.013	-0.033
	(0.674)	(0.311)
Female	-0.060	-0.048
	(0.243)	(0.355)
family_farm	-0.403***	-0.314***
	(0.000)	(0.000)
extra	0.042	0.086
	(0.464)	(0.139)
organic	0.104	0.100
	(0.202)	(0.226)
edu_sup_laurea	-0.009	-0.007
	(0.873)	(0.899)
Log_alt_med	-0.393***	-0.387***
	(0.000)	(0.000)
Log_area_inclinata	0.009	0.005

	(0.907)	(0.956)
Log_tess_sciolto	0.176**	0.152**
	(0.011)	(0.030)
Log_tess_medio	-0.234	-0.286**
	(0.102)	(0.047)
Log_tess_argilla	-0.035	-0.048
	(0.572)	(0.449)
Ln_fonte_interna	0.445***	0.437***
	(0.000)	(0.000)
Log_aiuti_EU	-0.402***	-0.411***
	(0.000)	(0.000)
Log_aiuti_nonEU	0.062**	0.062**
	(0.017)	(0.028)
Log_costoAEC	-0.045	-0.096**
	(0.218)	(0.011)
Log_assicurazioni	0.161***	0.118***
	(0.000)	(0.000)
nord_ovest	-1.177***	-1.128***
	(0.000)	(0.000)
nord_est	-1.103***	-1.090***
	(0.000)	(0.000)
sud	0.822***	0.836***
	(0.000)	(0.000)
isole	1.479***	1.508***
	(0.000)	(0.000)
Log_ROI	-0.388	-0.667
	(0.631)	(0.434)
Log_Leverage	2.383	1.909
	(0.426)	(0.550)
AIJFM_ma5lag	-0.336***	-0.341***
	(0.001)	(0.001)
AIAMJ_ma5lag	2.396***	2.290***
	(0.000)	(0.000)
AIJAS_ma5lag	0.574**	0.541**
	(0.014)	(0.022)
AIOND_ma5lag	-0.605***	-0.597***
	(0.000)	(0.000)

Anno_2013	0.104***	0.105***
	(0.000)	(0.000)
Anno_2014	0.131***	0.136***
	(0.000)	(0.000)
Anno_2015	0.257***	0.262***
	(0.000)	(0.000)
Anno_2016	0.314***	0.315***
	(0.000)	(0.000)
Log_sup_irr	1.733***	1.718***
	(0.000)	(0.000)
mean_Log_Htot_working		0.403***
		(0.000)
mean_Log_aiuti_nonEU		0.011
		(0.878)
mean_Log_assicurazioni		0.219***
		(0.001)
mean_Log_ROI		1.799
		(0.472)
mean_Log_Leverage		1.178
		(0.947)
Constant	-11.862	-37.109
	(0.635)	(0.776)
Observations	43,917	43,917
Number of ID	13,054	13,054
chi2	4531	4523
p	0.000	0.000

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-regional 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 WCST 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 WCST 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 WCST. 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 WCST 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 WCST. The most important seasons in conditioning the probability of adoption seem to be autumn and winter in which precipitations influence negatively, whereas conversely temperature and evapotranspiration do it positively. 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 WCST, therefore it indicates the influence of past climatic conditions on the farmers' decisional schemes of adoption.

However, these results have open more questions on the role of warm periods in irrigation adoption, in fact spring and summer values of precipitation, temperature, ET0 and AI are significant, but with opposite sign than what expected. Some suggestion can be related to the perception of famers which is more influenced by past climatic conditions during cold season, whereas they do not take into consideration (or they not perceive) changes in warm seasons. Anyway, light different regional patterns arose from our analysis.

In terms of intensity, the extension of the irrigated land with WCST mainly follow the decision pattern of adoption with only few regional differences. Among other, the most interesting differences are related to organic farming, cost of water of energy and financial leverage which seem to be relevant at macro-regional level in influencing positively the intensity of WCST adoption, but those variable lose significance at national level.

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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Appendixes

Table 4. Results of Random effects Probit model for macro regions.

	(1)	**(2)**	**(3)**	**(4)**	**(5)**
VARIABLES	**Probit Model RE -North West**	**Probit Model RE - North East**	**Probit Model RE - Centre**	**Probit Model RE - South**	**Probit Model RE - Islands**
Log_Htot_working	0.464***	0.474**	0.850***	0.537**	1.586***
	(0.003)	(0.011)	(0.000)	(0.021)	(0.000)
crop_alto_valore	1.858***	2.022***	0.616***	1.202***	3.604***
	(0.000)	(0.002)	(0.000)	(0.000)	(0.000)
crop_type_mixed	0.719*	1.197***	-0.156	1.193***	0.777
	(0.061)	(0.000)	(0.506)	(0.005)	(0.371)
livestock	-1.454***	-1.861	-2.899***	-4.101**	-12.796***
	(0.005)	(0.288)	(0.000)	(0.023)	(0.000)
Log_terreni_agricoli	-0.688***	-0.131	-0.276	0.034	1.244
	(0.002)	(0.772)	(0.441)	(0.969)	(0.449)
Log_SAU	-2.936***	-1.505	-2.323**	-4.519***	-2.359
	(0.005)	(0.265)	(0.028)	(0.009)	(0.430)
Log_SAU_Affitto	-0.163	0.230	-0.228	-0.344	1.370
	(0.704)	(0.693)	(0.532)	(0.651)	(0.207)
eta	0.011	0.025	-0.028	0.070	-0.151
	(0.806)	(0.656)	(0.373)	(0.121)	(0.227)
eta2	-0.000	-0.000	0.000	-0.001**	0.001
	(0.453)	(0.336)	(0.471)	(0.043)	(0.342)
Log_KWMacchine	0.047	-0.031	-0.345***	0.517**	-0.549*
	(0.595)	(0.845)	(0.002)	(0.014)	(0.067)
Female	0.269	-0.537*	-0.277*	-0.197	0.614
	(0.123)	(0.069)	(0.061)	(0.358)	(0.252)
family_farm	-1.140***	0.057	0.390	-0.488*	-1.674**
	(0.000)	(0.903)	(0.127)	(0.057)	(0.039)
extra	0.378*	-0.146	-0.578***	0.239	-0.964

	(0.065)	(0.639)	(0.001)	(0.411)	(0.107)
organic	0.983*	-0.652	0.621**	0.300	-0.978
	(0.082)	(0.345)	(0.023)	(0.249)	(0.262)
edu_sup_laurea	-0.126	-0.267	-0.077	-0.133	0.225
	(0.523)	(0.296)	(0.630)	(0.585)	(0.696)
Log_alt_med	-0.653***	-0.195**	-0.523***	-1.704***	-1.276***
	(0.000)	(0.021)	(0.000)	(0.000)	(0.000)
Log_area_inclinata	0.037	0.189	-0.534*	0.013	2.639*
	(0.901)	(0.763)	(0.094)	(0.981)	(0.052)
Log_tess_sciolto	0.301	-0.595	-0.110	0.474	-0.462
	(0.373)	(0.320)	(0.781)	(0.289)	(0.643)
Log_tess_medio	-0.858	-1.017*	-0.095	0.965	-2.643
	(0.149)	(0.076)	(0.903)	(0.383)	(0.254)
Log_tess_argilla	-0.204	-0.240	0.111	0.103	-2.084***
	(0.551)	(0.386)	(0.651)	(0.785)	(0.007)
Ln_fonte_interna	0.849***	0.182	0.473***	0.852***	2.786***
	(0.000)	(0.294)	(0.000)	(0.004)	(0.000)
Log_aiuti_EU	-0.337	-0.881***	0.086	-0.089	-3.267***
	(0.315)	(0.001)	(0.700)	(0.819)	(0.007)
Log_aiuti_nonEU	0.509***	0.200	0.317***	0.006	-0.086
	(0.000)	(0.129)	(0.003)	(0.974)	(0.772)
Log_costoAEC	0.540***	-0.176	0.099	0.598*	0.064
	(0.002)	(0.354)	(0.487)	(0.088)	(0.928)
Log_assicurazioni	0.554***	0.361***	-0.036	-0.033	0.578
	(0.000)	(0.004)	(0.791)	(0.910)	(0.225)
Log_ROI	-1.886	0.796	1.659	1.451	-19.375*
	(0.715)	(0.728)	(0.682)	(0.650)	(0.094)
Log_Leverage	-4.954	1.601	23.070*	89.208**	-55.998
	(0.640)	(0.957)	(0.081)	(0.012)	(0.413)
AIJFM_ma5lag	2.149***	-0.339	-1.380**	-8.866***	-0.776
	(0.000)	(0.642)	(0.012)	(0.000)	(0.825)
AIAMJ_ma5lag	3.143**	9.198	-6.861***	29.445***	-14.511
	(0.028)	(0.151)	(0.001)	(0.000)	(0.100)
AIJAS_ma5lag	-0.659	-4.344***	2.958	-11.269***	-32.330
	(0.534)	(0.000)	(0.155)	(0.000)	(0.128)
AIOND_ma5lag	-0.932*	-0.488	1.377***	-6.165***	3.292
	(0.085)	(0.605)	(0.003)	(0.000)	(0.286)

Anno_2013	0.255*	0.122	0.085	0.723***	0.018
	(0.057)	(0.558)	(0.515)	(0.000)	(0.941)
Anno_2014	-0.111	-0.100	0.342**	1.929***	0.863
	(0.543)	(0.622)	(0.023)	(0.000)	(0.110)
Anno_2015	-0.067	0.553*	0.548***	1.186***	0.573
	(0.834)	(0.086)	(0.006)	(0.000)	(0.299)
Anno_2016	0.134	0.573**	0.708***	1.825***	1.081
	(0.632)	(0.043)	(0.001)	(0.000)	(0.122)
Log_sup_irr	1.212***	2.073***	1.984***	3.575***	4.588***
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	63.620	-20.749	-196.003*	-701.686***	675.525
	(0.515)	(0.929)	(0.084)	(0.009)	(0.226)
lnsig2u					
Constant	2.201***	2.858	1.891***	2.997***	4.189
	(0.000)	(.)	(0.000)	(0.000)	(.)
Observations	9,955	9,903	9,877	9,823	4,359
Number of ID	2,645	2,874	3,260	2,903	1,372
chi2	329.3	451.4	501.1	1058	1623
p-value	0.000	0.000	0.000	0.000	0.000

Table 5. Results of Population average Probit model for macro regions.

	(1)	**(2)**	**(3)**	**(4)**
VARIABLES	**Probit Model-PA North West**	**Probit Model-PA North East**	**Probit Model-PA Centre**	**Probit Model-PA South**
Log_Htot_working	0.202**	0.137***	0.359***	0.015
	(0.015)	(0.001)	(0.000)	(0.763)
crop_alto_valore	1.008***	0.552***	0.271***	0.365***
	(0.000)	(0.000)	(0.000)	(0.000)
crop_type_mixed	0.712***	0.318***	-0.046	0.292***
	(0.000)	(0.000)	(0.600)	(0.004)
livestock	-0.405**	-0.531***	-1.187***	-1.111***
	(0.026)	(0.000)	(0.000)	(0.000)
Log_terreni_agricoli	-0.181*	-0.092	-0.107	-0.184

	(0.054)	(0.409)	(0.536)	(0.209)
Log_SAU	-1.013	-0.287	-0.742	-1.057***
	(0.127)	(0.366)	(0.112)	(0.002)
Log_SAU_Affitto	0.110	-0.038	-0.188	-0.129
	(0.611)	(0.844)	(0.209)	(0.397)
eta	-0.016	0.013	-0.014	0.024**
	(0.410)	(0.280)	(0.289)	(0.035)
eta2	0.000	-0.000	0.000	-0.000***
	(0.734)	(0.113)	(0.432)	(0.010)
Log_KWMacchine	0.000	-0.012	-0.134***	0.095**
	(0.998)	(0.776)	(0.006)	(0.033)
Female	0.029	-0.068	-0.075	-0.080
	(0.750)	(0.194)	(0.231)	(0.196)
family_farm	-0.279**	0.004	0.249**	-0.113*
	(0.034)	(0.972)	(0.032)	(0.078)
extra	0.142	-0.013	-0.182**	0.021
	(0.178)	(0.805)	(0.011)	(0.766)
organic	0.118	-0.340*	0.212*	-0.048
	(0.625)	(0.074)	(0.073)	(0.528)
edu_sup_laurea	-0.014	-0.056	-0.046	-0.017
	(0.863)	(0.413)	(0.497)	(0.793)
Log_alt_med	-0.200***	-0.015	-0.196***	-0.351***
	(0.000)	(0.577)	(0.000)	(0.000)
Log_area_inclinata	0.087	0.001	-0.317***	-0.024
	(0.573)	(0.993)	(0.002)	(0.899)
Log_tess_sciolto	-0.123	-0.199**	-0.090	0.196*
	(0.450)	(0.027)	(0.586)	(0.088)
Log_tess_medio	-0.989***	-0.295*	-0.085	0.227
	(0.004)	(0.075)	(0.788)	(0.390)
Log_tess_argilla	-0.306**	-0.064	0.053	0.048
	(0.047)	(0.394)	(0.610)	(0.583)
Ln_fonte_interna	0.429***	0.053	0.207***	0.198***
	(0.000)	(0.167)	(0.000)	(0.000)
Log_aiuti_EU	-0.326*	-0.197***	-0.060	0.097
	(0.066)	(0.003)	(0.568)	(0.215)
Log_aiuti_nonEU	0.096	0.066**	0.139**	-0.011
	(0.176)	(0.032)	(0.016)	(0.820)

Log_costoAEC	0.198**	-0.025	0.006	0.234***
	(0.021)	(0.624)	(0.926)	(0.004)
Log_assicurazioni	0.300***	0.078***	-0.018	-0.032
	(0.000)	(0.005)	(0.754)	(0.641)
Log_ROI	-2.007	-0.283	0.684	0.311
	(0.623)	(0.593)	(0.665)	(0.752)
Log_Leverage	-3.584	-5.613	7.625***	17.992**
	(0.492)	(0.689)	(0.005)	(0.020)
AIJFM_ma5lag	0.967***	-0.215	-0.683***	-2.326***
	(0.001)	(0.151)	(0.001)	(0.000)
AIAMJ_ma5lag	0.348	1.736***	-1.786**	7.778***
	(0.607)	(0.000)	(0.029)	(0.000)
AIJAS_ma5lag	0.193	-0.615***	0.573	-4.096***
	(0.688)	(0.003)	(0.472)	(0.000)
AIOND_ma5lag	-0.192	-0.175	0.531***	-1.412***
	(0.490)	(0.172)	(0.002)	(0.000)
Anno_2013	0.072	0.052	0.026	0.231***
	(0.203)	(0.293)	(0.565)	(0.000)
Anno_2014	-0.117	0.043	0.160***	0.505***
	(0.122)	(0.404)	(0.003)	(0.000)
Anno_2015	-0.205	0.191**	0.250***	0.344***
	(0.152)	(0.017)	(0.001)	(0.000)
Anno_2016	-0.093	0.165***	0.307***	0.539***
	(0.509)	(0.000)	(0.000)	(0.000)
Log_sup_irr	0.786***	0.565***	0.715***	1.024***
	(0.000)	(0.000)	(0.000)	(0.000)
Constant	54.815	47.420	-65.160**	-140.531**
	(0.370)	(0.670)	(0.042)	(0.018)
Observations	9,955	9,903	9,877	9,823
Number of ID	2,645	2,874	3,260	2,903
chi2	443.1	482.2	622.1	752.6
p	0	0	0	0

Table 6. Intensity analysis the estimation of the Tobit model at regional level (both random effects Tobit).

	(1)	(2)	(3)	(4)	(5)
VARIABLES	**Tobit Model-North West**	**Tobit Model-North East**	**Tobit Model-Centre**	**Tobit Model-South**	**Tobit Model-Islands**

Log_area_micro

Log_Htot_working	0.318***	0.325***	0.641***	0.193***	0.118**
	(0.002)	(0.000)	(0.000)	(0.000)	(0.040)
crop_alto_valore	1.591***	1.196***	0.576***	0.405***	0.436***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
crop_type_mixed	0.640***	0.672***	-0.082	0.356***	0.107
	(0.002)	(0.000)	(0.603)	(0.000)	(0.319)
livestock	-1.048***	-1.489***	-2.333***	-1.950***	-2.123***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Log_terreni_agricoli	-0.553***	-0.010	-0.037	-0.063	-0.032
	(0.001)	(0.933)	(0.877)	(0.700)	(0.882)
Log_SAU	-1.763***	-1.157***	-2.557***	-1.408***	-0.811***
	(0.003)	(0.003)	(0.000)	(0.000)	(0.002)
Log_SAU_Affitto	-0.334	0.338*	0.020	-0.172	0.074
	(0.170)	(0.054)	(0.939)	(0.191)	(0.620)
eta	0.011	0.009	-0.028	0.017	-0.022
	(0.723)	(0.729)	(0.319)	(0.215)	(0.201)
eta2	-0.000	-0.000	0.000	-0.000*	0.000
	(0.442)	(0.367)	(0.445)	(0.072)	(0.307)
Log_KWMacchine	0.013	-0.000	-0.175*	0.163***	-0.099
	(0.867)	(0.998)	(0.054)	(0.002)	(0.137)
Female	0.179	-0.154	-0.235*	-0.085	-0.061
	(0.203)	(0.162)	(0.095)	(0.263)	(0.519)
family_farm	-0.842***	0.014	0.295	-0.230***	-0.354***
	(0.000)	(0.942)	(0.140)	(0.005)	(0.001)
extra	0.248	-0.049	-0.428**	0.087	-0.134
	(0.123)	(0.677)	(0.011)	(0.318)	(0.201)
organic	0.843**	-0.286	0.531**	0.147	-0.025
	(0.013)	(0.251)	(0.027)	(0.116)	(0.850)
edu_sup_laurea	-0.057	-0.292**	-0.055	-0.044	0.123
	(0.713)	(0.023)	(0.703)	(0.618)	(0.277)
Log_alt_med	-0.415***	-0.044	-0.385***	-0.640***	-0.126**
	(0.000)	(0.431)	(0.000)	(0.000)	(0.023)
Log_area_inclinata	0.102	0.249	-0.557**	-0.078	0.438***
	(0.639)	(0.208)	(0.021)	(0.582)	(0.002)

Log_tess_sciolto	0.230	-0.390**	0.073	0.260**	0.045
	(0.297)	(0.012)	(0.749)	(0.024)	(0.633)
Log_tess_medio	-0.527	-0.626**	0.319	0.418*	-0.557**
	(0.190)	(0.027)	(0.539)	(0.092)	(0.019)
Log_tess_argilla	-0.131	-0.082	0.205	0.058	-0.239**
	(0.520)	(0.531)	(0.272)	(0.564)	(0.030)
Ln_fonte_interna	0.686***	0.136***	0.376***	0.301***	0.509***
	(0.000)	(0.007)	(0.000)	(0.000)	(0.000)
Log_aiuti_EU	-0.096	-0.492***	-0.058	0.069	-0.413***
	(0.635)	(0.000)	(0.754)	(0.435)	(0.000)
Log_aiuti_nonEU	0.177**	0.143***	0.241***	-0.056	-0.006
	(0.038)	(0.006)	(0.005)	(0.161)	(0.856)
Log_costoAEC	0.291***	-0.064	-0.012	0.094	-0.104
	(0.007)	(0.374)	(0.905)	(0.142)	(0.156)
Log_assicurazioni	0.323***	0.152***	0.012	0.021	0.038
	(0.000)	(0.000)	(0.902)	(0.687)	(0.428)
o.nord_ovest	-	-	-	-	-
Log_ROI	-0.270	-0.665	2.637	-0.878	-1.404
	(0.932)	(0.768)	(0.453)	(0.253)	(0.472)
Log_Leverage	-1.099	-15.722	9.348	19.256**	-6.225
	(0.926)	(0.438)	(0.262)	(0.015)	(0.356)
AIJFM_ma5lag	1.511***	-0.810**	-1.370***	-3.062***	-0.126
	(0.000)	(0.021)	(0.002)	(0.000)	(0.815)
AIAMJ_ma5lag	3.094***	3.557***	-4.757***	9.256***	-1.861
	(0.001)	(0.000)	(0.004)	(0.000)	(0.181)
AIJAS_ma5lag	-0.771	-1.046**	1.532	-3.219***	-7.307***
	(0.317)	(0.019)	(0.388)	(0.000)	(0.007)
AIOND_ma5lag	-0.716*	-0.756***	0.916**	-1.943***	-0.216
	(0.055)	(0.001)	(0.015)	(0.000)	(0.692)
Anno_2013	0.147	0.214**	0.010	0.245***	-0.005
	(0.135)	(0.025)	(0.928)	(0.000)	(0.910)
Anno_2014	-0.193*	0.244**	0.317***	0.589***	0.084
	(0.096)	(0.019)	(0.004)	(0.000)	(0.251)
Anno_2015	-0.098	0.654***	0.481***	0.391***	-0.006
	(0.633)	(0.000)	(0.001)	(0.000)	(0.935)
Anno_2016	0.115	0.375***	0.585***	0.645***	0.064

	(0.520)	(0.000)	(0.000)	(0.000)	(0.502)
Log_sup_irr	1.116***	1.748***	2.172***	2.097***	2.249***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	13.423	128.754	-103.774	-138.085**	69.378
	(0.891)	(0.409)	(0.163)	(0.026)	(0.212)
Observations	9,955	9,903	9,877	9,823	4,359
Number of ID	2,645	2,874	3,260	2,903	1,372
chi2	525.8	712.4	831.7	2744	1407
p-value	0.000	0.000	0.000	0.000	0.000