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

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Paper prepared for presentation at the 8th AIEAA Conference
“Tomorrow’s Food: Diet transition and its implications on health and the environment”

13-14 June, 2019
Pistoia, Italy

Summary

The Mediterranean basin is one of the main critical areas in terms of water scarcity and water stress. Southern European countries shown high levels of water scarcity with forecasted increased in frequency and impacts of droughts and endangering changes in precipitations. One of the main driver of this condition is irrigation for 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 are the factors driving the decision of farmers in adopting water saving technologies in their irrigation schemes.

In this paper it is developed an analysis on what are the principal determinants of Italian farmers’ adoption of sustainable irrigation technologies. In this study micro-irrigation (drip and sprinklers) and sub-irrigation technologies are considered sustainable technologies in water management as they can help water conservation reducing water stress. The main objective of the study is to analyze what are the main relevant factors influencing the farmer decisions in the adoption of sustainable irrigation technologies considering social, economic, productive, geographical and climatic aspects. The study has a micro prospective and it is focused on Italian farms.

This paper analyzes what are the principal factors influencing water efficient technology adoption using an econometric model with both a binary response (Logit) to understand the determinants of innovation and a Log-Log to investigate the determinants of the intensity of it using an unbalanced panel data from 2012 to 2016. The data used in this paper are from the Italian database of the Agricultural Accounting Information Network associated to climatic data from Euro-Mediterranean Center for Climate Change in order to test if climatic and weather conditions do influence sustainable irrigation technology adoptions.

Keywords: Water Conserving and Saving Technology, Sustainable irrigation, Italian agriculture, Water scarcity, Technology adoption

JEL Classification codes: Q01, Q12, Q25

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1. INTRODUCTION

World population is continuously growing and by 2050 it will reach 9.7 billion people (Undesa, 2018). One of the main challenge that humankind should face is to assure agricultural production patterns in order to guarantee food and drinkable water availability for all people, to avoid the intensification of inequalities between and within rich and poor countries and finally to reduce the possibilities of extreme scenarios such as mass migrations, uprisings and civil wars around the globe (Homer-Dixon, 1999). Nowadays almost 800 million people are undernourished and 2 billion suffer micronutrient deficiencies (FAO, IFAD and WFP, 2015). Projections on global food demand patterns draw a situation that could even worsen if economic growth and agricultural development would be hampered in providing enough available food for all.

One of the main constraints in guaranteeing global food security is water scarcity (Alexandratos and Bruinsma, 2012). Several causes such as climate change, population growth, desertification and urbanization are putting pressures on water resources and are exacerbating the water scarcity issue. This is particularly true for the allocation of water in the arid regions. 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 continent (De Angelis et al., 2017; Hoekstra and Mekonnen, 2016). Disinterest in this topic could lead to hard consequences to human security and geopolitical stability (Un, 2015). Despite this situation, in this last century water use increased all over the world doubling the rate of population growth over the same period (Un, 2018).

Agriculture is responsible for almost 70% of global freshwater withdrawal whose main use is for intensive irrigation of crops with the majority quantity that is not absorbed by plants, but lost through evaporation, percolation and runoff (Mea, 2005). Global water reservoirs declined steadily during the last century. One of the most important drivers of the increasing pressures on water resources was the excessive withdrawal and 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. This also has an impact on public health (Hoekstra and Mekonnen, 2012; Mea, 2005). Furthermore, climate change with the consequence of more frequent extremes adverse weather conditions and serious water shortages is worsening agriculture and food production in several sensitive zones such as in the arid and semi-arid areas of Latin America, Africa and the central part of Asia (Saravia-Matus et al., 2012). 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 (Mestre-Sanchís and Feijóo-Bello, 2009; Olsen and Bindi, 2002). Therefore, water demand for agricultural products may drastically increase due to potential evapotranspiration rises. Water peak requirements and higher water use per hectares have serious consequences related to erosions and fertility of soils. This in turn affect water supply through less endowments, excessive reservoirs withdrawals, and greater competition between agricultural and civil services uses (Mestre-Sanchís and Feijóo-Bello, 2009; Olsen and Bindi, 2002; Iglesias et al., 2009). Farmers are the main actors in making choices for applying adaptation strategies to climatic and productive conditions. Therefore, they 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.

Even southern Europe is one of the main areas exposed to climate change in which several countries with similar geographical and pedoclimatic characteristics share similar 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).

In Europe, there are considerable differences among countries in water use withdrawal composition and water availability i.e. 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 also higher levels of water scarcity than Northern ones with a forecasted increase in frequency and impacts of droughts and endangering changes in precipitation (Eu, 2011; Euc, 2012).

In 2000, the European Union, issuing the Water Framework Directive (WFD), put the base for a sustainable water management within all the Union members with the objective of improving the quality of European water basins and water use by 2015 (WFD, 2000). After that time, even if some goals have been reached, the main results are still far behind and important gaps must be filled in terms of water pollution and water withdrawal which remains higher than its natural rate of renovation especially in many Mediterranean countries (WFD Report, 2015). The WFD particularly points out the importance of water conservation in quantitative term supporting water saving policies in order to have a sustainable use of water resources in the long run (Zucaro, 2011). 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 sustainable development strategies (Sauer et al., 2010; FAO, 2017; Bazzani et al., 2005).

Italy is one of the major countries using irrigation for agricultural activities in Europe. Italian agriculture is second in Europe, only after Spain, for the extension of irrigated surfaces with 2.4 millions of ha of irrigated lands and 11 million cubic meters of water used for irrigation and average water use of 4666 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). The majority of Italian agricultural lands is equipped with low efficiency irrigation systems (62% of the total), whereas only 9.6% is equipped with efficient system (considering only drip irrigation), mostly distributed in the Center and Southern macro-areas, especially along the Apennine mountains and the two islands Sicily and Sardinia (Istat, 2010).

Sustainable water management may be pursued through various strategies such as water demand reduction, water availability increase and water efficiency improvement. Reaching 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. 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 improve 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 weed growth (Skaggs, 2001; Alcon et al., 2019).

One of the main issues in achieving sustainability in water management in agriculture is to understand what the main factors are driving the decision of farmers in adopting WCST in their irrigation schemes. An important literature in technology adoption emerged since the sixties (Rogers, 1971) exploring individual factors which influence the decision of implementing innovations with a growing branch of this literature focusing on agriculture both theoretically and empirically (Feder et al., 1985). 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 (Kounduri et al., 2006).

Most of the studies conducted referred to countries and areas with important water problems such as Israel (Yaron et al., 1992); Greece (Kounduri et al., 2006); Spain (Alcon et al., 2011; Alcon et al., 2019; Exposito and Berbel, 2019); Iran (Afrankhteh, 2014; Mohmmadzadeh et al., 2014); India (Dhawan, 2000; Namara et al., 2007; Singh et al., 2015); Tunisia (Foltz, 2003); Chile (Salazar and Rand, 2016; Hunencke et al., 2017); South Africa (Mango et al., 2018); China (He et al., 2007; Yu et al., 2008; Zhou et al., 2008); Madagascar (Moser and Barrett, 2006); Canada – the State of Alberta (Wheeler et al., 2010) –; United States as a whole as in Negri and Brooks, 1990), or as specific regions including several countries of US as in Knapp and Huang (2017) and Pokhrel et al. (2018) or as an individual country: California (Caswell and Zilberman, 1985; Green et al., 1996; Moreno and Sunding, 2005; Taylor and Zilberman, 2017); Hawaii (Sherestha and Gopalakrishan, 1993), Arkansas (Huang et al., 2017), Colorado (Schuck et al., 2005), and New Mexico (Skaggs, 2001) . Among the Mediterranean area, Italy has not been adequately analyzed as a whole with the only exception of some particular zones as 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) 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 second study, 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 but the lack of representability of the sample, due to the reduction of a large and highly capitalized farms database as AIDA based on national companies obliged to present balance sheets, 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.

The importance of deepening farmers' choices of WCST adoption in Italy is mainly related to the fact that the country presents highly diversified orographic and micro-climatic areas. 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 condition make Italy an important case-study within the Mediterranean countries which share similar climatic conditions and longitudinal positions.

The majority of the above mentioned studies with the exception of Bozzola (2014) and Kounduri et al. (2006) relies on one-year case-studies. Using cross-section data limits the analysis to the explanation of why a farmer chooses to use a new technology in that particular period considered and reduces the reliability of 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, etc.. (Kounduri et al., 2006).

This present 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 includes micro-irrigation both drip and sprinkling and sub-irrigation technologies. These different typologies of WCST may help water conservation in agriculture reducing water stress and improving efficiency of irrigation.

So far there have been no studies at country level on WCST adoption with an extensive use of micro data. In this paper, farm level data are used collected from the Italian database of Agricultural Accounting Information Network (*Rete di Informazione Contabile Agricola* - RICA). RICA is at the basis of the European FADN (Farm Accountancy Data Network), which is a 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 these informations 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 13592 farms for five years spanning from 2012 to 2016 for a comprehensive database of 45837 observations.

To test whether climatic and weather conditions do influence sustainable irrigation technology adoptions, the until now 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 potential evapotranspiration (ET0) (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.

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, represent the two intertwined aims of this study. The first aim mainly regards the recognition of which 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 land between irrigated and rainfed areas. Using a binary logit model for the farmers' decision making and a log-log 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, the empirical framework and the methodology is presented, in Section 3 data are described, while in Section 4 results and their discussion are presented.Finally, in Section 5 some main conclusions are reported by deriving some policy recommendations.

2.EMPIRICAL FRAMEWORK AND METHODS

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.

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, while they estimate the intensity of adoption using both a correlated random effects tobit model and a pooled fractional probit model.

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 aims are the population averaged clustered logit model and the fixed effects clustered model in order to consider heteroskedasticity and autocorrelation.

A regards 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:

$$Y_i^* = X_i^T \beta^* + \varepsilon^* \qquad (1)$$

where Y_i^* is the latent utility of the farmer related to irrigation technology, X_i^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). The farmer will adopt the WCST technology if his expectations of the difference between utility expectations of adopting WCST (Y_i^* $when\ Y = 1$) and not adopting WCST (Y_i^* $when\ Y = 0$) is positive (Huang et al., 2017). Since the utility of the farmer i_{th} Y_i^* 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:

$$Y = 1\ if\ Y_i^* > 0$$
$$Y = 0\ if\ Y_i^* \le 0$$

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

$$Pr\ (Y_i = 1)\ = P(X_i) = P\left(\varepsilon_i > X_{i,t}\ \beta^*\right) = 1 - \mathrm{F}(X_{i,t}\ \beta^*)$$

(2)

Where $F(.)$is the distribution function of ε^*which can be well approximated by a logistic distribution (Cramer, 2003). Therefore, the probability that a farmer will adopt WCST assume the form of the logit model, which has been extensively used in the literature on farmers' technology adoption (He et al., 2007; Trinh et al., 2018, Capitanio et al., 2015), 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, . Conversely (1- *Pr* ($Y_{i,t=0}$) is the probability of not adopting WCST (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:

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

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 exponential (Skaggs, 2001). Heteroskedasticity and autocorrelation are very common in binary panel models. In order to avoid inconsistency of the estimated coefficients due to underestimated standard errors, it has been used a population averaged clustered approach (Neuhaus et al., 1991; Neuhaus, 1992).

The second econometric model - the fixed effects clustered model - in the Log-Log form, allows analyzing the intensity of WCST adoption since farmers decides to adopt only partially and after an aridity period. Moreover, defining the elasticities of the WCST used in fields with respect to the main characteristics may be relevant for policy makers. For intensity of adoption, the dependent variable, the logarithm of the extension of fields under WCST for each i*th* farmer is considered. In this form the Log-Log model may be defined as:

$$Log\left(Y_{i,t}\right) = \alpha + \beta_{i,t}\mathrm{Log}\mathrm{X}_{i,t} + \varepsilon_{i,t} \quad (6)$$

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

The Log-Log model, extensively used to estimate elasticity between the dependent variables and the explanatory variables (Wooldridge, 2010; Greene, 2003), allows studying the dynamics of farmers' choice. To the best of our knowledge, until now only Asrlan et al. (2014) have analyzed the intensity of adoption applying a different methodology related to the specific definition of the dependent variable. Moreover, the parsimonious requirement in terms of few and weaker assumptions to justify the fixed-effects estimator and the within model transformation by subtracting the mean value provides unbiased estimates. Another advantage of this methodology is the possibility to control for unobserved heterogeneity.

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. Therefore, to solve both problems and obtain a consistent 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). As indicated by Cameron and Miller (2015), standard errors have been clustered at level of municipalities in order to obtain both the smallest and the most efficient level of clustering. Finally, after having performed the Hausman test on the consistency of the random effects with respect to fixed effects, the rejection of the null hypothesis implies that the fixed effects model is preferred (Greene, 2003). The overall fixed effects model with clustered standard errors resulted in a less efficient model than a random effects with robust standard errors, but resulted in a more robust model with consistent coefficient estimators (Ullah and Gilles, 2011).

3 DATA DESCRIPTION

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 1 and in Table 2 Climatic variables are shown. 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.

3.1 Farm characteristics

3.1.1 Economic dimension (UDE)

The economic dimension of the farm can highly influence the propensity to adopt WCST (Alcon et al., 2019;) this has been captured with the use of dummy variables indicating the eight level of the UDE INEA classification of the economic dimension (no class; 0 - 4000€; 4000€ – 8000€; 8000 – 25000€; 25000€ – 50000€; 50000€-100000€; 100000€ – 500000€; 500000€ - 1000000€; more than 1000000€).

3.1.2 Total work (LogHwork)

Another 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).

3.1.3 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).

3.1.4 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.

3.1.4 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.

3.1.5 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.

3.1.6 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.

3.1.7 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.

3.1.8 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.

3.2. Farmer characteristics

3.2.1 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.

3.2.2 Young (Young)

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). In order to test this assumption a dummy variable indicating whether the farmer is younger than forty years old has been created.

3.2.3 Age (Log Age)

As mentioned above the age of the farmer in logarithmic term has been considered in order to verify how much age is important in influencing the decision of whether or not adopting WCST (Afrakhteh et al., 2015; Doss and Morris., 2001; Salazar and Rand, 2016).

3.2.4 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.

3.2.5 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.

3.2.6 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.

3.3 Geographic characteristics

3.3.1 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.

3.3.2 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).

3.3.3 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.

3.4 Water use characteristics

3.4.1 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.

3.4.2 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.

3.4.3 Water Source (No Source, Source Body, Source Surface Water, Source Pit, Source Pond, Source Tank, Source Other)

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). A set of variables have been created to consider water sources in terms of land irrigated with the following type of water sources: absence of source, Water Authority, Surface water (rivers and lakes), Pit, Artificial Ponds (property or collective), Water Tanks, Other Sources (different from the above). All the areas of land with each type of water source have been used to create a continue variables in logarithmic form.

3.5 Financial characteristics

3.5.1 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.

3.5.2 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).

3.5.3 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).

3.6 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.

3.6.1 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.

3.6.2 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.

3.6.3 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.

3.6.4 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.

3.6.5 Reference Evapotranspiration (ET0)

Reference Evapotranspiration (known also as Potential Evapotranspiration) (ET0) 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 ET0 in different time and space (Allen et al., 1998). ET0 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 ET0, or their rate (Cumulated Precipitation / ET0) can be used as an indicator of crop water requirements. ET0 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).

3.6.6 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:

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

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)

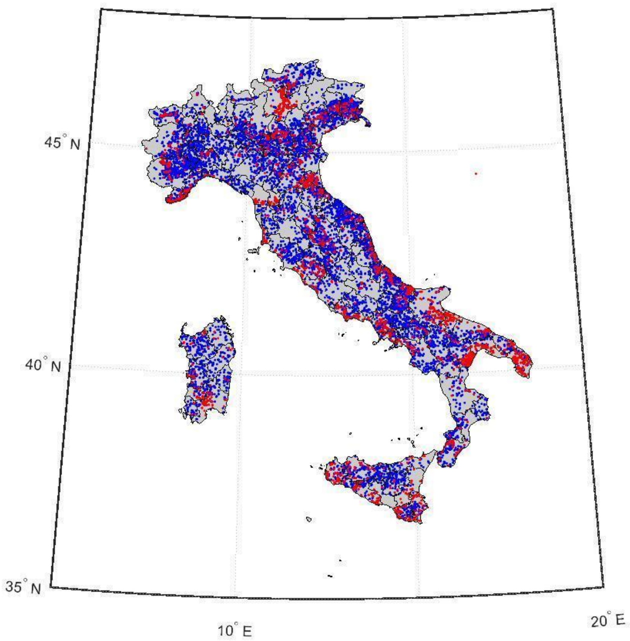
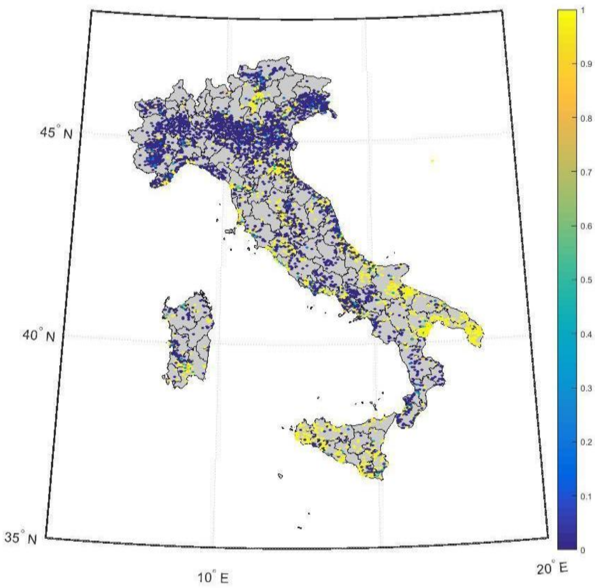


Fig 2. Area under WCST on proportion over the total irrigated land for each farm from 2012 to 2012. (Our own elaboration)



4. MAIN RESULTS AND DISCUSSION

All the results are reported from Table 3 to Table 6. Distinguishing between all the Italian farmers and the macro-areas of Italy (North-west, North-east, Centre, South and Islands), the first two tables present the robust-errors population averaged logit estimations, while the last two estimations regard the clustered fixed-effects estimation. Within each estimation, different models are compared in terms of weather variables included and for robustness check.

All the coefficients of the two estimations within the different models present more or less constant magnitudes and the same signs for the variables included indicating that both the Logit model and the Log-Log model 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.

4.1 Results of the Logit model

Table 3 and Table 4 present the micro-irrigation technologies adoption based on population averaged logit model with robust standard errors or White-Huber standard errors, in order to cope with heteroskedasticity and autocorrelation issues. The first estimation is over the all sample considering all Italian farms, while the second is at macro-regional levels based on only the more significant explanatory variables of the first estimation. This latter has been conducted in order to consider if it is statistically relevant a different decision pattern among the different macro areas in Italy as the descriptive statistics have underlined in Fig. 1 and Fig. 2. In both estimations the odds ratio are reported instead of the coefficients.

The logit model 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. The odds-ratio 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. For instance, a positive change of 1% in the size of UAA, holding the other variables at a fixed value, reduces the probability to adopt WCST for the average farmer of about 0.38%.

As expected crop type variables (olives, fruits, viticulture, horticulture, oil seeds and mixed production) are highly statistically significant and positively influence the probability of adopting WCST. All of them have high values, the most influential are fruticulture, viticulture and horticulture since they are the higher valuable cultivations. 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 size of the farm 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 might depend on diseconomy of scale related to the use of sophisticated technologies which rely on time available, human skills and labor and not only dimensions. This result is 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.

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 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 especially in . 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 as proportion over the whole utilized agricultural land.

As regards the farmers' characteristics, Family Farm is highly significant, but with negative coefficient revealing that if a farm is conducted principally by a 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.

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.

The estimated coefficient of Female, Organic, and Extra are not significative, suggesting that those elements are not essential for adopting WCST. Besides, the Young dummy variable is not significative meaning that being under forty years old does not influence the probability of adoption WCST. Conversely, the variable Age is highly significant and it has negative impacts on the dependent variable suggesting that older farmers have less probability to adopt WCST than younger farmers, in line with Alcon et al. (2019), Mango et al. (2018), Namara et al. (2007) and Huang et al. (2017). Moreover, this result indicates that using a continue variable is better than a dummy in capturing the willingness to undertake investments in new technologies.

As expected the estimated coefficient of the variable indicating the level of education (High Education) is positive, confirming that high levels of education positively 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.

The odds-ratios 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.

All variables related to water source are highly significant all of them with positive signs. Among the most significant one there are land with water availability from a basin authority, superficial water, wells and ponds, all these dummy variables increase the probability of adopting WCST. As expected water costs (considering also energy and electricity costs) positively influence the probability for a farmer to adopt WCST.

For the financial characteristics, 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. As regards the last two variables which describe the financial situations of Italian farms, ROI and Leverage, they show not significant odds ratios, meaning that farmers' decision is not related to the indebtment of farm and to the capability to generate an adequate return on investments.

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 adopt WCST systems and continue to show a higher propensity in adopting the macro-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 odds ratio meaning that for a farm located in those regiones the availability of adopting WCST is reduced.

As regards the climate explanatory variables, highly significance of the odds ratio is shown in the logit estimation for most of the seasons and for all the different moving average considered. The only variable - not included in the tables - because of low significance is the minimum average both if it is considered in terms of season and in terms of different moving average.

All the estimated coefficients are significant for seasonal maximum temperature and cumulative precipitations for all the different moving averages considered. However, some of them present counterintuitive signs especially for spring and summer. In fact, the estimated coefficients of the warm season 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 autumn and winter 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 the hot seasons hotter.

ET0 is highly significant and as expected only for winter season too. Whereas for spring season either the estimated coefficient is also significant, but the sign is opposite than what expected (negative) with not many possible explanations on this effect on the dependent variable. ET0 for summer and autumn are not significant.

The AI is highly significant for all the seasons for the 5 years moving average, but either in this case the signs of spring and summer seasons are opposite to what expected (negative) 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, higher levels of the aridity index reduce the probability of WCST adoption, this is because higher levels AI, calculated as the rate between precipitation and evapotranspiration, means that precipitation had covered part of the water needs for the development of crops. This pattern occurs also with 3 years moving average, with the only difference that the autumn AI variable is significant.

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 ET0 and precipitation with statistical significance in determining the adoption of WCST. 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 an AI are significant but with opposite sign than what expected.

It has been carried out an analysis at macro-area level running four different population averaged logit models. The results are very similar to the general model and not many differences arise between macro areas. The main differences are that age, education and family farm lose statistical significance in the regional models (apart for the Centre), suggesting that within macro areas those factors seem to do not 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.

All the water source variables are significant as in the general model, only for North-East both pond and tank are not significant and for Centre only tank. For these two regions also EU funds lose statistical significance. Also for the climatic variables the pattern is similar to the general model with not apparent intuitive scheme for none of the macro areas.

4.2 Results of the Log-Log model

The second model focuses more on the intensity of adoption in the sub-sample of the farmer adopting WCST, in terms of elasticity so the coefficient represents the change in land under WCST by 1% change of the explanatory variables. In other words, the log-log model indicates the incremental extension of lands with WCST. The results are shown in the appendix (Table 5 and 6). In this model, most of the dummy variables have been omitted because of the properties of the Fixed Effect technique, so it is not possible to give any indications for crop type, gender, extra income and organic. The model has lost significance compared to the logit model and only water source variables and total hours of work in the farm are highly significant as in the previous analysis.

Anyway some differences arise. The total machine power of the farm becomes significant and positive in determining the incremental extension of WCST, whereas external funds (either from EU or Not Eu), insurance and cost of water of energy, which are significant in the logit model, become not significant. On the other hand, the mixed texture of the soil is significant with positive sign , meaning that if farmers using WCST have a rise of 1% of hectare of land with mixed texture, this will increase the irrigated area with WCST of the 0.3% .

Considering the climate variable there is a high loss of significance compared to the logit model, only the AI in autumn is significant with negative effect as expected. Autumnal precipitation and maximum temperature with 5 years moving average are significant, but with negative signs whose relationship does not seems relevant for the explanation of the intensity of adoption . All other variables are non significant. Although the second model presents less significance in terms of climate variables, the importance of autumn over the warmer season in the irrigation decision strategy remains relevant. Combining these results with those of the logit model, can highlight that climate do matter in the initial decision of adoption, but not in the incremental extension of the irrigated areas with WCST.

The log-log model has also been used to analyse the effects on the intensity of adoption on land of WCST irrigation for the Italian macro-areas. The overall results follow the scheme of the national analysis just described above. The only difference is that the power of machines and mixed soil texture are not significant anymore. On the other hand, it becomes highly significant the sandy texture of soil with positive sign for North-East and South regions indicating that sandy soil, which has low water retention properties, influences the extension of irrigated land with WCST as expected.

5. 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 macroarea 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 a young male and he has at least a secondary education level. The probability of adoption increases if he is the direct owner of the land, which is of small extension with access to water, but the type of water source does not matter much (even if there is evidence that consortium and well increase the probability of WCST adoption). 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) and they are carried out with a high availability 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 climate change occurring in autumn and winter than in warmer seasons.

In terms of intensity, the extension of the irrigated land with WCST increases the higher is both the availability of work and of the technological capital, these two together can be considered as a proxy of the economic dimension of the farm. The quality of the soil is also a key element for the extension of WCST. The access to water is also important in determining the extension of WCST area, but there is a bit of ambiguities about which type of water source is more important.

The study has both internal and external validity and it can be easily replicated in other countries if extended datasets would be available. The main limitation of this study is the necessity of using a fixed effect model for the study of WCST extension area which cannot allow estimating the effects for time-invariant aspects of the individuals on the dependent variable losing important aspects on geographical and socio-demographic differences. Further studies should take into consideration this last aspect trying to link the two models controlling for endogeneity due to not random sub-sampling as suggested by Heckman (1979).

Anyway, this study puts the base for next analyses on the determinants of sustainable technology adoption in irrigation which may strongly help to cope with the future challenges of the Italian agricultural sector due to Climate Change and water resource scarcity.

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APPENDIX

Tab. 1. Descriptive statistics of farms' and farmers' socio-economic, geographical, financial, and water use characteristics..

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	N	mean	p50	sd	min	max
Female	45,830	0.218	0	0.413	0	1
Young	45,830	0.127	0	0.333	0	1
family_farm	45,830	0.857	1	0.350	0	1
organic	45,830	0.0473	0	0.212	0	1
nord_ovest	45,830	0.222	0	0.416	0	1
nord_est	45,830	0.221	0	0.415	0	1
centro	45,830	0.222	0	0.416	0	1
sud	45,830	0.224	0	0.417	0	1
isole	45,830	0.111	0	0.314	0	1
micro_irr	45,824	0.186	0	0.389	0	1
Log_area_micro	45,823	0.686	0.451	0.639	0.451	6.133
crop_type_olive	45,830	0.0405	0	0.197	0	1
crop_type_wine	45,830	0.123	0	0.329	0	1
crop_type_fruits	45,830	0.121	0	0.326	0	1

crop_type_cow	45,830	0.0916	0	0.288	0	1
crop_type_cereal	45,830	0.113	0	0.316	0	1
crop_type_erbivori	45,830	0.145	0	0.352	0	1
crop_type_granivori	45,830	0.0478	0	0.213	0	1
crop_type_mixed	45,830	0.0911	0	0.288	0	1
crop_type_veg	45,830	0.118	0	0.322	0	1
crop_type_seminativi	45,830	0.110	0	0.313	0	1
UDE_inea_0	45,830	4.36e-05	0	0.00661	0	1
UDE_inea_1	45,830	0.00179	0	0.0423	0	1
UDE_inea_2	45,830	0.0232	0	0.150	0	1
UDE_inea_3	45,830	0.224	0	0.417	0	1
UDE_inea_4	45,830	0.212	0	0.408	0	1
UDE_inea_5	45,830	0.216	0	0.412	0	1
UDE_inea_6	45,830	0.256	0	0.436	0	1
UDE_inea_7	45,830	0.0343	0	0.182	0	1
UDE_inea_8	45,830	0.0329	0	0.178	0	1
extra	45,830	0.258	0	0.437	0	1
edu_sup_laurea	45,830	0.304	0	0.460	0	1
Log_eta	45,830	3.970	3.989	0.265	2.773	4.575
Log_Htot_working	45,826	8.077	7.993	0.681	4.094	12.41

Log_lavoratori	45,830	0.935	0.693	0.838	0	6.928
Log_terreni_agricoli	45,830	13.19	13.01	0.549	12.73	17.16
Log_SAU	45,830	4.036	3.871	0.497	3.508	7.058
Log_SAU_Affitto	45,830	3.140	2.795	0.617	2.735	6.647
Log_KWMacchine	44,285	4.794	4.820	0.943	0	8.134
Log_Costi_Meccanizz	45,830	9.239	9.094	0.486	8.639	13.38
Log_valore_macchine	45,830	15.52	15.51	0.0191	15.50	16.20
Log_alt_med	45,830	4.990	5.338	1.384	0	7.611
Log_area_inclinata	45,830	2.062	1.845	0.639	1.845	7.281
Log_tess_sciolto	45,830	1.830	1.627	0.623	1.627	7.260
Log_tess_argilla	45,830	1.375	1.174	0.640	1.174	6.631
Log_tess_medio	45,830	3.823	3.649	0.528	3.321	7.638
Log_sup_irr	45,632	2.605	2.254	0.620	2.225	6.912
Log_fonte_assente	45,632	-5.227	-5.230	0.123	-5.230	4.982
Log_fonte_consorzio	45,823	2.132	1.836	0.645	1.836	6.909
Log_fonte_superficiale	45,823	-0.872	-0.953	0.515	-0.953	5.167
Log_fonte_pozzo	45,823	0.874	0.651	0.640	0.651	6.042
Log_fonte_laghetto	45,823	-1.484	-1.529	0.420	-1.529	5.887
Log_fonte_cisterna	45,823	-4.473	-4.494	0.313	-4.494	4.095
Log_fonte_altro	45,823	-0.797	-0.896	0.528	-0.896	5.932

Log_aiuti_EU	45,830	9.892	9.709	0.546	9.435	14.52
Log_aiuti_PubCC	45,830	6.724	6.608	0.551	6.608	13.37
Log_aiuti_nonEU	45,830	8.365	8.003	0.643	8.003	13.57
Log_assicurazioni	45,830	7.778	7.552	0.575	7.381	13.00
Log_costo_acqua_elett_combust	45,830	8.656	8.428	0.563	8.236	13.59
Log_ROI	45,625	11.97	11.97	0.0127	11.93	12.66
Log_Leverage	45,786	7.716	7.716	0.00368	7.590	8.409
Number of ID	2,260	2,260	2,260	2,260	2,260	2,260

Tab.2. Descriptive statistics of Climate variables.

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	N	mean	p50	sd	min	max
Tmax90ileJFM_ma	284,922	10.90	11.39	2.664	-0.118	15.52
Tmax90ileAMJ_ma	284,922	23.13	23.70	2.390	12.52	27.12
Tmax90ileJAS_ma	284,922	25.68	26.46	2.610	13.90	29.84
Tmax90ileOND_ma	284,922	16.54	16.86	3.077	4.361	23.16
Tmin10ileJFM_ma	284,922	1.331	1.200	4.477	-12.37	11.66
Tmin10ileAMJ_ma	284,922	9.679	10.21	3.009	-2.867	15.06

Tmin10ileJAS_ma	284,922	16.23	16.49	3.389	2.406	23.50
Tmin10ileOND_ma	284,922	3.120	2.994	4.832	-10.64	14.22
TaveJFM_ma	284,922	6.439	6.576	3.434	-5.118	13.59
TaveAMJ_ma	284,922	16.15	16.78	2.481	5.146	19.72
TaveJAS_ma	284,922	21.23	21.88	2.887	8.469	25.70
TaveOND_ma	284,922	10.16	10.36	3.826	-1.882	18.58
PrecJFM_ma	284,922	88.82	85.24	25.31	34.58	196.2
PrecAMJ_ma	284,922	101.7	100.7	44.51	10.70	266.4
PrecJAS_ma	284,922	93.37	82.38	54.15	10.24	344.3
PrecOND_ma	284,922	130.9	129.6	24.55	59.41	243.9
ET0JFM_ma	284,922	111.5	104.3	29.85	51.04	208.9
ET0AMJ_ma	284,922	280.8	286.4	39.49	158.2	376.0
ET0JAS_ma	284,922	306.5	312.3	49.84	154.9	410.7
ET0OND_ma	284,922	106.3	97.60	36.64	41.84	230.5
AIJFM_ma	284,922	0.874	0.806	0.335	0.193	2.672
AIAMJ_ma	284,922	0.397	0.359	0.241	0.0334	1.445
AIJAS_ma	284,922	0.352	0.270	0.286	0.0280	1.884
AIOND_ma	284,922	1.445	1.404	0.615	0.294	4.427
Tmax90ileJFM_ma5lag	271,354	10.88	11.36	2.665	-0.118	15.52
Tmax90ileAMJ_ma5lag	271,354	23.16	23.72	2.391	12.52	27.12

Tmax90ileJAS_ma5lag	271,354	25.67	26.45	2.620	13.90	29.84
Tmax90ileOND_ma5lag	271,354	16.51	16.83	3.067	4.361	22.97
Tmin10ileJFM_ma5lag	271,354	1.309	1.178	4.473	-12.37	11.66
Tmin10ileAMJ_ma5lag	271,354	9.655	10.19	3.008	-2.867	15.06
Tmin10ileJAS_ma5lag	271,354	16.20	16.46	3.389	2.406	23.50
Tmin10ileOND_ma5lag	271,354	3.086	2.959	4.840	-10.64	14.01
TaveJFM_ma5lag	271,354	6.419	6.556	3.434	-5.118	13.59
TaveJAS_ma5lag	271,354	21.20	21.85	2.889	8.469	25.70
TaveOND_ma5lag	271,354	10.12	10.32	3.828	-1.882	18.42
PrecJFM_ma5lag	271,354	87.19	83.76	24.55	34.58	196.2
PrecAMJ_ma5lag	271,354	101.1	100.2	44.08	10.70	266.4
PrecJAS_ma5lag	271,354	92.92	81.62	54.00	10.24	334.9
PrecOND_ma5lag	271,354	131.0	129.6	24.68	59.41	243.9
ET0JFM_ma5lag	271,354	111.7	104.5	29.89	51.04	208.9
ET0AMJ_ma5lag	271,354	281.1	286.8	39.28	161.1	376.0
ET0JAS_ma5lag	271,354	306.7	312.4	49.95	154.9	410.7
ET0OND_ma5lag	271,354	106.5	97.71	36.61	41.84	230.5
AIJFM_ma5lag	271,354	0.855	0.793	0.323	0.193	2.672
AIAMJ_ma5lag	271,354	0.394	0.356	0.239	0.0334	1.445
AIJAS_ma5lag	271,354	0.350	0.267	0.285	0.0280	1.884

AIOND_ma5lag	271,354	1.445	1.402	0.616	0.294	4.427
Tmax90ileJFM_ma3lag	271,354	10.92	11.40	2.686	-0.118	15.80
Tmax90ileAMJ_ma3lag	271,354	23.17	23.67	2.434	12.29	27.75
Tmax90ileJAS_ma3lag	271,354	25.73	26.52	2.623	13.90	30.71
Tmax90ileOND_ma3lag	271,354	16.58	16.89	3.093	4.361	23.28
Tmin10ileJFM_ma3lag	271,354	1.307	1.225	4.514	-12.88	11.66
Tmin10ileAMJ_ma3lag	271,354	9.705	10.22	3.031	-2.867	15.17
Tmin10ileJAS_ma3lag	271,354	16.28	16.58	3.424	2.406	23.64
Tmin10ileOND_ma3lag	271,354	3.116	2.976	4.847	-10.79	14.19
TaveJFM_ma3lag	271,354	6.426	6.603	3.457	-5.592	13.72
TaveAMJ_ma3lag	271,354	16.17	16.80	2.489	5.146	19.70
TaveJAS_ma3lag	271,354	21.26	21.90	2.895	8.469	25.86
TaveOND_ma3lag	271,354	10.19	10.40	3.838	-1.916	18.63
PrecJFM_ma3lag	271,354	89.48	84.49	28.49	31.53	200.3
PrecAMJ_ma3lag	271,354	102.3	100.8	45.39	9.438	266.4
PrecJAS_ma3lag	271,354	93.37	81.63	55.14	7.893	351.4
PrecOND_ma3lag	271,354	130.5	129.2	28.30	55.34	243.9
ET0JFM_ma3lag	271,354	111.4	104.5	30.12	51.04	208.8
ET0AMJ_ma3lag	271,354	280.6	285.7	39.75	158.1	378.0
ET0JAS_ma3lag	271,354	306.9	312.5	50.15	154.9	419.1

ET0OND_ma3lag	271,354	106.5	97.93	36.74	41.84	233.5
AIJFM_ma3lag	271,354	0.884	0.810	0.377	0.173	3.050
AIAMJ_ma3lag	271,354	0.400	0.360	0.245	0.0293	1.445
AIJAS_ma3lag	271,354	0.351	0.266	0.289	0.0213	1.884
AIOND_ma3lag	271,354	1.440	1.365	0.651	0.276	4.427
Number of ID	2,260	2,260	2,260	2,260	2,260	2,260

Tab. 3. Results of the Logit Model, population average with Robust SE. The value displayed are Odds Ratio and t-stat n brackets.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	1 Logit Model	2 Logit Model	2a Logit Model	3 Logit Model	3a Logit Model	4 Logit Model	4a Logit Model	5 Logit Model
Log_Htot_working	1.278***	1.294***	1.280***	1.274***	1.279***	1.291***	1.289***	1.275***
	(6.298)	(6.539)	(6.339)	(6.205)	(6.355)	(6.490)	(6.489)	(6.352)
crop_type_olive	3.038***	2.962***	2.885***	2.962***	2.998***	2.637***	2.593***	3.182***
	(7.654)	(7.397)	(7.248)	(7.519)	(7.623)	(6.592)	(6.471)	(8.319)
crop_type_wine	5.558***	5.288***	5.227***	5.253***	5.238***	5.172***	5.131***	5.433***
	(15.31)	(14.90)	(14.93)	(15.08)	(15.13)	(14.76)	(14.75)	(15.39)
crop_type_fruits	8.226***	7.925***	7.704***	7.323***	7.397***	7.465***	7.525***	7.792***
	(19.38)	(18.96)	(18.87)	(18.55)	(18.76)	(18.53)	(18.69)	(19.26)
crop_type_mixed	4.634***	4.614***	4.455***	4.309***	4.285***	4.565***	4.525***	4.425***
	(13.84)	(13.79)	(13.57)	(13.37)	(13.37)	(13.91)	(13.87)	(13.60)
crop_type_veg	9.350***	9.364***	8.900***	8.822***	8.763***	9.374***	9.281***	9.340***
	(21.23)	(21.09)	(20.79)	(21.04)	(21.05)	(21.46)	(21.47)	(21.70)
crop_type_seminativi	4.524***	4.521***	4.386***	4.343***	4.317***	4.507***	4.490***	4.412***
	(14.74)	(14.78)	(14.63)	(14.74)	(14.74)	(14.94)	(14.96)	(15.04)
crop_type_cow	0.334***	0.331***	0.317***	0.297***	0.296***	0.354***	0.354***	0.291***
	(-5.321)	(-5.356)	(-5.628)	(-5.887)	(-5.937)	(-5.153)	(-5.209)	(-5.937)
crop_type_erbivori	0.782	0.747*	0.750*	0.735*	0.735**	0.812	0.814	0.682**
	(-1.552)	(-1.809)	(-1.811)	(-1.951)	(-1.964)	(-1.320)	(-1.313)	(-2.378)
Log_terreni_agricoli	1.010	0.908	0.931	0.902	0.918	0.932	0.968	0.937
	(0.119)	(-1.217)	(-0.895)	(-1.292)	(-1.079)	(-0.883)	(-0.405)	(-0.797)
Log_UAA	0.318***	0.360***	0.380***	0.367***	0.373***	0.341***	0.346***	0.375***
	(-4.412)	(-3.935)	(-3.663)	(-3.918)	(-3.880)	(-4.161)	(-4.093)	(-4.688)
Log_UAA_rented	0.735***	0.701***	0.705***	0.710***	0.711***	0.728***	0.741***	0.703***
	(-3.140)	(-3.651)	(-3.597)	(-3.550)	(-3.532)	(-3.205)	(-3.028)	(-3.625)
Log_eta	0.652***	0.618***	0.623***	0.677***	0.670***	0.640***	0.636***	0.659***
	(-4.414)	(-4.945)	(-4.880)	(-4.033)	(-4.159)	(-4.570)	(-4.624)	(-4.590)
Log_KWMacchine	1.009	0.971	0.982	0.974	0.972	0.971	0.982	
	(0.272)	(-0.898)	(-0.575)	(-0.809)	(-0.879)	(-0.897)	(-0.550)	
Female	0.984	0.992	0.983	1.004	1.003	0.990	0.989	
	(-0.308)	(-0.159)	(-0.324)	(0.0750)	(0.0537)	(-0.189)	(-0.216)	
family_farm	0.821***	0.799***	0.797***	0.808***	0.804***	0.835***	0.834***	0.823***
	(-2.891)	(-3.280)	(-3.343)	(-3.117)	(-3.197)	(-2.622)	(-2.643)	(-2.909)
extra	0.994	1.023	1.011	1.013	1.012	0.976	0.968	
	(-0.118)	(0.421)	(0.196)	(0.234)	(0.226)	(-0.448)	(-0.599)	
organic	1.130	1.106	1.109	1.161*	1.171*	1.103	1.100	
	(1.383)	(1.135)	(1.174)	(1.714)	(1.823)	(1.114)	(1.081)	
edu_sup_laurea	1.116**	1.100*	1.096*	1.131**	1.127**	1.117**	1.103*	1.143**
	(1.980)	(1.702)	(1.650)	(2.214)	(2.156)	(1.978)	(1.750)	(2.445)
Log_alt_med	0.821***	0.754***	0.761***	0.722***	0.726***	0.734***	0.755***	0.714***
	(-10.13)	(-12.15)	(-12.13)	(-14.43)	(-14.52)	(-13.90)	(-13.03)	(-15.30)
Log_area_inclinata	0.963	1.003	0.980	0.960	0.963	0.981	0.978	
	(-0.360)	(0.0347)	(-0.199)	(-0.395)	(-0.366)	(-0.187)	(-0.211)	

Log_tess_sciolto	1.056	1.031	1.031	1.050	1.050	1.011	1.007	
	(0.613)	(0.340)	(0.343)	(0.549)	(0.555)	(0.129)	(0.0774)	
Log_tess_medio	0.545***	0.603***	0.583***	0.637**	0.623**	0.616**	0.585***	0.595***
	(-3.104)	(-2.598)	(-2.682)	(-2.370)	(-2.497)	(-2.549)	(-2.793)	(-3.675)
Log_tess_argilla	0.856**	0.917	0.895	0.918	0.910	0.898	0.878*	0.888*
	(-2.045)	(-1.149)	(-1.440)	(-1.148)	(-1.264)	(-1.425)	(-1.714)	(-1.772)
Log_fonte_consorzio	3.141***	3.121***	3.092***	2.951***	2.949***	3.102***	3.128***	2.869***
	(21.23)	(20.80)	(20.84)	(19.98)	(20.03)	(20.55)	(20.79)	(19.61)
Log_fonte_superficiale	1.533***	1.603***	1.583***	1.575***	1.569***	1.591***	1.585***	1.549***
	(10.82)	(11.75)	(11.62)	(11.36)	(11.36)	(11.53)	(11.49)	(10.90)
Log_fonte_pozzo	2.584***	2.628***	2.582***	2.561***	2.545***	2.603***	2.597***	2.522***
	(24.21)	(24.15)	(23.86)	(23.76)	(23.65)	(24.00)	(24.08)	(23.06)
Log_fonte_laghetto	1.765***	1.754***	1.739***	1.741***	1.742***	1.732***	1.736***	1.741***
	(11.37)	(11.03)	(10.88)	(10.86)	(10.90)	(10.77)	(10.88)	(10.92)
Log_fonte_cisterna	1.264***	1.289***	1.278***	1.279***	1.277***	1.296***	1.285***	1.283***
	(3.826)	(4.089)	(3.980)	(3.982)	(3.971)	(4.145)	(4.054)	(4.066)
Log_fonte_altro	1.233***	1.277***	1.259***	1.263***	1.258***	1.275***	1.257***	
	(5.827)	(6.764)	(6.465)	(6.617)	(6.520)	(6.652)	(6.232)	
Log_aiuti_EU	0.703***	0.693***	0.686***	0.701***	0.699***	0.685***	0.670***	0.693***
	(-5.220)	(-5.395)	(-5.589)	(-5.252)	(-5.264)	(-5.475)	(-5.800)	(-5.122)
Log_aiuti_nonEU	1.101***	1.102***	1.099***	1.111***	1.104***	1.121***	1.112***	1.128***
	(2.873)	(2.884)	(2.857)	(3.190)	(3.002)	(3.351)	(3.128)	(3.597)
Log_costo_acqua_elett_combust	1.175***	1.169***	1.172***	1.162***	1.159***	1.176***	1.178***	1.192***
	(3.481)	(3.337)	(3.422)	(3.189)	(3.156)	(3.412)	(3.488)	(3.615)
Log_assicurazioni	1.190***	1.147***	1.146***	1.145***	1.142***	1.154***	1.149***	1.137***
	(5.008)	(3.929)	(3.974)	(3.905)	(3.842)	(4.092)	(3.989)	(3.638)
Log_ROI	0.971	1.019	0.997	0.890	0.906	0.913	0.916	
	(-0.0358)	(0.0222)	(-0.00322)	(-0.132)	(-0.116)	(-0.103)	(-0.102)	
Log_Leverage	2.704	3.598	5.135*	3.271	3.305	3.495	3.709	
	(1.096)	(1.330)	(1.873)	(1.270)	(1.276)	(1.194)	(1.256)	
nord_ovest	0.643***	0.533***	0.633***	0.552***	0.572***	0.512***	0.645***	0.570***
	(-5.294)	(-6.293)	(-4.837)	(-6.338)	(-6.249)	(-5.758)	(-4.569)	(-6.096)
nord_est	0.902	0.489***	0.642***	0.462***	0.485***	0.430***	0.533***	0.451***
	(-1.245)	(-6.275)	(-4.044)	(-6.740)	(-6.573)	(-6.980)	(-5.834)	(-6.967)
sud	2.084***	2.121***	2.170***	2.044***	2.189***	1.528***	1.579***	2.106***
	(9.579)	(8.748)	(9.171)	(8.355)	(9.486)	(4.433)	(4.821)	(8.857)
isole	3.632***	2.001***	2.264***	3.509***	3.915***	1.708***	1.722***	3.474***
	(13.43)	(4.756)	(5.956)	(10.44)	(12.27)	(3.450)	(3.549)	(10.55)
Tmax90ileJFM_ma5lag		1.194***						
		(4.136)						
Tmax90ileAMJ_ma5lag		0.679***						
		(-8.997)						
Tmax90ileJAS_ma5lag		1.154***						
		(3.687)						
Tmax90ileOND_ma5lag		1.190***						
		(3.775)						
PrecJFM_ma5lag		0.991***				1.002*		
		(-6.751)				(1.910)		
PrecAMJ_ma5lag		1.011***				1.016***		
		(6.239)				(7.395)		
PrecJAS_ma5lag		1.005***				1.005***		
		(4.616)				(3.495)		
PrecOND_ma5lag		0.994***				0.989***		
		(-6.550)				(-10.56)		
Tmax90ileJFM_ma3lag			1.235***					
			(7.857)					
Tmax90ileAMJ_ma3lag			0.777***					
			(-7.901)					
Tmax90ileJAS_ma3lag			1.009					
			(0.294)					
Tmax90ileOND_ma3lag			1.074***					
			(3.219)					
PrecJFM_ma3lag			0.998**				1.002***	
			(-2.415)				(3.585)	
PrecAMJ_ma3lag			1.006***				1.009***	
			(6.240)				(6.796)	
PrecJAS_ma3lag			1.004***				1.007***	
			(4.422)				(6.738)	
PrecOND_ma3lag			0.992***				0.991***	
			(-7.574)				(-10.72)	
AIJFM_ma5lag				0.834**				0.821**
				(-2.152)				(-2.319)
AIAMJ_ma5lag				5.084***				5.056***
				(4.940)				(4.973)
AIJAS_ma5lag				2.815***				2.893***
				(4.370)				(4.499)
AIOND_ma5lag				0.546***				0.534***
				(-9.606)				(-9.883)
AIJFM_ma3lag					0.948			
					(-1.214)			
AIAMJ_ma3lag					3.492***			
					(6.914)			
AIJAS_ma3lag					2.899***			

					(7.166)			
AIOND_ma3lag					0.616***			
					(-9.460)			
ET0JFM_ma5lag						1.036***		
						(7.688)		
ET0AMJ_ma5lag						0.995*		
						(-1.732)		
ET0JAS_ma5lag						1.002		
						(0.651)		
ET0OND_ma5lag						0.996		
						(-1.046)		
ET0JFM_ma3lag							1.025***	
							(8.191)	
ET0AMJ_ma3lag							0.996**	
							(-2.030)	
ET0JAS_ma3lag							1.003	
							(1.285)	
ET0OND_ma3lag							1.001	
							(0.275)	
Constant	0.0479	0.0330	0.0104	0.191	0.105	0.00245	0.00164	266.0***
	(-0.241)	(-0.254)	(-0.364)	(-0.124)	(-0.173)	(-0.430)	(-0.468)	(4.833)
Observations	44,083	44,083	44,083	44,083	44,083	44,083	44,083	45,819
Number of ID	13,055	13,055	13,055	13,055	13,055	13,055	13,055	13,562
Population Averaged	Robust	Robust	Robust	Robust	Robust	Robust	Robust	Robust
rank	41	49	49	45	45	49	49	36
rc	0	0	0	0	0	0	0	0
chi2_dis	2.092	1.677	1.679	1.685	1.683	1.828	1.879	1.839
chi2_dev	92205	73936	73994	74260	74196	80579	82817	84268
dispers	0.631	0.615	0.620	0.622	0.624	0.613	0.616	0.617
deviance	27806	27113	27348	27420	27488	27037	27173	28284
phi	1	1	1	1	1	1	1	1
dif	8.84e-07	7.93e-07	8.17e-07	3.76e-07	9.76e-07	6.06e-07	7.95e-07	7.20e-07
tol	1.00e-06	1.00e-06	1.00e-06	1.00e-06	1.00e-06	1.00e-06	1.00e-06	1.00e-06
g_avg	3.377	3.377	3.377	3.377	3.377	3.377	3.377	3.378
g_min	1	1	1	1	1	1	1	2
g_max	5	5	5	5	5	5	5	5
N_g	13055	13055	13055	13055	13055	13055	13055	13562
df_pear	44083	44083	44083	44083	44083	44083	44083	45819
p	0	0	0	0	0	0	0	0
chi2	2704	2888	2895	2787	2780	2957	2942	2837
df_m	40	48	48	44	44	48	48	35

z-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Tab. 4. Results of the Logit Model by Macro Areas: North-West; North-East, Centre, South, Islands.

	(1)	(2)	(3)	(4)	(5)
VARIABLES	1 Logit Model- Nord Ovest	2 Logit Model- Nord Est	3 Logit Model- Centro	4 Logit Model- Sud	5 Logit Model- Centro
Log_Htot_working	1.334**	1.209**	1.815***	0.773***	1.494***
	(2.153)	(2.495)	(6.084)	(-2.654)	(3.110)
crop_type_olive	17.32***		1.451	1.232	2.945**
	(4.900)		(0.854)	(0.734)	(2.291)
crop_type_wine	6.160***	6.407***	1.692**	2.706***	2.644**
	(4.705)	(9.383)	(2.092)	(3.603)	(2.264)
crop_type_fruits	14.62***	7.105***	6.083***	4.410***	3.692***
	(7.521)	(9.725)	(8.035)	(5.013)	(2.782)
crop_type_mixed	8.938***	4.170***	2.700***	3.768***	1.770
	(5.644)	(7.211)	(4.291)	(4.551)	(1.561)
crop_type_veg	32.58***	5.224***	8.286***	5.192***	2.260
	(10.47)	(7.119)	(10.54)	(6.161)	(0.833)
crop_type_seminativi	7.511***	3.052***	4.163***	3.376***	1.346
	(5.575)	(6.324)	(7.169)	(5.467)	(0.803)
crop_type_cow	0.587	0.733	0.260***	0.101***	0.0108***
	(-0.840)	(-1.189)	(-2.663)	(-4.962)	(-3.991)
crop_type_erbivori	1.153	0.768	0.353***	0.626	0.254***
	(0.313)	(-0.631)	(-2.714)	(-1.058)	(-2.884)
Log_terreni_agricoli	0.875	0.940	0.562**	1.506	1.397
	(-0.672)	(-0.374)	(-2.505)	(1.402)	(0.739)
Log_SAU	0.0924**	0.392**	0.225***	0.232**	0.494
	(-2.017)	(-1.989)	(-2.866)	(-2.042)	(-1.368)
Log_SAU_Affitto	1.426	1.179	0.493***	0.823	1.125
	(0.782)	(0.547)	(-3.048)	(-0.629)	(0.410)
Log_eta	0.625	0.640**	0.687*	0.720	0.377
	(-1.619)	(-2.307)	(-1.826)	(-1.638)	(-1.143)
family_farm	0.685	1.091	1.506**	0.942	0.675
	(-1.442)	(0.375)	(1.982)	(-0.493)	(-1.347)
edu_sup_laurea	1.149	0.947	1.261**	0.945	1.448*

	(0.904)	(-0.432)	(1.969)	(-0.449)	(1.943)
Log_alt_med	0.769***	0.876***	0.745***	0.525***	0.641*
	(-3.658)	(-2.621)	(-6.349)	(-6.527)	(-1.930)
Log_tess_medio	0.233***	0.746	1.500	0.908	0.420**
	(-2.746)	(-1.368)	(1.088)	(-0.181)	(-2.212)
Log_tess_argilla	0.736	0.914	1.228	1.257	0.844
	(-1.238)	(-0.675)	(1.434)	(1.186)	(-0.967)
Log_fonte_consorzio	2.491***	2.298***	2.671***	15.46***	3.831***
	(4.453)	(9.061)	(6.003)	(10.34)	(6.145)
Log_fonte_superficiale	1.730***	1.488***	1.458***	1.489**	1.315*
	(3.191)	(4.988)	(6.500)	(2.356)	(1.659)
Log_fonte_pozzo	3.052***	1.701***	2.284***	3.685***	3.721***
	(7.825)	(6.733)	(8.639)	(12.13)	(5.971)
Log_fonte_laghetto	1.429*	1.233	1.847***	2.373**	2.347***
	(1.793)	(1.248)	(8.493)	(2.529)	(5.486)
Log_fonte_cisterna	1.445***	1.068	1.252	1.378***	1.274
	(4.129)	(0.306)	(1.454)	(2.832)	(1.018)
Log_aiuti_EU	0.663	0.638***	0.824	1.770***	0.467***
	(-1.311)	(-3.523)	(-1.052)	(3.468)	(-2.717)
Log_aiuti_nonEU	1.651***	1.100*	1.408***	0.982	0.931
	(4.047)	(1.718)	(3.724)	(-0.190)	(-0.750)
Log_costo_acqua_elett_combust	1.619***	1.038	1.145	1.680***	1.115
	(2.905)	(0.314)	(1.339)	(3.771)	(0.620)
Log_assicurazioni	1.794***	1.114**	0.946	1.106	1.329
	(4.361)	(2.186)	(-0.516)	(0.747)	(1.465)
AIJFM_ma5lag	2.454***	1.135	0.419***	0.0537***	1.883
	(4.169)	(1.015)	(-3.245)	(-8.910)	(1.033)
AIAMJ_ma5lag	2.676	21.53***	0.000366***	134.8***	0.102
	(1.174)	(5.485)	(-6.298)	(4.578)	(-1.176)
AIJAS_ma5lag	2.075	0.391***	269.3***	4.054	0.0380
	(1.105)	(-2.655)	(5.939)	(1.069)	(-0.876)
AIOND_ma5lag	0.882	0.776***	2.650***	0.133***	3.280
	(-0.509)	(-3.872)	(3.944)	(-5.542)	(0.767)
Constant	4.051	16.03	2,291***	0.00302	489.8
	(0.374)	(1.142)	(2.598)	(-1.349)	(1.293)
Observations	10,167	10,121	10,183	10,268	5,080
Number of ID	2,688	2,935	3,332	3,034	1,573
Population Averaged	Robust	Robust	Robust	Robust	Robust
rank	32	31	32	32	32
rc	0	0	0	0	0
chi2_dis	3.220	0.896	1.643	2.650	1.684
chi2_dev	32740	9064	16734	27212	8553
dispers	0.438	0.741	0.504	0.568	0.584
deviance	4455	7500	5129	5829	2968
phi	1	1	1	1	1
dif	2.04e-07	7.28e-07	3.18e-07	6.45e-07	4.60e-07
tol	1.00e-06	1.00e-06	1.00e-06	1.00e-06	1.00e-06
N_g	2688	2935	3332	3034	1573
df_pear	10167	10121	10183	10268	5080
p	0	0	0	0	0
chi2	633.0	486.8	755.4	851.7	350.0
df_m	31	30	31	31	31

z-statistics in parentheses
* p<0.05, * p<0.1

Tab. 5. Results of the Log-Log Model with Fixed Effects, SE Clustered by Municipality. The value displayed are Odds Ratio and t-stat n brackets.

	(1)	(2)	(3)	(4)	(5)
VARIABLES	1 Log Log Model	2 Log Log Model	3 Log Log Model	4 Log Log Model	5 Log Log Model
Log_Htot_working	0.101***	0.101***	0.102***	0.101***	0.102***
	(5.656)	(5.670)	(5.561)	(5.400)	(5.512)
Log_SAU_Affitto	0.0601	0.0628	0.119*	0.119*	0.120**
	(0.650)	(0.686)	(1.953)	(1.936)	(1.968)
Log_KWMacchine	0.0426*	0.0423*	0.0432*	0.0448*	0.0444*
	(1.932)	(1.927)	(1.868)	(1.940)	(1.922)
Log_tess_sciolto	0.0865	0.0823	0.0987	0.104	0.101
	(1.039)	(0.998)	(1.247)	(1.315)	(1.268)
Log_tess_medio	0.334***	0.326***	0.393***	0.398***	0.398***
	(3.217)	(3.108)	(3.083)	(3.135)	(3.137)
Log_fonte_consorzio	0.431***	0.430***	0.434***	0.434***	0.434***
	(6.310)	(6.299)	(6.446)	(6.461)	(6.457)
Log_fonte_superficiale	0.112*	0.112*	0.112*	0.111*	0.111*
	(1.866)	(1.877)	(1.883)	(1.850)	(1.850)
Log_fonte_pozzo	0.324***	0.325***	0.327***	0.326***	0.327***
	(8.412)	(8.463)	(8.590)	(8.568)	(8.585)
Log_fonte_laghetto	0.159***	0.160***	0.161***	0.162***	0.161***
	(4.084)	(4.189)	(4.264)	(4.288)	(4.283)

Log_aiuti_EU	-0.0583	-0.0500	-0.0476	-0.0458	-0.0499
	(-1.325)	(-1.154)	(-1.096)	(-1.047)	(-1.141)
Log_aiuti_nonEU	0.00377	0.00492	0.00387	0.00329	0.00406
	(0.517)	(0.674)	(0.533)	(0.452)	(0.558)
Log_costo_acqua_elett_combus t	0.0356	0.0351	0.0351	0.0345	0.0344
	(1.353)	(1.316)	(1.316)	(1.280)	(1.279)
Log_assicurazioni	0.00571	0.00769	0.00698	0.00806	0.00658
	(0.577)	(0.776)	(0.707)	(0.817)	(0.667)
Tmax90ileJFM_ma5lag				0.0240	
				(1.387)	
Tmax90ileAMJ_ma5lag				-0.000294	
				(-0.0154)	
Tmax90ileJAS_ma5lag				0.00784	
				(0.477)	
Tmax90ileOND_ma5lag				-0.0441**	
				(-2.404)	
PrecJFM_ma5lag				0.000717	0.000494
				(1.441)	(0.957)
PrecAMJ_ma5lag				-5.17e-05	-0.000412
				(-0.0728)	(-0.407)
PrecJAS_ma5lag				-0.000639	-0.000650
				(-1.043)	(-1.022)
PrecOND_ma5lag				-0.000873**	-0.000663
				(-2.060)	(-1.419)
Log_SAU	0.189	0.188			
	(1.003)	(1.014)			
Log_tess_argilla	-0.00551	-0.00584			
	(-0.0431)	(-0.0453)			
Log_fonte_cisterna	0.00510	0.00486			
	(0.369)	(0.353)			
AIJFM_ma5lag		0.0401	0.0399		
		(1.353)	(1.347)		
AIAMJ_ma5lag		0.136	0.137		
		(1.004)	(1.018)		
AIJAS_ma5lag		-0.204	-0.213		
		(-1.356)	(-1.398)		
AIOND_ma5lag		-0.0629**	-0.0620**		
		(-2.037)	(-2.007)		
ET0JFM_ma5lag					-0.00139
					(-0.849)
ET0AMJ_ma5lag					-0.00170
					(-1.026)
ET0JAS_ma5lag					0.00157
					(1.257)
ET0OND_ma5lag					0.00105
					(0.556)
Constant	-2.420***	-2.429***	-2.204***	-1.909**	-2.104**
	(-3.221)	(-3.235)	(-3.468)	(-2.084)	(-2.364)
Observations	8,294	8,294	8,294	8,294	8,294
R-squared	0.211	0.214	0.213	0.214	0.213
Number of ID	2,878	2,878	2,878	2,878	2,878
Fixed Effects	Cluster Comune	Cluster Comune	Cluster Comune	Cluster Comune	Cluster Comune
g_min	1	1	1	1	1
F	19.03	17.04	17.84	16.30	14.68
df_a	2877	2877	2877	2877	2877
r2_w	0.211	0.214	0.213	0.214	0.213
df_b	16	20	17	21	21
tss	7452	7452	7452	7452	7452
ll_0	2824	2824	2824	2824	2824
ll	3806	3821	3817	3823	3818
r2_a	0.209	0.212	0.211	0.212	0.211
mss	51.82	52.50	52.35	52.63	52.39
rmse	0.153	0.153	0.153	0.153	0.153
r2	0.211	0.214	0.213	0.214	0.213
df_r	1150	1150	1150	1150	1150
N_clust	1151	1151	1151	1151	1151
df_m	15	19	16	20	20
rss	194.0	193.3	193.4	193.1	193.4
rank	16	20	17	21	21
rho	0.909	0.906	0.908	0.911	0.907
sigma	0.627	0.617	0.625	0.634	0.621
sigma_e	0.190	0.189	0.189	0.189	0.189
r2_b	0.617	0.631	0.626	0.609	0.632
r2_o	0.643	0.655	0.650	0.636	0.654
corr U | Xb	0.331	0.328	0.354	0.342	0.350
sigma_u	0.597	0.587	0.595	0.605	0.591
ui	0.597	0.587	0.595	0.605	0.591
N_g	2878	2878	2878	2878	2878
g_max	5	5	5	5	5
g_avg	2.882	2.882	2.882	2.882	2.882

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Tab. 6. Results of the Log-Log model by Macro Areas: North-West, North-East, Centre, South, Islands.

	(1)	(2)	(3)	(4)	(5)
VARIABLES	1 Log Log Model-Nord Ovest	2 Log Log Model-Nord Est	3 Log Log Model-Centro	4 Log Log Model-Sud	5 Log Log Model-Isola
Log_Htot_working	0.0835**	0.123**	0.0984	0.0625***	0.0238
	(2.272)	(2.504)	(1.413)	(3.098)	(0.860)
Log_SAU_Affitto	0.114	0.196	-0.0269	0.0387	-0.0484
	(0.780)	(1.261)	(-0.124)	(0.468)	(-0.774)
Log_KWMacchine	0.0470	0.0497	0.223	0.0231	-0.0559
	(0.917)	(1.320)	(1.576)	(0.804)	(-1.091)
Log_tess_sciolto	-0.142	0.803**	-0.0846	0.0745**	-0.00284
	(-0.395)	(2.120)	(-1.324)	(2.227)	(-0.111)
Log_tess_medio	0.302	0.490	0.100	0.228*	0.126
	(0.552)	(1.454)	(0.516)	(1.664)	(0.498)
Log_fonte_consorzio	0.493***	0.197**	0.417***	0.690***	0.870***
	(2.783)	(2.168)	(3.241)	(4.940)	(5.437)
Log_fonte_superficiale	0.0892*	0.247**	0.0604	0.159**	0.296***
	(1.856)	(2.157)	(0.804)	(2.431)	(5.109)
Log_fonte_pozzo	0.185	0.192***	0.200***	0.667***	0.553***
	(1.402)	(4.714)	(2.777)	(10.00)	(6.857)
Log_fonte_laghetto	0.481***	0.0459	0.159***	0.0729	0.0639**
	(16.86)	(0.346)	(2.864)	(1.509)	(2.581)
Log_aiuti_EU	0.0541	-0.103**	-0.0399	0.0844	0.0127
	(0.224)	(-2.264)	(-0.240)	(0.993)	(0.576)
Log_aiuti_nonEU	0.0312	-0.0124	-0.0158	0.00635	0.00454
	(0.984)	(-0.775)	(-0.502)	(0.733)	(0.573)
Log_costo_acqua_elett_combust	-0.0126	-0.0201	0.0614	0.0680**	-0.00258
	(-0.319)	(-0.281)	(0.780)	(1.969)	(-0.111)
Log_assicurazioni	0.0145	0.0215	-0.0432	-0.0113	0.00210
	(0.390)	(1.416)	(-0.746)	(-0.706)	(0.0839)
AIJFM_ma5lag	0.0721	-0.0857	-0.0616	-0.0184	0.173*
	(0.852)	(-1.129)	(-0.523)	(-0.145)	(1.785)
AIAMJ_ma5lag	-0.125	0.864	0.862	0.261	0.00239
	(-0.558)	(1.568)	(1.441)	(0.881)	(0.00251)
AIJAS_ma5lag	0.182	-0.149	-0.596	-0.0788	-0.634
	(0.553)	(-0.640)	(-1.556)	(-0.212)	(-1.051)
AIOND_ma5lag	-0.0421	-0.146**	-0.209	0.0623	0.400**
	(-0.753)	(-2.046)	(-1.301)	(0.550)	(2.327)
Constant	-2.112	-2.953**	-0.841	-3.419***	-1.036
	(-0.571)	(-2.206)	(-0.453)	(-3.705)	(-0.929)
Observations	1,104	1,933	1,361	2,716	1,180
R-squared	0.122	0.187	0.130	0.503	0.323
Number of ID	402	627	606	856	387
FE Averaged	Robust				
g_min	1	1	1	1	1
Tcon	0	0	0	0	0
Tbar	2.746	3.083	2.246	3.173	3.049
F	.	10.71	1.750	35.02	7.921
df_a	401	626	605	855	386
r2_w	0.122	0.187	0.130	0.503	0.323
df_b	16	17	17	17	17
tss	688.6	1381	1010	2352	1234
ll_0	386.5	602.1	316.8	931.3	652.7
ll	458.1	801.6	411.3	1882	882.8
r2_a	0.108	0.179	0.119	0.500	0.313
mss	3.905	11.32	6.487	40.32	7.380
rmse	0.161	0.161	0.180	0.121	0.115
r2	0.122	0.187	0.130	0.503	0.323
df_r	206	298	199	279	164
N_clust	207	299	200	280	165
df_m	15	16	16	16	16
rss	28.19	49.38	43.54	39.78	15.47
rank	16	17	17	17	17
rho	0.909	0.933	0.872	0.900	0.952
sigma	0.671	0.759	0.678	0.465	0.646
sigma_e	0.203	0.196	0.243	0.147	0.141
r2_b	0.469	0.311	0.500	0.766	0.642
r2_o	0.482	0.281	0.508	0.782	0.633
corr	-0.000456	-0.153	0.303	0.143	0.312
sigma_u	0.640	0.733	0.633	0.441	0.630

ui	0.640	0.733	0.633	0.441	0.630
N_g	402	627	606	856	387
g_max	5	5	5	5	5
g_avg	2.746	3.083	2.246	3.173	3.049
FE		Cluster - Comune	Cluster - Comune	Cluster - Comune	Cluster - Comune

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1