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Introduction

Crop and livestock growth are directly affected by climatic conditions, making the agricultural sector vulnerable to climate change (EEA, 2017). Studies show that the Mediterranean region is likely the most climate-vulnerable in Europe (Metzger et al., 2006; Reidsma et al., 2010). Soil quality will deteriorate as the southern climate gets warmer and drier, water shortages will increase and growing seasons will shorten (IPCC, 2001). These changes are detrimental to the agricultural sector in southern Europe. Yields and revenues will diminish and become more variable and the surface area suitable for traditional crop growth will become smaller (Bindi & Olesen, 2011). To reduce these negative effects and exploit the potential benefits of climate change, adaptation measures need to be implemented. A predominant form of adaptation and the focus of this study is irrigation.

Farmers face two opposing challenges concerning irrigation. Farmers need irrigation to compensate for moisture deficiencies and droughts (Smit & Skinner, 2002). Therefore, on the one hand, as the climate gets warmer and drier, the need for irrigation increases. On the other hand, climate, among other factors, is putting pressure on freshwater availability. Agriculture is, with 70% globally and 40% in Europe, the most water-consuming sector (EEA, 2019; FAO, 2012). Consequently, it is both a big contributor to and a victim of water scarcity. The combination of these two challenges—increased irrigation need and pressure on irrigation water use—leads to a need for more efficient irrigation systems.

The literature on irrigation as a measure to adapt to climate change is vast. On the one hand, there are studies which analyse the driving factors for the decision to irrigate, focussing on climate as one of these factors (e.g., Negri et al., 2005; Olen et al., 2016). On the other hand, there are studies which focus on the value of irrigation as a climate adaptation measure, in terms of farm economic outcomes (e.g., Finger et al., 2011; Chatzopoulos & Lippert, 2016).

Most of these studies—both the irrigation choice studies and the valuation studies—are limited to a comparison between irrigated and rainfed farming (e.g., Mendelsohn & Dinar, 2003; Schlenker et al., 2005), few of them focus on irrigation efficiency as a climate adaptation measure. We position our paper within the irrigation choice literature. The main research question for this paper is 'How does the choice for certain irrigation technologies change with a changing climate?' Irrigated agriculture is less vulnerable to climate change because it is less dependent on precipitation. However, crop vulnerability increases when water is scarce and competition for water is high, as is often the case in warm and dry regions (Reidsma et al., 2010). In those areas, water has to be used more efficiently. The use of modern irrigation technologies allows farmers to achieve the same output with less water and hedge against the risk of profit loss during periods of water shortage. We, therefore, hypothesise that more efficient irrigation options, such as sprinkler irrigation and—even more so—drip irrigation, are adopted in warmer and drier climates (Mendelsohn & Dinar, 2003; Rosa, 2022).

For a cross-sectional data analysis of climate impacts like this, a dataset with high climate variability is needed. Italy covers multiple climatic zones, ranging from the warm and dry Mediterranean climate to the cold and humid alpine climate (Chelli et al., 2017). We distinguish four different irrigation options: no irrigation (rainfed farming) and surface, sprinkler and drip irrigation (Sauer et al., 2010). We have access to the fractions of Italian farmers' total land surfaces that are irrigated with each of the possible irrigation options. This type of data is called 'compositional data'. Compositional data are relative data with a constant-sum restriction, such as percentages which must sum to 100% (Aitchison, 1982; Greenacre, 2021). We consequently model the fractions of farmers' land that are treated with each of the options as a function of climatic and control variables.

Several researchers have used compositional data for analysing irrigation adoption. Frisvold and Bai (2016) and Mendelsohn and Dinar (2003) use the log ratio of surface areas irrigated with different irrigation systems as the dependent variable in their analysis. This approach encounters a major limitation: it does not allow for structural zeros. Structural zeros, in contrast to sampling zeros, are true zero values, i.e., they are not the result of measurement error or rounding (Tsagris, 2018). In irrigation choice data, these are cases where farmers do not at all adopt a certain irrigation option. In our data sample, only 0.5% of farmers adopt all four irrigation options meaning that 99.5% of observations have a zero value for at least one of the options. For log-ratio models, these zeros are removed by transforming the [0,1] data to the (0,1) interval. Pronti et al. (2020) have looked at the fractions of farmers' land that are irrigated with innovative irrigation technologies using a tobit model. This approach only allows for two options: innovatively irrigated land versus traditionally irrigated land. Pokhrel et al. (2018) analyse the factors determining the choice between different irrigation systems using a fractional model. Although this approach is suitable for modelling irrigation technology choices, it assumes that the decision to adopt an irrigation technology and the decision on the intensity of adoption (the land share) are made simultaneously, which has frequently been shown not to be the case in agricultural technology adoption (Siyum et al., 2022; Workie & Tasew, 2023; Yigezu et al., 2018).

The contribution of this paper lies in developing an approach which overcomes these three limitations. The approach is inspired by the double hurdle model of Cragg (1971) and uses two steps. Cragg states that the decision to acquire—or the decision to adopt a technology—and the decision on the amount of the acquisition—or the intensity of adoption—are often two distinct processes. We consequently first model the decision of the farmer to adopt each of the irrigation options or not, using a multivariate probit model. With this step, we allow for structural zeros. The second step is a zero-adjusted Dirichlet regression (ZADR) model to estimate the ratio in which the adopted (non-zero) irrigation options occur (Tsagris & Stewart, 2018). This second regression is run on a subsample of farms which adopt at least two different options. Using a formula which combines both models, we predict each farm's compositional response. To answer the research question we calculate the marginal effects of the climate variables on this compositional response.

In the following section, we provide some background on irrigation efficiency and its relevance for agricultural policymaking. Next, we explain the methods used in this paper, followed by an overview of the variables chosen and the data sources used. Lastly, we explain the results in and conclude. In the appendix, we compare our results with the results of two alternative approaches.

Background

Besides rainfed farming, we distinguish three different irrigation methods in this study: surface, sprinkler and drip irrigation. Surface irrigation is the application of water through gravitational flow. This can be done by either flooding the entire field or by directing water into narrow channels or strips of land. With sprinkler irrigation, water is pumped through pipes and then sprayed onto the crops via rotating sprinkler heads, mimicking natural rainfall. Drip irrigation entails pressurized conveyance of water through a pipe system to the fields, where it drips in a slow, controlled manner onto the root zone of each plant through emitters or drippers (Brouwer et al., 1988). Sprinkler and drip irrigation allow for more controllable water application—via frequent irrigation with smaller amounts of water—and allow better uniformity of water distribution (Asrey et al., 2018; BIO Intelligence Service, 2012).

The three methods differ in their degree of water efficiency. The principal sources of water losses in agriculture are deep percolation and surface runoff (Holzapfel & Mariño, 2008). Both issues arise mostly in surface irrigation. With sprinkler systems, water is lost through evaporation and lateral runoff (Jägermeyr et al., 2015). Also, strong wind can divert the water sprayed by sprinklers (Brouwer et al., 1988). Water losses for drip irrigation are minimal.

Depending on the water efficiency measure used, studies find different efficiencies for the three methods. Holzapfel and Mariño (2008) find efficiencies for surface, sprinkler and drip irrigation of 10-85%, 50-90% and 65-95% respectively, whereas Sauer et al. (2010) find efficiencies of 25-55, 60-86 and 80-93% and Jägermeyr et al. (2015) mention efficiency values of 30-60, 50-70 and 70-90%. Although these values lie relatively far apart, all references agree on surface irrigation as the least efficient and drip irrigation as the most efficient method. Although drip irrigation is most efficient, it has a high initial investment cost. Because of this, its application is often limited to high-value crops (Asrey et al., 2018).

Because of increasing water stress, moving from less to more efficient irrigation systems should be a focal point of agricultural policymaking. The Water Framework Directive, which was established in 2000 with the objective of protecting European waters, encourages member states to implement water-saving irrigation techniques (Article 11, WFD) (European Parliament, 2000). Through the Common Agricultural Policy (CAP), the European Commission aims to ensure that its agricultural sector contributes to these water policies. Two of the CAP's specific objectives are related to improved irrigation efficiency: (4) 'Contributing to climate mitigation and adaptation' by adjusting irrigation practices (volumes and scheduling) to actual weather patterns farmers play an active role in adapting to climate change, and (5) 'Efficient management of natural resources' by promoting optimization of the available irrigation volumes (European Commission, 2020; "Italy CAP Strategic Plan," 2022). Under the CAP's Pillar I, income support for farmers is made conditional on adherence to environmental requirements, including sensible water use. Also under Pillar II 'Rural Development', funding is made available for improved water management and increased water efficiency (Rossi, 2019). However, water metering needs to be in place to demonstrate the water efficiency gains resulting from these investments (European Parliament, 2013). Various policy instruments exist to encourage water use efficiency, among which subsidies, advisory services for farms, water cost recovery (scarcity pricing), water licensing and providing limited support to newly irrigated areas (Gruère et al., 2020).

In Italy's CAP Strategic Plan 2023-2027 the budget foreseen for the development of innovative and more efficient irrigation infrastructure, better adapted to the climate, is 880 million euros. The Strategic Plan aims at more effective (related to crop needs) and more water-efficient irrigation, based on water balances which take into account crop type, field capacity, soil type, weather and seasonal trends, etc. The Strategic Plan emphasises that water stress is most severe during those times of the year when irrigation requirements are highest, highlighting the importance of efficient irrigation. Improved irrigation efficiency is considered protection against the adverse effects of climate-related extreme events (i.e., droughts) and can lead to a reduction in insurance premiums. In this context, it is interesting to understand whether improved irrigation efficiency is currently being used as a climate adaptation strategy by farmers, i.e., whether more efficient irrigation options are being used in warmer and drier regions in Italy. If this is not the case, this potentially means that there are shortcomings in Italy's approach to increasing irrigation efficiency or that farmers are finding other ways to adapt to climate change.

Method

This study introduces a two-step modelling framework inspired by the double hurdle model of Cragg (1971). First, we run a multivariate probit model which predicts whether a farmer will adopt each of the irrigation options (1) or not (0). This is what Cragg (1971) calls the 'participation decision'. Then we proceed with the ZADR model proposed by Tsagris and Stewart (2018) to predict the ratios in which the non-zero options occur, the 'consumption decision'. We use the combination of both steps to predict the compositional response of each farmer using Equation 1 (Feng et al., 2017). With the two steps, we allow the same factors to influence the participation decision and the consumption decision differently, but this does not necessarily have to be the case.

$$\boldsymbol{Y}_j = \left(\tilde{Y}_{1j}, \tilde{Y}_{2j}, \tilde{Y}_{3j}, \tilde{Y}_{4j}\right) = \left(\frac{Y_{1j}D_{1j}}{\sum Y_{ij}D_{ij}}, \frac{Y_{2j}D_{2j}}{\sum Y_{ij}D_{ij}}, \frac{Y_{3j}D_{3j}}{\sum Y_{ij}D_{ij}}, \frac{Y_{4j}D_{4j}}{\sum Y_{ij}D_{ij}}\right) \tag{1}$$

In this equation, i stands for the irrigation option, where $1 =$ no irrigation, $2 =$ surface irrigation, $3 =$ sprinkler irrigation and $4 =$ drip irrigation. Y_{ij} is the binary value predicted by the multivariate probit. This is equal to 1 if the model predicts that farmer j is likely to adopt ($P > 0.5$) irrigation system i. D_{ij} is the fraction of farmer j's land irrigated with irrigation system i predicted by the ZADR model. Because the compositional response always has to sum to 1, the binary values predicted by the probit model cannot all equal 0. For this reason, we consider observations for which the multivariate probit predicts only zero values erroneous and check whether these occur before calculating the compositional responses.

The multivariate probit model corresponds to multiple binary probit models—one for each irrigation option i—of which the error terms are multivariate normally distributed. This is a valid assumption because the decision to adopt one irrigation option is closely related to choices for other irrigation options. For the ZADR model, Tsagris and Stewart (2018) make an adjustment to the log-likelihood of the 'standard' Dirichlet regression[1]. Dirichlet regressions can only take values between 0 and 1. The authors circumvent this by splitting the compositional vector $\boldsymbol{Y}$ into $\boldsymbol{B}$ possible subsets of non-zero components. The parameters are then estimated by maximising the sum of the Dirichlet log-likelihoods for each subset. There are four irrigation options for which the fractions can either be zero or non-zero, resulting in $\boldsymbol{B} = 2^4 = 16$ possible combinations. Table 1 illustrates these 16 possible combinations based on this study's data (explained in Data and variable selection). The table shows the means and standard deviations of the irrigated fractions in each of these subsets.

[Table 1]

The case where each of the options has a 0% fraction (first row of Table 1) does not comply with the constant-sum constraint of compositional data and does not occur in the dataset. The cases where 100% of a farm's surface area is irrigated with a single irrigation option, cannot be treated with a Dirichlet regression since there are no fractions to predict. These are rows two to five in Table 1. We, therefore, estimate the ZADR based on a subset of farms which adopt at least two different irrigation options. Consequently, the resulting log-likelihood is the sum of $\boldsymbol{B} = 11$ separate log-likelihoods (i.e., the last 11 rows of Table 1)[2].

Running the ZADR on only a subset of farms likely induces a selection bias. Sample selection bias occurs when some unobservables in the probit model are correlated with the unobservables in the ZADR model. If these unobservables are correlated with the ZADR's included explanatory variables, this leads to a bias in the estimates for these variables (Vella, 1998). This problem is overcome by adding a correction term which accounts for this dependence to the ZADR: the generalised residuals derived from the multivariate probit model (Gourieroux et al., 1987). These generalised residuals are, by construction, uncorrelated with the explanatory variables in the first-step multivariate probit model. By adding these residuals we run into a generated regressor problem which is avoided by bootstrapping the ZADR's standard errors (Mason & Smale, 2013; Murakami et al., 2021)[3].

We cluster the standard errors of both the probit model and the ZADR at the province level because we cannot assume that errors within provinces are uncorrelated. The decision of a farmer to adopt a certain irrigation technology is likely influenced by the irrigation adoption of the surrounding farms (Di Falco et al., 2020; Foster & Rosenzweig, 1995; Genius et al., 2014). By allowing correlation within provinces we partly account for this spatial dependence.

Data and variable selection

This study covers one specific country in the climate-vulnerable Mediterranean region. Italy represents an interesting study region because it has already suffered from climate change and will likely continue doing so (Brunetti et al., 2004; Giannakopoulos et al., 2009). Previous studies have shown that economic damage to agriculture caused by climate change in Italy is significant, especially in the South (Bozzola et al., 2018; Van Passel et al., 2017). Nonetheless, also the North will suffer from climate change (De Salvo et al., 2013). Because of this, Italy is expected to be one of Europe's countries which would benefit most from climate adaptation measures, making it a suitable subject for this study. Together with Spain, Italy is the EU country with the largest irrigated area, the largest volumes of irrigation water and the highest water consumption per irrigated hectare (Rossi, 2019).

The base dataset is farm-level data from 11,707 farms collected in 2021 by RICA, the Italian Farm Accountancy Data Network. Only 6,158 of these farms have an irrigable surface area[4]—i.e., fields which are connected to irrigation water grids—and thus face the irrigation choice. All other farms are excluded from the analysis. Another 282 farms are removed due to data incorrectness or incompleteness (e.g., irrigated surface area > irrigable surface area). For privacy reasons, RICA does not provide the exact locations of farms but only the province in which they are located. The dataset covers 105 out of 107 Italian provinces. All variables which are not available at the farm level come from publicly available sources and are aggregated to the province level to combine with the RICA data.

Table 2 gives an overview of the independent variables to include in the regression models, based on the existing irrigation choice literature. For each variable, we provide a hypothesis for the direction of the variable impact, i.e., whether we assume that the variable has a positive effect on the adoption of more efficient irrigation technologies or not. We base both the choice of variables and the hypotheses on a literature review of irrigation choice studies of which we provide the references in the table. Important variables which we did not come across in literature are not mentioned in the table but are elaborated upon here. The dependent variables are the fractions of land that farmers allocate to each irrigation technology.

We obtain the degree days variable by taking the sum of all daily temperatures exceeding 8°C over the growing season (Massetti et al., 2016). We define the growing season as the period from March 1st until September 30th (Di Falco et al., 2014). The precipitation variable is the sum of all rainfall over the growing season, in cm. For both variables, we take the 30-year mean, from 1991 until 2020. The 30-year mean of weather is climate, and we assume that farmers adapt their irrigation infrastructure in response to long-term climate rather than to yearly weather variations. We assume that rainfall directly influences the decision to irrigate or not since irrigation can substitute for precipitation. Additionally, we assume that rainfall indirectly influences the decision to adopt efficient irrigation options through its correlation with (ground)water availability, although this correlation decreases the more extreme the rainfall periods are. Besides the 30-year means, we also include variables for 30-year trends in the climate variables[5]. We are interested in whether farms respond to the temperature/precipitation increases/decreases which they have experienced through the adoption of different irrigation options.

An important determinant of irrigation technology choice is cost. Sprinkler and drip irrigation systems are energy-using and labour and water-saving as opposed to surface irrigation. Water, labour and energy prices are thus important drivers for irrigation technology selection (Caswell & Zilberman, 1985; Dinar et al., 1992; Dinar & Yaron, 1990; Frisvold & Bai, 2016; Mendelsohn & Dinar, 2003; Negri & Brooks, 1990). Per farm plot, we have data on energy and water expenditures, as well as hourly labour expenditures. We calculate average expenditures per farm—in euros per hectare for energy and water, and euros per hour for labour[6]—and then take the weighted mean expenditures per region, where the weight is defined by RICA such that sample statistics can be extrapolated to the full population of Italian farms. By using region-level costs rather than farm-level costs we avoid endogeneity of these variables in our model. Otherwise, costs might be a result of irrigation technology choice and not the reverse.

Not all irrigation options are suitable for every crop type (Rosa, 2022; Sauer et al., 2010). Therefore, crop choice is an important determinant in the irrigation decision. However, Negri and Brooks (1990) omit crop choice from their irrigation choice model because annual cropping decisions are taken after irrigation technologies are implemented, making it an endogenous variable. Depending on whether the crops included in a data sample are perennial or annual, crop choice is thus endogenous. Green et al. (1996) also found that irrigation choice is different for perennial as opposed to annual crops. We, therefore, include a dummy variable ‘perennial’ which is equal to one if the majority of the farm’s income comes from perennial crops. Additionally, we include a dummy variable ‘livestock’ which is equal to one if the farm’s core business is animal production. Similar to the study by Pronti et al. (2020), we expect these farms to be less willing to invest in costly irrigation systems.

We add several farm-specific variables which do not occur in the irrigation choice literature: whether the farm is family-run, whether it is organic and the fraction of a farm’s total utilised agricultural area which is rented. We assume this latter fraction to be relevant since farmers are less incentivised to invest in land improvement when the land is not their own. Thus, we expect more capital-intensive irrigation technologies to be adopted by farmers with little to no rented land. We expect family-run farms to be more conservative and therefore less willing to invest in newer technologies such as drip irrigation. The effect of organic farming is uncertain: on the one hand, farmers’ pro-environmental reasons for choosing organic farming may also apply to using abundant volumes of water for irrigation. On the other hand, farmers may need more irrigation to compensate for the lack of chemical additives. We also add two province-specific variables: GDP per capita (Kummu et al., 2020) and population density (ISTAT, 2020). The hypothesis for these two variables is that in wealthier regions or regions with more mouths to feed, there are higher fractions of (efficiently) irrigated land.

Another variable worth mentioning is water source. In literature, a distinction is made between surface water and groundwater, where reliance on groundwater is associated with more likely adoption of modern irrigation technologies and access to surface water with the adoption of gravity irrigation systems (Caswell & Zilberman, 1985; Dinar et al., 1992; Negri & Brooks, 1990). Besides individually sourced groundwater and surface water (through water abstraction licenses), irrigation water in Italy can be delivered by consortia. Water from consortia can come from either groundwater or surface water sources. The majority of farmers are part of a collective irrigation network, known as a Reclamation and Irrigation Consortium (RIC) (Molle et al., 2019). In terms of irrigation, these RICs are responsible for the rational use of water for irrigation purposes and the provision, regulation and quantitative and qualitative protection of irrigation water (Regione Lombardia, n.d.). In practice, RICs are mainly occupied with infrastructural irrigation works and the water costs mentioned earlier are paid to these RICs. We create a province-level dummy variable which states which water source is predominant in the province in terms of irrigable surface area. We use province-level data from the Italian agricultural census (ISTAT, 2010), rather than farm-level data because farm-level water source is likely endogenous. This variable is also an indication of water availability since regions in which groundwater is extracted are regions in which water is less readily available.

[Table 2]

Results

Descriptive statistics

Figure 1 shows the fractions of land irrigated with each irrigation option, considering the entire sample. The fractions per region are composed of the weighted mean fractions of all farms located within the region. We see that rainfed fractions are high, apart from in the far south and north of Italy. Surface irrigation mostly prevails in the northwest. Sprinkler irrigation is used throughout the whole of Italy. High fractions of drip irrigation are found mostly in Puglia, the heel of the boot.

[Figure 1]

The average water cost in our sample is 46.45 €/ha, ranging from 5.71 €/ha in the Marche region, up to 288.86 €/ha in Liguria. This is in line with the price ranges reported in the 'Atlas of Italian irrigation systems' CREA (2014). The low water cost in Marche does not mean that water is almost free of charge there, but that few of the farms in our sample located in this region pay for water. Descriptive statistics of all model variables are provided in Appendix B. We also show maps for the climatic variables. The descriptives of the subsample used for the ZADR (farms which adopt at least two irrigation systems) are similar to those of the rest of the sample.

Results from the multivariate probit model

The results of the multivariate probit model are provided in Appendix C. We standardise all continuous variables. A likelihood ratio test shows that the correlations between the equations' error terms are significantly different from zero ($\chi^2_6 = 736.15, p = 0.00$). This means that the use of a multivariate probit—rather than individual probit models—is important.

Many of the variables are not statistically significant determinants of irrigation system adoption. This does not necessarily mean that the covariates are not important for this decision.

For some variables, depending on the width of the 95% confidence intervals (CIs), we can still reasonably say that one effect (in terms of sign) is more compatible with our data than the opposite effect (Amrhein et al., 2019). Looking at the CIs, we find that temperature is only statistically significant for sprinkler adoption. Higher temperatures result in higher probabilities of adopting sprinkler irrigation. Although not statistically significant, the CI of the degree days variable for surface irrigation is predominantly negative meaning that higher temperatures likely lead to lower probabilities of adopting this option. Precipitation has no statistically significant effect on the adoption of any of the irrigation types. However, looking at the CI, lower levels of precipitation likely encourage the use of drip irrigation, as hypothesized. The trend in growing season degree days does not affect irrigation system adoption. The trend in precipitation has a negative effect on the use of surface irrigation, i.e., farms which experience precipitation increases are less likely to adopt surface irrigation. The CIs indicate that sprinkler irrigation becomes more likely with the experienced precipitation increases. As expected, farms experiencing more frost days per year are more likely to adopt sprinkler irrigation since this serves as a frost protection measure. More frost days lead to less likely adoption of surface irrigation or rainfed farming.

Family-directed firms are more likely to adopt surface irrigation and less likely to adopt sprinkler or drip irrigation. This confirms that these firms are perhaps more hesitant to switch to newer technologies. The variable ‘age’ is not statistically significant. On larger farms, rainfed farming is more likely. Drip irrigation is less likely. This is explained by the large investment necessary to cover a large surface area with infrastructure for drip irrigation. Farms located in less-favoured areas are more likely to adopt drip irrigation, in line with the findings of Molle et al. (2019). These farms receive more support for technology investment. As expected, livestock farms have a lower probability of adopting drip irrigation, likely also because of the costly investment. Farms with perennial crops, on the other hand, are more likely to adopt drip irrigation. They are significantly less likely to use any of the other three options. In line with Mendelsohn and Dinar (2003), we find that clayey soils discourage the irrigation use.

Drip irrigation is used less in regions where the predominant water sources are surface water and consortium water. This confirms the existing literature which states that drip irrigation is used in places where groundwater use prevails. Farms located in regions where water predominantly comes from consortia are more likely to use surface irrigation, despite the responsibility of consortia to preserve irrigation water. Higher labour costs lead to a higher likelihood of rainfed farming or adoption of drip irrigation and a lower likelihood of surface irrigation. This is in line with surface irrigation as a more labour-intensive irrigation method. Higher water costs do not discourage farmers from irrigating; this variable has a negative coefficient for rainfed farming. On the contrary, water costs are positively correlated with the probability of adopting surface irrigation, the most water-consuming technology. Consortia in Italy usually charge a flat rate per hectare, rather than a volumetric price (Berbel et al., 2019; CREA, 2014). This likely discourages them from investing in water-saving irrigation technologies. The fact that both variables—consortium water as the predominant water source, and water costs—have coefficients of the same sign was to be expected, since RICs are the organisations which collect the water charges. This may raise concerns regarding the correlation between these variables. However, the correlations between water costs and the water source dummies are low[7]. Furthermore, when we exclude the three cost variables from the multivariate probit and the ZADR, the results remain stable.

Results from the zero-adjusted Dirichlet regression

Table C - 2 in Appendix C shows the regression output of the ZADR model. The estimates in bold are those which are statistically significant. The generalised residuals from the first hurdle are statistically significant for rainfed farming, sprinkler irrigation and drip irrigation. Meaning that there is a selection bias, especially for these components. This is reasonable because, by running the ZADR on a subset of farms which adopt at least two irrigation options, we remove mostly farms which are 100% rainfed, sprinkler irrigated or drip irrigated (1,185, 687 and 737 farms respectively, see Table 1).

Family-directed firms likely have lower degrees of sprinkler and drip irrigation, in line with the results of the probit model. In regions where mainly consortium water is used, there are higher degrees of surface irrigation and lower degrees of drip irrigation. The drip irrigation coefficients for both consortium water and surface water are negative, meaning that higher drip-irrigated fractions are found in regions where individually sourced groundwater prevails. In line with the multivariate probit model, regions in which the majority of water comes from consortia have higher degrees of surface irrigation. As mentioned earlier, water metering is not the norm in Italy (Berbel et al., 2019; CREA, 2014), meaning that the fixed rate charged by these consortia does not discourage farmers from having high fractions of surface irrigation.

Perennial crop farms have larger shares of irrigated land (negative coefficient for rainfed farming), drip irrigation in particular. They have significantly lower fractions of sprinkler irrigation. Our results suggest that farm size does not affect the degree of irrigation technology adoption. We hypothesized that larger farms are more likely to invest in capital-intensive irrigation technologies because they can realise economies of scale and because, with irrigation, they have the potential to benefit from climate warming (Vanschoenwinkel & Van Passel, 2018). However, to have a large share of efficiently irrigated land, farms with large surface areas also need to irrigate a very large area. This is potentially a reason why the farm size variable has a significant influence on rainfed farming and the adoption of drip irrigation in the probit models, but not in the ZADR model.

Temperature positively influences the adoption intensity of sprinkler irrigation. Our data suggests that surface-irrigated fractions are negatively influenced by higher temperatures. Rainfed and drip-irrigated fractions are relatively insensitive to temperature. The amount of precipitation over the growing season does not significantly affect the degree of adoption of any of the options. Neither does the trend in growing season degree days, i.e., the temperature increase/decrease which farms have experienced over the past 30 years does not influence their irrigated fractions. The trend in precipitation levels, however, does play a role in their adoption intensity decisions. Figure 2 illustrates these findings on graphs. The plots show how the fractions of each of the irrigation technologies change in response to both the mean and trend in growing season degree days and precipitation, predicted by the ZADR model. All other independent variables are set to their mean (continuous variables) or mode (categorical variables).

[Figure 2]

Looking at the graphs, we see that the fraction of surface-irrigated land decreases with temperature and the fractions of sprinkler-irrigated land increase, from a particular point. Rainfed fractions increase up to a certain temperature, from where they start to decrease. In the graph, the rainfed fraction is highest at around 2050 degree days (≈ 17.6°C). 67 out of 107 provinces have temperatures lower than this threshold. These results suggest that a large number of farms adapt to climate change by reducing their surface-irrigated land shares (and increasing rainfed fractions). When temperatures exceed a certain threshold, however, we find that farmers invest in sprinkler irrigation. The initial switch from surface irrigation to rainfed farming can be either out of necessity (i.e., water is scarce so farmers have no irrigation water available) or because farmers switch to more heat and drought-resistant varieties. Crop switching has been shown to have great potential in reducing climate-induced agricultural losses (Rising & Devineni, 2020) and farmers in the Mediterranean region are found to adapt to high temperatures by choosing crops which are less sensitive to higher temperatures and are traditionally rainfed (Vanschoenwinkel et al., 2022). However, since expertise is needed for growing a certain crop, it is unlikely that farmers will switch to heat-resistant crops as an initial reaction and subsequently invest in sprinkler irrigation systems. Drip irrigation appears to be relatively insensitive to growing season degree days. The high costs of installing and implementing this technology, The graphs for mean growing season precipitation and trends in the growing season degree days confirm that irrigated fractions are relatively insensitive to these variables. The curves of all four options are relatively flat in these graphs. The limited effect of precipitation is in line with a study by Mendelsohn and Dinar (2003), who found that irrigation substitutes for temperature but not for precipitation.

For the precipitation trend, we find similar responses as those for temperature, although these graphs are less straightforward to interpret. Farms which have experienced precipitation increases (right of the vertical line) have higher fractions of rainfed farming and sprinkler irrigation and lower fractions of surface irrigation. Farms which have experienced precipitation decreases (left of the vertical line) have lower fractions of rainfed farming, as expected. We would hypothesize that farms that have seen their climate become drier would make the switch to more efficient irrigation systems. Oddly, these farms have higher fractions of surface irrigation. If we look at the maps of the climate variables, shown in Appendix B, we see that the regions which have become drier are those regions which have the highest rainfall on average. Surface irrigation is not suitable in areas with too much rainfall: Negri and Brooks (1990) state that unexpected rainfall after (heavy) surface irrigation leads to crop damage discouraging the use of surface irrigation in regions with a lot of rainfall. These wet regions becoming drier might make surface irrigation more suitable for these farmers.

Comparing the regression tables of the multivariate probit model and the ZADR, we find that the coefficient signs are mostly consistent across both models. However, we do not find that the same variables are significant in both models. For example, the multivariate probit finds a positive significant effect of perennial farming on the adoption of drip irrigation and negative significant effects for the other options. The signs of the ZADR estimates point in the same direction, but perennial crop farms do not have significantly higher fractions of drip-irrigated land or lower fractions of surface-irrigated land. Consequently, we conclude that the adoption decision and the intensity-of-adoption decision are made separately and the use of this double hurdle-like approach is appropriate.

Predicting the compositional response

The results of the previous two sections can now be used to predict the compositional response of each farm, by plugging the results of both models into Equation 1. We ensure that the multivariate probit model does not predict zero values for all four irrigation options, because this would mean that the constant-sum constraint is not met.

Table 3 shows how the average compositional response changes when temperatures increase by 1°C (+ 214 degree days over the growing season, frost days variable remains unaltered) and the case where rainfall decreases by 1 cm over the growing season. All other covariates are kept constant. This is equivalent to calculating the marginal effects of temperature and precipitation on the irrigation choice, as has been done by Ahmed and Schmitz (2015) for (discrete) crop choices. In addition to these marginal effects, we calculate changes in the irrigated fractions resulting from a more realistic change in climate. Under RCP 4.5—an intermediate climate scenario—temperatures in Italy will likely increase by 2.5°C by 2061-2090 in comparison to the reference period 1971-2000. By the end of the century, precipitation will likely decrease by 1.5% (Baronetti et al., 2022). This 1.5% is equivalent to 0.16-1.18 cm of precipitation in our sample. These results confirm the limited effect of mean precipitation on the irrigated shares. Looking at the combined effect of temperature and precipitation (right column in Table 3), the effect of a temperature increase clearly dominates. Note that these results differ from the graphs shown in Figure 2, since they are calculated from the combination of both models rather than just the ZADR.

[Table 3]

Because the standard deviations are large, we know that there is a lot of variation over the sample. Figure 3 shows how the effects of the climate scenario vary across the country. The effect of this change in climate is predominantly positive for the adoption of sprinkler irrigation and negative for the rainfed fractions. In Piemonte (North West) we see a switch from surface irrigation to rainfed farming. This is the region which currently still has the most surface irrigation (Figure 1).

[Figure 3]

Conclusion

With this research, we attempted to determine whether farmers adapt to climate change by switching between irrigation options and how. Based on the results, we can confirm that surface irrigation will phase out of the irrigation mix in Italy with increasing temperatures, as it has been doing already (CREA, 2014). We can also confirm that the adoption of sprinkler irrigation will likely increase with warming and rainfed fractions will decrease.

From the ZADR's results, we conclude that farms located in cooler regions respond to increasing temperatures by reducing their surface-irrigated fractions and switching to rainfed farming (Figure 3 shows that this is the case for Piemonte). However, from a certain temperature threshold, this strategy likely becomes unprofitable and farmers increase their land shares irrigated with sprinkler irrigation. The highest fractions of sprinkler-irrigated land are found in the North of Italy, where water availability is highest. Farms with sprinkler irrigation in regions with lower water availability are more likely to irrigate when water is available, rather than based on crop needs. The same conclusion cannot be drawn for drip irrigation. The model does not predict an increase in the adoption of drip irrigation under climate warming, suggesting that farmers are not making the transition to this highly efficient irrigation method autonomously. This is presumably due to the high capital costs associated with such irrigation systems, suggesting that support policies are needed to initiate this transition. However, support for investments in irrigation can only be given to farms in case water-saving targets are measured and met. This requires water metering systems to be in place (European Commission, 2021), which is currently lacking in Italy.

The results show that farms which are located in regions where irrigation water is predominantly obtained through consortia have higher fractions of inefficiently irrigated land. Consortium membership likely offers farmers abundant volumes of water at a fixed tariff, making them less aware of water scarcity and less inclined to reduce their water consumption. Although RICs are responsible for the 'qualitative and quantitative protection of irrigation water' this is not visible in the regression outputs. Closely related to this conclusion is the finding that higher water costs do not encourage farmers to transition from surface to sprinkler irrigation, or from sprinkler to drip irrigation, although this likely only holds for fixed water costs per hectare. With our results, we cannot make claims about the effectiveness of volumetric excise taxes on water as a measure for stimulating the adoption of more efficient irrigation technologies, since currently farmers' water consumption is insufficiently reflected in their water bills.

Although this paper solves some of the statistical limitations related to previous irrigation choice studies, it also has some setbacks. Farms which currently have no irrigable surface area have been excluded from the analysis, reducing the data sample considerably. If irrigation networks are expanded, these farms will face the irrigation choice in the future. Secondly, the RICA dataset only contains data on legal water extraction and irrigation. According to Molle et al. (2019), public authorities in Italy are not fully capable of preventing illegal or excessive water abstraction. This may mean that a large part of the 'rainfed' agriculture in the dataset is indeed irrigated. Further future research could look at the economic value of switching to more efficient irrigation options, rather than at the actual choices of farmers. As mentioned in the introduction, many studies have already attempted at valuing irrigation as a climate adaptation measure. Vanschoenwinkel and Van Passel (2018), for example, show that the positive marginal effect of temperature on farmland values increases with the share of land that is irrigated. One could analyse how economic climate change impacts differ depending on the irrigation options used and their land shares. Future research could also look at how increasing irrigation efficiency compares to other water-saving strategies. For example, and as mentioned previously, studies have pointed toward the planting of less water-intensive crops as a way to reduce water demand (McCord et al., 2018; Rosa, 2022). It would be interesting to see how both strategies compare to one another in terms of farm preferences, effectiveness (in reducing water consumption) and economic feasibility.

[1] We provide an explanatory note on the Dirichlet distribution and its log-likelihood formula in Appendix A, based on the work of Maier, M. J. (2014). *DirichletReg: Dirichlet Regression for Compositional Data in R* (Research Report Series / Department of Statistics and Mathematics, Issue. https://epub.wu.ac.at/4077/.

[2] For the estimation of this regression, we use the 'zadr' function from the R package 'Compositional' R Core Team. (2020). *R: A language and environment for statistical computing*. In R Foundation for Statistical Computing. https://www.R-project.org/, Tsagris, M., Athineou, G., Alenazi, A., & Adam, C. (2023). *Compositional: Compositional Data Analysis*. In (Version 6.1) https://CRAN.R-project.org/package=Compositional.

[3] A generated regressor problem occurs when a regressor, in this case the generalised residual, is generated from the data. This leads to their standard errors being too small. Bootstrapping is considered a solution to this issue.

[4] Irrigable surface area is defined as the 'maximum area that can potentially be irrigated during the reference crop year based on the capacity of the technical systems and the amount of water

available under normal conditions' ISTAT. (2010). *6° Censimento dell'agricoltura*. http://dati-censimentoagricoltura.istat.it/ .

[5] This 30-year trend is derived from regressing the two climatic variables on a continuous variable 'year'. The trend is then equal to the slope, i.e., the estimated coefficient for the years variable.

[6] Preferable would be a price per m^3 for water and a price per kWh for energy, but these are not deducible from the data.

[7] The point-biserial correlation between water costs and the dummy 'Source – consortium water' is 0.08, the dummy 'Source – groundwater' is -0.01 and the dummy 'Source – surface water' is -0.12.

References

Ahmed, M. N., & Schmitz, P. M. (2015). Climate change impacts and the value of adaptation - can crop adjustments help farmers in Pakistan? *International Journal of Global Warming*, *8*(2), 231. https://doi.org/10.1504/ijgw.2015.071954

Aitchison, J. (1982). The Statistical Analysis of Compositional Data. *Journal of the Royal Statistical Society. Series B (Methodological)*, *44*(2), 139-177. http://www.jstor.org/stable/2345821

Amrhein, V., Greenland, S., & McShane, B. (2019). Scientists rise up against statistical significance. *Nature*, *567*, 305-307. https://doi.org/https://doi.org/10.1038/d41586-019-00857-9

Asrey, R., Kumar, S., & Meena, N. K. (2018). Chapter 7 - Influence of Water Quality on Postharvest Fruit and Vegetable Quality. In M. W. Siddiqui (Ed.), *Preharvest Modulation of Postharvest Fruit and Vegetable Quality* (pp. 169-187). Academic Press. https://doi.org/https://doi.org/10.1016/B978-0-12-809807-3.00007-X

Ballabio, C., Panagos, P., & Monatanarella, L. (2016). Mapping topsoil physical properties at European scale using the LUCAS database. *Geoderma*, *261*, 110-123. https://doi.org/10.1016/j.geoderma.2015.07.006

Baronetti, A., Dubreuil, V., Provenzale, A., & Fratianni, S. (2022). Future droughts in northern Italy: high-resolution projections using EURO-CORDEX and MED-CORDEX ensembles. *Climatic Change*, *172*(3), 22. https://doi.org/10.1007/s10584-022-03370-7

Berbel, J., Borrego-Marin, M. M., Exposito, A., Giannoccaro, G., Montilla-Lopez, N. M., & Roseta-Palma, C. (2019). Analysis of irrigation water tariffs and taxes in Europe. *Water Policy*, *21*(4), 806-825. https://doi.org/10.2166/wp.2019.197

Bindi, M., & Olesen, J. E. (2011). The responses of agriculture in Europe to climate change. *REGIONAL ENVIRONMENTAL CHANGE*, *11*(S1), 151-158. https://doi.org/10.1007/s10113-010-0173-x

BIO Intelligence Service. (2012). *Water saving potential in agriculture in Europe: findings from the existing studies and application to case studies, Final report* European Commission DG ENV.

Bozzola, M., Massetti, E., Mendelsohn, R., & Capitanio, F. (2018). A Ricardian analysis of the impact of climate change on Italian agriculture. *European Review of Agricultural Economics*, *45*(1), 57-79. https://doi.org/10.1093/erae/jbx023

Brouwer, C., Prins, K., Kay, M., & Heibloem, M. (1988). Irrigation Water Management: Irrigation Methods. In *Training manual no 5*. FAO.

Brunetti, M., Buffoni, L., Mangianti, F., Maugeri, M., & Nanni, T. (2004). Temperature, precipitation and extreme events during the last century in Italy. *Global and Planetary Change*, *40*(1-2), 141-149. https://doi.org/10.1016/s0921-8181(03)00104-8

Caswell, M., & Zilberman, D. (1985). The Choices of Irrigation Technologies in California. *American Journal of Agricultural Economics*, *67*(2), 224-234. https://doi.org/10.2307/1240673

Chatzopoulos, T., & Lippert, C. (2016). Endogenous farm-type selection, endogenous irrigation, and spatial effects in Ricardian models of climate change. *European Review of Agricultural Economics*, *43*(2), 217-235. https://doi.org/10.1093/erae/jbv014

Chelli, S., Wellstein, C., Campetella, G., Canullo, R., Tonin, R., Zerbe, S., & Gerdol, R. (2017). Climate change response of vegetation across climatic zones in Italy. *Climate Research*, *71*(3), 249-262. https://www.jstor.org/stable/24897503

Cornes, R. C., van der Schrier, G., van den Besselaar, E. J. M., & Jones, P. D. (2018). An Ensemble Version of the E-OBS Temperature and Precipitation Data Sets. *Journal of*

Geophysical Research: Atmospheres, *123*(17), 9391-9409. https://doi.org/10.1029/2017jd028200
Cragg, J. G. (1971). Some Statistical Models for Limited Dependent Variables with Application to the Demand for Durable Goods. *Econometrica*, *39*(5), 829-844. https://doi.org/10.2307/1909582
CREA. (2014). *Atlas of Italian irrigation systems* (R. Zucaro & A. Corapi, Eds.). INEA. www.sigrian.crea.gov.it
CREA. (2022). *Banca Dati Valutazione - Tabelle dati*. https://rica.crea.gov.it/APP/documentazione/
De Salvo, M., Raffaelli, R., & Moser, R. (2013). The impact of climate change on permanent crops in an Alpine region: A Ricardian analysis. *Agricultural Systems*, *118*, 23-32. https://doi.org/https://doi.org/10.1016/j.agsy.2013.02.005
Di Falco, S., Adinolfi, F., Bozzola, M., & Capitanio, F. (2014). Crop Insurance as a Strategy for Adapting to Climate Change. *Journal of Agricultural Economics*, *65*(2), 485-504. https://doi.org/10.1111/1477-9552.12053
Di Falco, S., Doku, A., & Mahajan, A. (2020). Peer effects and the choice of adaptation strategies. *Agricultural Economics*, *51*(1), 17-30. https://doi.org/https://doi.org/10.1111/agec.12538
Dinar, A., Campbell, M. B., & Zilberman, D. (1992). Adoption of improved irrigation and drainage reduction technologies under limiting environmental conditions. *Environmental & Resource Economics*, *2*(4), 373-398. https://doi.org/10.1007/bf00304968
Dinar, A., & Yaron, D. (1990). Influence of Quality and Scarcity of Inputs on the Adoption of Modern Irrigation Technologies. *Western Journal of Agricultural Economics*, *15*(2), 224-233. http://www.jstor.org.kuleuven.e-bronnen.be/stable/40988086
EEA. (2017). *Climate change, impacts and vulnerability in Europe 2016: An indicator-based assessment*. Office for Official Publications of the European Communities. https://www.eea.europa.eu/publications/climate_report_2_2004
EEA. (2019). *The European environment — state and outlook 2020. Knowledge for transition to a sustainable Europe*. P. O. o. t. E. Union. https://www.eea.europa.eu/publications/soer-2020
European Commission. (2020). *EU Agriculture in numbers: Performance of the nine specific objectives of the CAP*. https://agriculture.ec.europa.eu/system/files/2020-05/analytical-factsheet-eu-level_en_0.pdf
Commission Delegated Regulation (EU) 2022/126 (2021).
Regulation (EU) No 1305/2013 (2013).
Directive 2000/60/Ec of the European Parliament and of the Council of 23 October 2000 establishing a framework for Community action in the field of water policy, 73 (2000). http://data.europa.eu/eli/dir/2000/60/oj
FAO. (2012). *Coping with water scarcity: An action framework for agriculture and food security* (FAO Water Reports, Issue.
Feng, X., Zhu, J., Lin, P.-S., & Steen-Adams, M. M. (2017). Composite likelihood approach to the regression analysis of spatial multivariate ordinal data and spatial compositional data with exact zero values. *Environmental and Ecological Statistics*, *24*(1), 39-68. https://doi.org/10.1007/s10651-016-0360-0
Finger, R., Hediger, W., & Schmid, S. (2011). Irrigation as adaptation strategy to climate change—a biophysical and economic appraisal for Swiss maize production. *Climatic Change*, *105*(3), 509-528. https://doi.org/10.1007/s10584-010-9931-5

Finkel, H. J., & Nir, D. (1983). Criteria for the Choice of Irrigation Method. In *Handbook of Irrigation Technology* (pp. 231). CRC Press. https://doi.org/https://doi.org/10.1201/9781351072656

Foster, A. D., & Rosenzweig, M. R. (1995). Learning by Doing and Learning from Others: Human Capital and Technical Change in Agriculture. *Journal of Political Economy*, *103*(6), 1176-1209. https://doi.org/10.1086/601447

Frisvold, G., & Bai, T. (2016). Irrigation Technology Choice as Adaptation to Climate Change in the Western United States. *Journal of Contemporary Water Research & Education*, *158*(1), 62-77. https://doi.org/10.1111/j.1936-704x.2016.03219.x

Frisvold, G. B., & Deva, S. (2012). Farm Size, Irrigation Practices, and Conservation Program Participation in the US Southwest. *Irrigation and Drainage*, *61*(5), 569-582. https://doi.org/https://doi.org/10.1002/ird.1676

Genius, M., Koundouri, P., Nauges, C., & Tzouvelekas, V. (2014). Information Transmission in Irrigation Technology Adoption and Diffusion: Social Learning, Extension Services, and Spatial Effects. *American Journal of Agricultural Economics*, *96*(1), 328-344. https://doi.org/https://doi.org/10.1093/ajae/aat054

Giannakopoulos, C., Le Sager, P., Bindi, M., Moriondo, M., Kostopoulou, E., & Goodess, C. M. (2009). Climatic changes and associated impacts in the Mediterranean resulting from a 2 °C global warming. *Global and Planetary Change*, *68*(3), 209-224. https://doi.org/10.1016/j.gloplacha.2009.06.001

Gourieroux, C., Monfort, A., Renault, E., & Trognon, A. (1987). Generalised residuals. *Journal of Econometrics*, *34*(1), 5-32. https://doi.org/https://doi.org/10.1016/0304-4076(87)90065-0

Green, G., Sunding, D., Zilberman, D., & Parker, D. (1996). Explaining Irrigation Technology Choices: A Microparameter Approach. *American Journal of Agricultural Economics*, *78*(4), 1064-1072. https://doi.org/10.2307/1243862

Greenacre, M. (2021). Compositional Data Analysis. *Annual Review of Statistics and Its Application*, *8*(1), 271-299. https://doi.org/10.1146/annurev-statistics-042720-124436

Gruère, G., Shigemitsu, M., & Crawford, S. (2020). Agriculture and water policy changes. https://doi.org/doi:https://doi.org/10.1787/f35e64af-en

Hansen, B. E. (2022). *Jackknife Standard Errors for Clustered Regression*. University of Wisconsin. https://www.ssc.wisc.edu/~bhansen/papers/tcauchy.pdf

Holzapfel, E. A., & Mariño, M. A. (2008). Irrigation in Agriculture. In S. E. Jørgensen & B. D. Fath (Eds.), *Encyclopedia of Ecology* (pp. 2033-2039). Academic Press. https://doi.org/https://doi.org/10.1016/B978-008045405-4.00628-5

IPCC. (2001). *Climate Change 2001: Impacts, Adaptation, and Vulnerability. Contribution of WGII to the TAR of the IPCC*. C. U. Press. https://www.ipcc.ch/report/ar3/wg2/

ISTAT. (2010). *6° Censimento dell'agricoltura*. http://dati-censimentoagricoltura.istat.it/

ISTAT. (2020). *Demographic indicators*. http://dati.istat.it/Index.aspx?DataSetCode=dcis_inddemog1&Lang=en

Italy CAP Strategic Plan, Ministero dell'Agricoltura della Sovranità Alimentare e delle Foreste, 3654 (2022). https://www.reterurale.it/downloads/PSP_Italia_15112022.pdf

Jägermeyr, J., Gerten, D., Heinke, J., Schaphoff, S., Kummu, M., & Lucht, W. (2015). Water savings potentials of irrigation systems: global simulation of processes and linkages. *Hydrol. Earth Syst. Sci.*, *19*(7), 3073-3091. https://doi.org/10.5194/hess-19-3073-2015

Kummu, M., Taka, M., & Guillaume, J. H. A. (2020). Gridded global datasets for Gross Domestic Product and Human Development Index over 1990-2015. *Scientific Data*, *5*(180004). https://doi.org/10.1038/sdata.2018.4

Kurukulasuriya, P., Kala, N., & Mendelsohn, R. (2011). Adaptation and climate change impacts: A structural Ricardian model of irrigation and farm income in Africa. *Climate Change Economics*, *2*(2), 149–174. https://doi.org/10.1142/S2010007811000255

Kurukulasuriya, P., & Mendelsohn, R. (2008). Crop switching as a strategy for adapting to climate change. *African Journal of Agricultural and Resource Economics*, *02*(1), 56970. https://EconPapers.repec.org/RePEc:ags:afjare:56970

Maier, M. J. (2014). *DirichletReg: Dirichlet Regression for Compositional Data in R* (Research Report Series / Department of Statistics and Mathematics, Issue. https://epub.wu.ac.at/4077/

Mason, N. M., & Smale, M. (2013). Impacts of subsidized hybrid seed on indicators of economic well-being among smallholder maize growers in Zambia. *Agricultural Economics*, *44*(6), 659-670. https://doi.org/10.1111/agec.12080

Massetti, E., Mendelsohn, R., & Chonabayashi, S. (2016). How well do degree days over the growing season capture the effect of climate on farmland values? *Energy Economics*, *60*, 144-150. https://doi.org/https://doi.org/10.1016/j.eneco.2016.09.004

McCord, P., Waldman, K., Baldwin, E., Dell'Angelo, J., & Evans, T. (2018). Assessing multi-level drivers of adaptation to climate variability and water insecurity in smallholder irrigation systems. *World Development*, *108*, 296-308. https://doi.org/https://doi.org/10.1016/j.worlddev.2018.02.009

Mendelsohn, R., & Dinar, A. (2003). Climate, Water, and Agriculture. *Land Economics*, *79*(3), 328-341. https://doi.org/10.2307/3147020

Metzger, M. J., Rounsevell, M. D. A., Acosta-Michlik, L., Leemans, R., & Schröter, D. (2006). The vulnerability of ecosystem services to land use change. *Agriculture, Ecosystems & Environment*, *114*(1), 69-85. https://doi.org/10.1016/j.agee.2005.11.025

Molle, F., Sanchis-Ibor, C., & Avellà-Reus, L. (2019). *Irrigation in the Mediterranean: Technologies, Institutions and Policies* (Vol. 22). Cham: Springer International Publishing AG.

Moreno, G., & Sunding, D. L. (2005). Joint Estimation of Technology Adoption and Land Allocation with Implications for the Design of Conservation Policy. *American Journal of Agricultural Economics*, *87*(4), 1009-1019. https://doi.org/10.1111/j.1467-8276.2005.00784.x

Murakami, E., Yamada, E., & Sioson, E. P. (2021). The impact of migration and remittances on labor supply in Tajikistan. *Journal of Asian Economics*, *73*, 101268. https://doi.org/https://doi.org/10.1016/j.asieco.2020.101268

Negri, D. H., & Brooks, D. H. (1990). Determinants of Irrigation Technology Choice. *Western Journal of Agricultural Economics*, *15*(2), 213-223. http://www.jstor.org.kuleuven.e-bronnen.be/stable/40988085

Negri, D. H., Gollehon, N. R., & Aillery, M. P. (2005). The Effects of Climatic Variability on US Irrigation Adoption. *Climatic Change*, *69*(2), 299-323. https://doi.org/10.1007/s10584-005-1817-6

Negri, D. H., Hanchar, J. J., & United States Department of Agriculture, Economic Research Service,. (1989). *Water Conservation Through Irrigation Technology* (All U.S. Government Documents (Utah Regional Depository), Issue. https://digitalcommons.usu.edu/govdocs/119

Olen, B., Wu, J., & Langpap, C. (2016). Irrigation Decisions for Major West Coast Crops: Water Scarcity and Climatic Determinants. *American Journal of Agricultural Economics*, *98*(1), 254-275. https://doi.org/10.1093/ajae/aav036

Pokhrel, B. K., Paudel, K. P., & Segarra, E. (2018). Factors affecting the choice, intensity, and allocation of irrigation technologies by U.S. cotton farmers [Article]. *Water (Switzerland)*, *10*(6), Article 706. https://doi.org/10.3390/w10060706

Pronti, A., Auci, S., & Mazzanti, M. (2020). *What are the factors driving the adoption and intensity of sustainable irrigation technologies in Italy?* [Working Paper]. CERCIS.

R Core Team. (2020). *R: A language and environment for statistical computing*. In R Foundation for Statistical Computing. https://www.R-project.org/

Regione Lombardia. (n.d., 31-08-2021). *Consorzi di bonifica e irrigazione: cosa sono*. Retrieved 02-02-2022 from www.regione.lombardia.it

Reidsma, P., Ewert, F., Lansink, A. O., & Leemans, R. (2010). Adaptation to climate change and climate variability in European agriculture: The importance of farm level responses. *European Journal of Agronomy*, *32*(1), 91-102. https://doi.org/10.1016/j.eja.2009.06.003

Rising, J., & Devineni, N. (2020). Crop switching reduces agricultural losses from climate change in the United States by half under RCP 8.5. *Nature Communications*, *11*(1), 4991. https://doi.org/10.1038/s41467-020-18725-w

Rosa, L. (2022). Adapting agriculture to climate change via sustainable irrigation: biophysical potentials and feedbacks. *Environmental Research Letters*, *17*(6), 063008. https://doi.org/10.1088/1748-9326/ac7408

Rossi, R. (2019). *Irrigation in EU agriculture*. European Parliament

Sauer, T., Havlík, P., Schneider, U. A., Schmid, E., Kindermann, G., & Obersteiner, M. (2010). Agriculture and resource availability in a changing world: The role of irrigation. *Water Resources Research*, *46*(6). https://doi.org/https://doi.org/10.1029/2009WR007729

Schlenker, W., Hanemann, W. M., & Fisher, A. C. (2005). Will U.S. Agriculture Really Benefit from Global Warming? Accounting for Irrigation in the Hedonic Approach. *American Economic Review*, *95*(1), 395-406. https://doi.org/10.1257/0002828053828455

Seo, S. N., & Mendelsohn, R. (2008). Measuring impacts and adaptations to climate change: a structural Ricardian model of African livestock management. *Agricultural Economics*, *38*(2), 151-165. https://doi.org/10.1111/j.1574-0862.2008.00289.x

Siyum, N., Giziew, A., & Abebe, A. (2022). Factors influencing adoption of improved bread wheat technologies in Ethiopia: empirical evidence from Meket district. *Heliyon*, *8*(2), e08876. https://doi.org/10.1016/j.heliyon.2022.e08876

Smit, B., & Skinner, M. W. (2002). Adaptation options in agriculture to climate change: a typology.

Smithson, M., & Verkuilen, J. (2006). A better lemon squeezer? Maximum-likelihood regression with beta-distributed dependent variables. *Psychol Methods*, *11*(1), 54-71. https://doi.org/10.1037/1082-989x.11.1.54

Tsagris, M. (2018). *Modelling structural zeros in compositional data* (Working papers, Issue.

Tsagris, M., Athineou, G., Alenazi, A., & Adam, C. (2023). *Compositional: Compositional Data Analysis*. In (Version 6.1) https://CRAN.R-project.org/package=Compositional

Tsagris, M., & Stewart, C. (2018). A Dirichlet Regression Model for Compositional Data with Zeros. *Lobachevskii Journal of Mathematics*, *39*(3), 398-412. https://doi.org/10.1134/S1995080218030198

Van Passel, S., Massetti, E., & Mendelsohn, R. (2017). A Ricardian Analysis of the Impact of Climate Change on European Agriculture. *Environmental and Resource Economics*, *67*(4), 725-760. https://doi.org/DOI 10.1007/s10640-016-0001-y

Vanschoenwinkel, J., & Van Passel, S. (2018). Climate response of rainfed versus irrigated farms: the bias of farm heterogeneity in irrigation. *Climatic Change*, *147*(1-2), 225-234. https://doi.org/10.1007/s10584-018-2141-2

Vanschoenwinkel, J., Vancauteren, M., & Van Passel, S. (2022). How do Western European farms behave and respond to climate change? A simultaneous irrigation-crop decision model [Article; Early Access]. *Climate Change Economics*, 38, Article 2250009. https://doi.org/10.1142/s2010007822500099

Vella, F. (1998). Estimating Models with Sample Selection Bias: A Survey. *The Journal of Human Resources*, *33*(1), 127-169. https://doi.org/10.2307/146317

Workie, D. M., & Tasew, W. (2023). Adoption and intensity use of malt barley technology package by smallholder farmers in Ethiopia: A double hurdle model approach. *Heliyon*, *9*(8), e18477. https://doi.org/https://doi.org/10.1016/j.heliyon.2023.e18477

Yigezu, Y. A., Mugera, A., El-Shater, T., Aw-Hassan, A., Piggin, C., Haddad, A., . . . Loss, S. (2018). Enhancing adoption of agricultural technologies requiring high initial investment among smallholders. *Technological Forecasting and Social Change*, *134*, 199-206. https://doi.org/https://doi.org/10.1016/j.techfore.2018.06.006

Tables

Table 1: Mean fractions (and standard deviations) for each irrigation type and each of the 16 subsets

None	Surface	Sprinkler	Drip	#
0	0	0	0	0
100%	0	0	0	1,185
0	100%	0	0	323
0	0	100%	0	687
0	0	0	100%	737
35.8% (28.8%)	64.2% (28.8%)	0	0	351
0	51.8% (30.5%)	48.2% (30.5%)	0	39
0	0	57.2% (28.4%)	42.8% (28.4%)	227
49.2% (29.6)	0	0	50.8% (29.6)	611
0	55.1% (28.7%)	0	44.9% (28.7%)	29
45.1% (28.6%)	0	54.9% (28.6%)	0	1,152
32.6% (25.5%)	33.2% (27.0%)	34.2% (25.1%)	0	78
0	32.0% (22.2%)	30.3% (22.8%)	37.7% (21.7%)	10
30.1% (24.2%	0	39.7% (26.0%)	30.2% (25.0%)	354
25.9% (24.1%)	47.1% (32.5%)	0	27.0% (27.1%)	62
25.7% (24.0%)	30.9% (24.4%)	17.0% (14.9%)	26.4% (22.9%)	31
38.9% (40.8%)	11.1% (28.9%)	28.0% (38.5%)	22.0% (36.9%)	5,876

Table 2: Variable descriptions and hypotheses

Variable	Source/RICA	References	Hypothesis
Growing season degree days	E-OBS (Cornes et al., 2018)	Dinar et al. (1992); Dinar and Yaron (1990); Mendelsohn and Dinar (2003); Negri and Brooks (1990); Negri et al. (1989); Olen et al. (2016)	Sprinkler irrigation is used under cooler temperatures because too high temperatures lead to evaporative losses.
Growing season precipitation	E-OBS (Cornes et al., 2018)	Mendelsohn and Dinar (2003); Negri and Brooks (1990)	Irrigation can be a substitute for precipitation, thus farms with little rainfall are more likely irrigated. Surface irrigation is used less in places with much rainfall since rainfall after surface irrigation can cause crop damage.
Frost days	E-OBS (Cornes et al., 2018)	Frisvold and Bai (2016); Negri and Brooks (1990); Olen et al. (2016)	Sprinkler use increases with frost days because it is better suited for frost protection.
Farm size	RICA: SAU Irrigata	Dinar et al. (1992); Dinar and Yaron (1990); Finkel and Nir (1983); Frisvold and Bai (2016); Genius et al. (2014); Negri and Brooks (1990); Pronti et al. (2020); Vanschoenwinkel et al. (2022)	Effect of farm size is uncertain. Most references agree: sprinkler and drip irrigation require greater investment, therefore acting as a barrier to smaller farms. Larger farms can realise economies of scale. But, larger farms may encounter less financial pressure to improve water effectiveness.
Perennial	OTE	Green et al. (1996); Pronti et al. (2020)	Farms with perennial crops are more likely to invest in efficient irrigation options.
Livestock	OTE	Pronti et al. (2020)	Farms whose core business is animal husbandry are less likely to invest in efficient irrigation options.
Age	RICA: ANNO_NASCITA	(Dinar et al., 1992); Dinar and Yaron (1990); Genius et al. (2014); Molle et al. (2019); Pokhrel et al. (2018)	Effect of age is uncertain. Farming experience enables farmers to make more informed decisions, positively influencing modern technology adoption. But, young farmers receive more investment support for new technologies under Rural Development Policies and have a longer planning horizon.
Off-farm activities	RICA: Attivita Extra Aziendale	Frisvold and Deva (2012); Pokhrel et al. (2018); Pronti et al. (2020)	Income from off-farm activities reduces the likelihood of adopting more efficient irrigation systems because the risk of income loss is lower.
Rented	RICA: (SAU_Affitto + SAU_Comodato)/SAU	Pokhrel et al. (2018); Pronti et al. (2020)	Farmers are more likely to invest in capital-intensive infrastructure (such as sprinkler and drip irrigation) when they own the land.
Less-favoured area	RICA: ZSVA	Molle et al. (2019)	Farms located in mountain areas or other areas affected by environmental constraints are more likely to invest in new technologies (they also receive more financial support for this).

Variable	Source/RICA	References	Hypothesis
Water source	ISTAT (2010)	Caswell and Zilberman (1985); Dinar et al. (1992); Green et al. (1996); Moreno and Sunding (2005); Negri and Brooks (1990)	Farmers with access to surface water are more likely to choose surface irrigation and less likely to choose sprinkler irrigation. Farmers using groundwater are more likely to adopt modern (drip) irrigation systems.
Soil type	RICA: Sup_Tess_	Frisvold and Bai (2016); Mendelsohn and Dinar (2003); Negri and Brooks (1990)	Sandy soils decrease the likelihood of using surface irrigation and increase the likelihood of using sprinkler or drip irrigation. The effect of clay is uncertain. One source claims that high clay content leads to higher efficiency in surface irrigation, whereas another concludes that clayey soils discourage the adoption of all irrigation systems, especially surface irrigation.
Available Water Capacity	AWC (Ballabio et al., 2016)	Dinar et al. (1992); Frisvold and Bai (2016); Kurukulasuriya et al. (2011); Mendelsohn and Dinar (2003); Negri and Brooks (1990); Negri et al. (2005)	Soil that can hold water is more attractive for irrigation. Surface irrigation requires a higher water-holding capacity than sprinkler or drip irrigation.
Slope	SUP_ACC	Frisvold and Bai (2016); Mendelsohn and Dinar (2003); Negri and Brooks (1990); Negri et al. (2005)	Flatter slopes are more favourable to surface irrigation, steeper slopes cause water run-off.
Altitude	ALT_MED	Mendelsohn and Dinar (2003)	Irrigation adoption decreases with higher altitudes.

Source/RICA: in case the variable comes from the RICA database, we mention the corresponding RICA variable label. Labels and variable descriptions can be found on the RICA website (CREA, 2022).

Table 3: Predicted change in the adoption of irrigation options (in %) as a result of a temperature increase, a precipitation increase, or both

	Temperature		**Precipitation**		**RCP 4.5**
	+1°C	**+2.5°C**	**-1 cm**	**-1.5%**	**+2.5°C and -1.5%**
No irrigation	-5.74	-14.25	-0.20	-0.15	-14.33
	(22.81)	(37.75)	(3.69)	(2.99)	(37.87)
Surface irrigation	-1.79	-4.75	-0.02	-0.005	-4.78
	(11.07)	(18.64)	(1.29)	(0.16)	(18.70)
Sprinkler irrigation	9.54	24.24	0.04	0.04	24.35
	(22.94)	(36.28)	(0.68)	(0.68)	(36.36)
Drip irrigation	-2.01	-5.25	0.18	0.12	-5.25
	(13.78)	(21.06)	(3.39)	(2.91)	(21.03)

Figures

Figure 1: Fractions of agricultural land surface irrigated with each option, per region

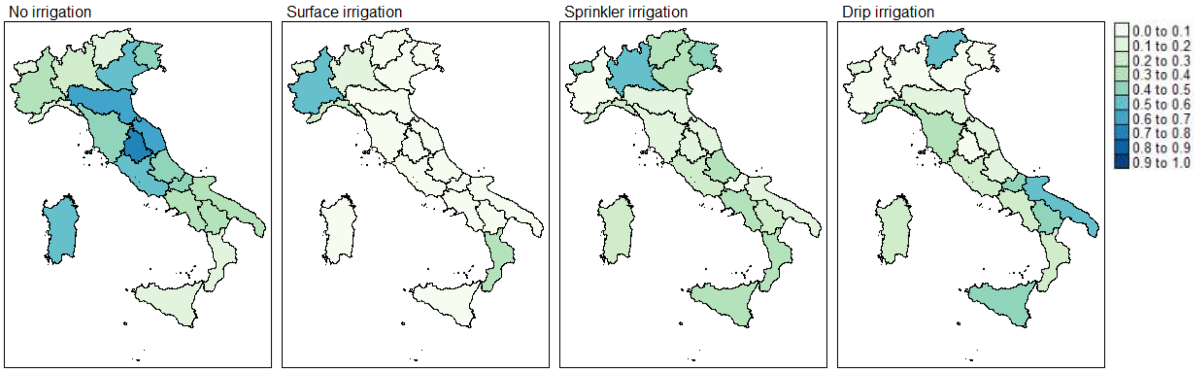


Figure 2: ZADR's predictions of the irrigation response to degree days (left) and precipitation (right)

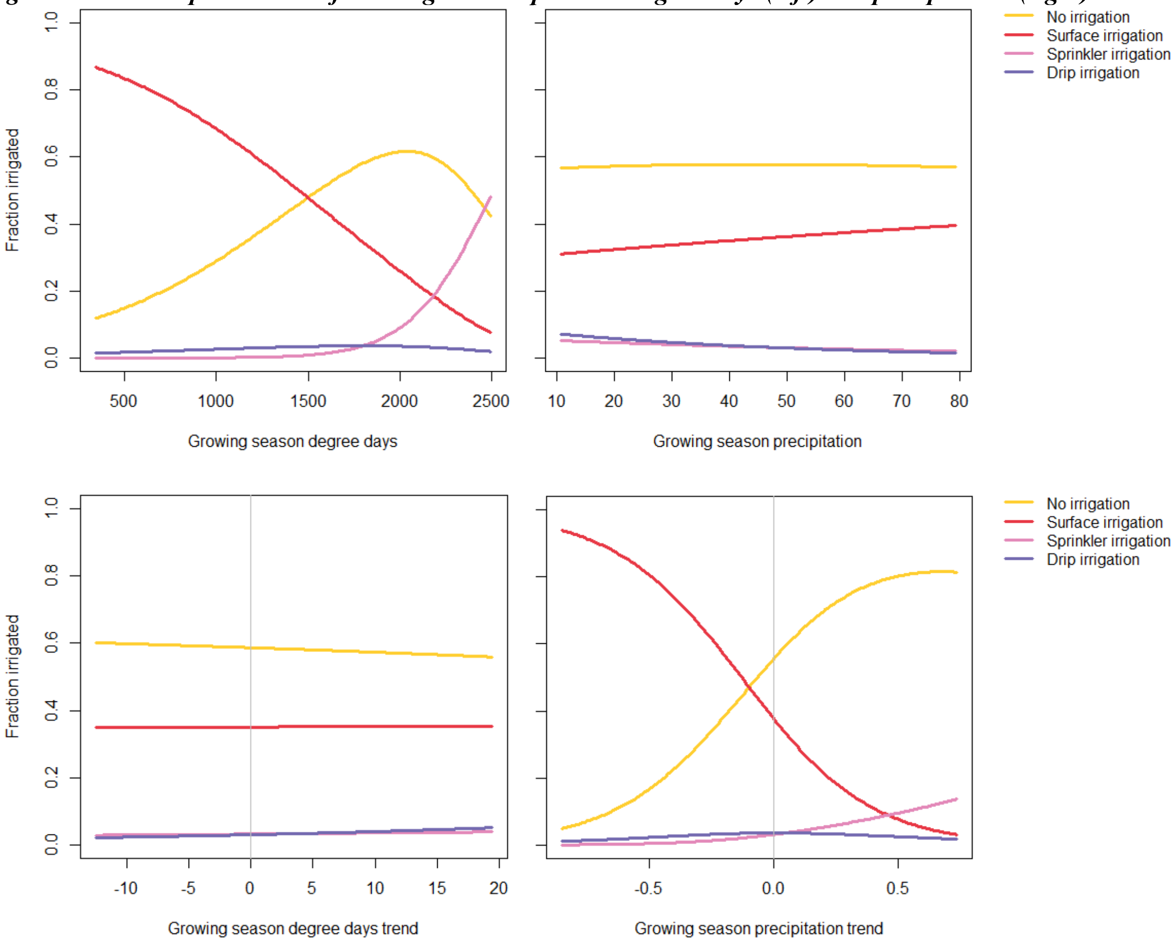
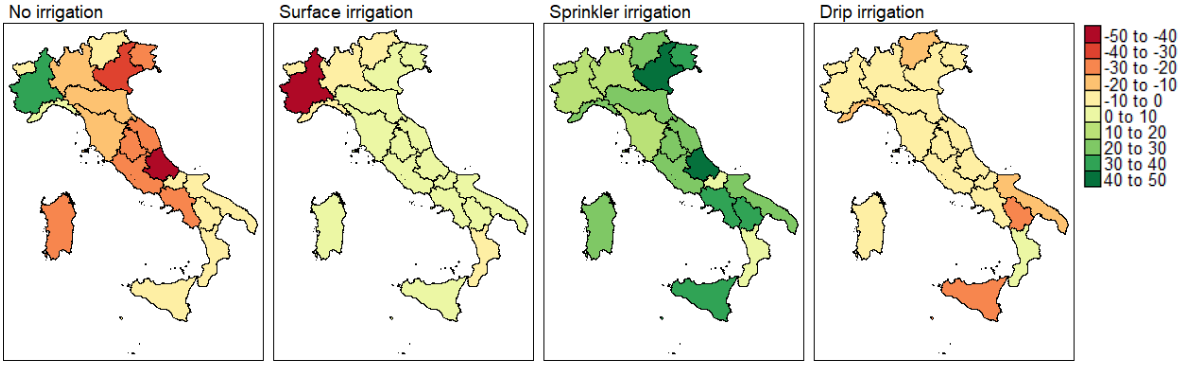


Figure 3: Predicted change in the adoption of irrigation options (in %) as a result of a 2.5°C increase and a 1.5% precipitation decrease



Appendix

Appendix A: Note on Dirichlet regression

The fractions y_i are Dirichlet distributed with α_i the shape parameter for each variable. The distribution, with $B(\alpha_i)$ the multinomial beta function and $\Gamma(\cdot)$ the gamma function, can be represented as in Eq. (A - 1).

$$f\ (\boldsymbol{y}|\boldsymbol{\alpha}) = \frac{1}{B(\boldsymbol{\alpha})}\prod_{i=1}^{4} {y_i}^{(\alpha_i - 1)} = \frac{\Gamma(\sum_{i=1}^{4}\alpha_i)}{\prod_{i=1}^{4}\Gamma(\alpha_i)}\prod_{i=1}^{4} {y_i}^{(\alpha_i - 1)} \tag{A - 1}$$

In this equation 4 is the number of possible irrigation options, y_i is the fraction of land irrigated with option i and $\sum_{i=1}^{4} y_i = 1\ \forall i$ is the constant-sum constraint. The log-likelihood function derived from the above distribution is the following:

$$\ell_i(\boldsymbol{y}|\boldsymbol{\alpha}) = \log\Gamma\left(\sum_{i=1}^{4}\alpha_i\right) - \sum_{i=1}^{4}\log\Gamma(\alpha_i) + \sum_{i=1}^{4}(\alpha_i - 1)\log(y_i) \tag{A - 2}$$

The parameter α_i can be modelled linearly using a log link function. Note that $\log(y_i = 0) = -\infty$. This means that the Dirichlet distribution is only defined for the interval (0,1), which is the reason why 'standard' Dirichlet regression cannot accommodate structural zeros.

The zero-adjusted log-likelihood developed by Tsagris and Stewart (2018) is shown in Eq. (A - 3).

$$\ell_i(\boldsymbol{y}|\boldsymbol{\alpha}) = \log\Gamma\left(\sum_{i=1}^{4}\alpha_i\right) - \sum_{i=1}^{4}\log\Gamma(\alpha_i) + \sum_{i=1}^{4}(\alpha_i - 1)\log(y_i) \tag{A - 3}$$

Note on the ZADR

When two or more components have estimates of the same sign for a variable, the one with the largest parameter in absolute terms will prevail over the other(s) as the variable increases in value. We use an example from this paper to illustrate this. As we see in the results, the frost days coefficient for sprinkler irrigation is more positive (3.2936) than the coefficient for drip irrigation (0.2012) and the coefficients for rainfed farming and surface irrigation are both negative (-0.6907and -1.4029 respectively). This means that, as the fractions of rainfed farming and surface irrigation get closer to zero with increasing numbers of frost days, sprinkler irrigation will push the fraction of drip irrigation downwards although it has a positive coefficient (to keep the constant-sum constraint).

Appendix B: Descriptive statistics

Table B - 1: Descriptive statistics for all continuous variables

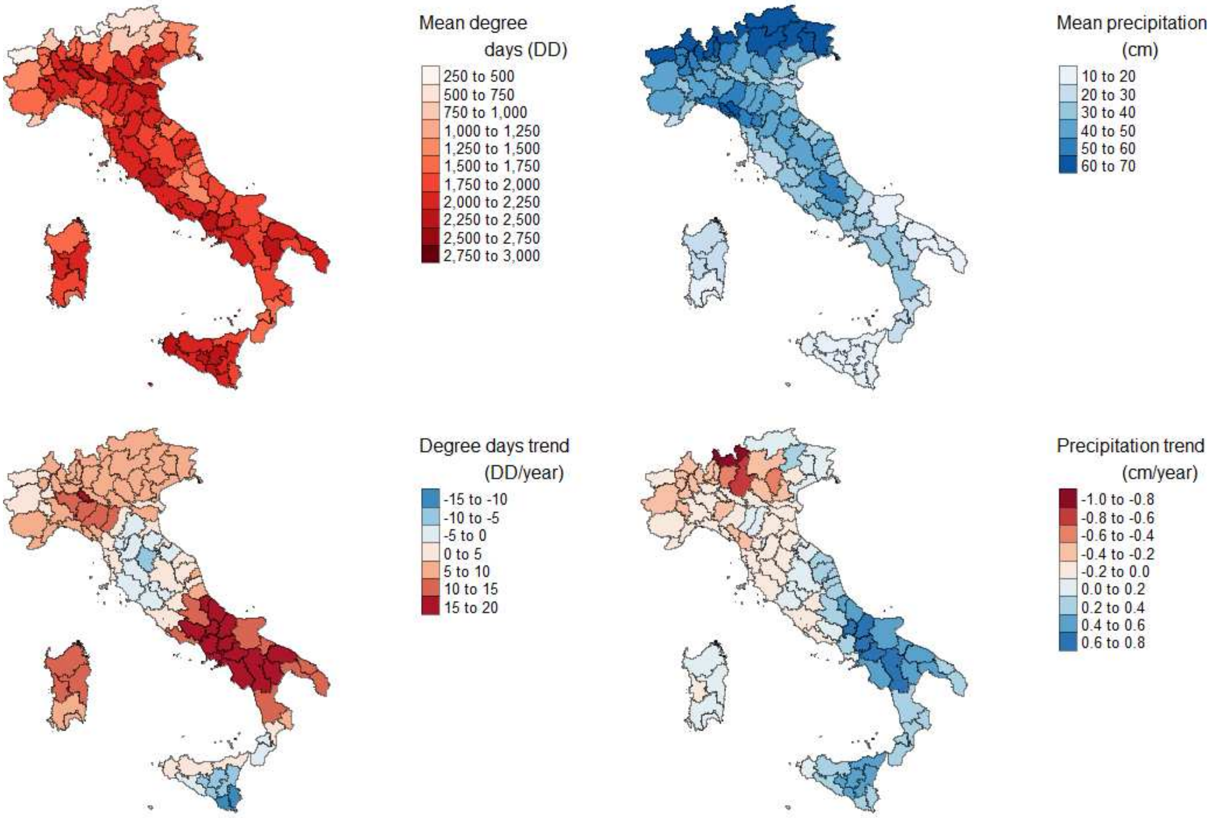
Variable	Variable description	Min	Mean	Max	SD
Mean growing degree days	Sum of the degree days (> 8°C) from March to September, averaged over 30 years (1991-2020)	346.0	1787.0	2490.0	533.0
Growing degree days trend	30-year trend in growing season degree days (1991-2020) derived from a linear regression of growing degree days on years	-12.0	6.7	19.0	6.0
Mean growing season precipitation	Sum of all rainfall (in cm) from March to September, averaged over 30 years (1991-2020)	11.0	41.0	79.0	16.0
Growing season precipitation trend	30-year trend in growing season precipitation (1991-2020) derived from a linear regression of growing season precipitation on years	-0.9	0.0	0.7	0.3
Frost days	Number of days per year with temperatures < 0°C (1991-2020)	0.0	22.0	130.0	34.0
Age	Age of the (oldest) farm head	20.0	60.0	96.0	13.0
Rented	Percentage of the farm that is rented or shared	0.0%	53.0%	100.0%	41.0%
Farm size	Utilised Agricultural Area (ha)	0.0	33.0	1265.0	58.0
Available water capacity	The difference between the 33 kPa and the 1500 kPa soil water content (volume fraction) (Ballabio et al., 2016)	0.093	0.110	0.130	0.009
Altitude	Average altitude of the farm plot (m)	1.0	230.0	2021.0	291.0
Water cost	Yearly water expenditure (€/ha), averaged over the region	5.7	46.0	289.0	53.0
Electricity cost	Yearly electricity expenditure (€/ha), averaged over the region	31.0	287.0	1884.0	392.0
Labour cost	Labour expenditure per hour worked on the holding (€/hour), averaged over the region	5.6	9.3	13.0	1.3
GDP per capita	GDP per capita (PPP) in 2015, in thousands 2011 international US dollars	22.0	35.0	43.0	7.4
Population density	Number of inhabitants per km²	36.0	201.0	2574.0	245.0

Table B - 2: Descriptive statistics for all categorical variables

Variable	**Variable description**	**Percentages per category**	
Off-farm activities	Dummy variable stating whether the farm head engages in off-farm activities or not	No 90%	Yes 10%
Family	Dummy variable stating whether the farm is family-led or not	No 63%	Yes 37%
Organic	Dummy variable stating whether the farm has at least one organic product or not	No 84%	Yes 16%
LFA	Dummy variable stating whether the farm is located in a less-favoured area or not	No 57%	Yes 43%

Soil type	Soil type of the largest part of the farm's agricultural area	Loose texture	Limy-clayey texture	Medium texture
		11%	6%	83%
Slope	Slope for the largest part of the farm's agricultural area	Level	Sloping	Steep
		69%	25%	6%
Perennial crops	Dummy variable stating whether the farm's main income source is perennial crops or not	No	Yes	
		68%	33%	
Livestock farming	Dummy variable stating whether the farm's main income source is livestock farming or not	No	Yes	
		80%	20%	
Water source	Predominant water source in the region	Underground	Surface	Consortium
		24%	8%	68%

Figure B - 1: Maps showing the four climate variables: (i) mean growing season degree days, (ii) mean precipitation, (iii) growing season degree days trend, (iv) growing season precipitation trend



Appendix C: Regression results

Table C - 1: Regression results of the multivariate probit model

	No irrigation			Surface irrigation			Sprinkler irrigation			Drip irrigation		
	Estimate	95% CI		Estimate	95% CI		Estimate	95% CI		Estimate	95% CI	
(Intercept)	**0.8148**	0.1959	1.4338	**-1.0669**	-1.7235	-0.4103	0.3687	-0.3254	1.0629	**0.7839**	0.0655	1.5023
Mean growing season degree days	-0.1100	-0.3842	0.1642	-0.4268	-0.8730	0.0194	**0.4622**	0.0919	0.8324	-0.0429	-0.3735	0.2877
Growing season degree days trend	0.0279	-0.0736	0.1294	-0.0961	-0.2476	0.0553	0.0091	-0.1511	0.1692	0.0402	-0.0722	0.1525
Mean growing season precipitation	0.0920	-0.1775	0.3614	0.0881	-0.1908	0.3670	-0.0517	-0.3093	0.2060	-0.1411	-0.3525	0.0704
Growing season precipitation trend	0.1373	-0.0401	0.3148	**-0.6409**	-0.9021	-0.3796	0.1449	-0.0303	0.3202	0.0297	-0.1705	0.2298
Frost days	**-0.4211**	-0.7472	-0.0951	**-0.6558**	-1.3072	-0.0043	**0.7669**	0.3357	1.1980	0.2217	-0.1543	0.5977
Age	0.0336	-0.0155	0.0826	0.0225	-0.0307	0.0758	-0.0183	-0.0691	0.0325	-0.0371	-0.0814	0.0073
Family	-0.0065	-0.1292	0.1162	**0.2445**	0.0694	0.4196	**-0.1408**	-0.2677	-0.0139	**-0.4825**	-0.5923	-0.3727
Off-farm income	0.0507	-0.1224	0.2239	-0.1118	-0.3082	0.0845	-0.0769	-0.2353	0.0815	-0.0957	-0.2461	0.0546
Organic farming	0.0956	-0.0322	0.2234	-0.0302	-0.2102	0.1499	-0.0909	-0.2370	0.0552	0.0293	-0.0912	0.1497
Less-favoured area	-0.0104	-0.2210	0.2002	-0.2454	-0.5241	0.0332	-0.0256	-0.1902	0.1390	**0.2531**	0.0034	0.5029
Rented	-0.0190	-0.0650	0.0270	0.0573	-0.0040	0.1186	0.0361	-0.0077	0.0799	0.0123	-0.0257	0.0504
Water source (base = groundwater)												
Consortium water	0.0063	-0.2816	0.2941	**0.6642**	0.3053	1.0230	0.0281	-0.2780	0.3342	-0.2956	-0.5950	0.0039
Surface water	0.0468	-0.5352	0.6288	0.0973	-0.6546	0.8492	0.3248	-0.2458	0.8954	**-0.6800**	-1.1079	-0.2522
Farm size	**0.0775**	0.0055	0.1495	0.0695	-0.0033	0.1422	0.0440	-0.0198	0.1078	**-0.1276**	-0.2211	-0.0342
Perennial crops	**-0.5828**	-0.7908	-0.3748	**-0.3403**	-0.5869	-0.0938	**-0.1842**	-0.3550	-0.0133	**0.5786**	0.3734	0.7838
Livestock farming	0.0991	-0.0928	0.2909	-0.0161	-0.2534	0.2212	0.0752	-0.1743	0.3247	**-0.9750**	-1.2921	-0.6579
Soil (base = loose texture)												
Limy-clayey texture	**0.2874**	0.0654	0.5094	0.2042	-0.0536	0.4620	-0.0214	-0.3070	0.2642	**-0.3183**	-0.5712	-0.0654
Medium texture	0.1108	-0.0852	0.3068	0.0602	-0.0793	0.1997	0.0874	-0.0609	0.2356	**-0.1980**	-0.3647	-0.0313
Available water-holding capacity	0.0853	-0.0597	0.2304	0.0993	-0.1133	0.3119	0.0147	-0.1439	0.1734	-0.0183	-0.1603	0.1238
Slope (base = flat)												
Sloping	0.0900	-0.0581	0.2382	-0.2026	-0.4794	0.0741	**-0.2050**	-0.3879	-0.0220	-0.1301	-0.3415	0.0812
Steep	**0.1931**	0.0062	0.3799	-0.0968	-0.5208	0.3272	-0.2101	-0.4667	0.0464	**-0.2979**	-0.5952	-0.0005
Altitude	0.0469	-0.0831	0.1768	**0.2509**	0.0009	0.5010	-0.1549	-0.3249	0.0151	**-0.1119**	-0.2179	-0.0059
Water cost	**-0.3882**	-0.5973	-0.1792	**0.2433**	0.0295	0.4572	0.1364	-0.0459	0.3187	0.0697	-0.1011	0.2404
Electricity cost	0.0182	-0.2083	0.2448	**-0.2835**	-0.4931	-0.0739	0.0205	-0.1478	0.1888	0.0228	-0.1736	0.2192
Labour cost	**0.1844**	0.0533	0.3155	**-0.3480**	-0.5178	-0.1782	0.0982	-0.0460	0.2424	0.1192	-0.0029	0.2413
GDP per capita	**0.3198**	0.1073	0.5323	-0.2374	-0.5650	0.0902	-0.0208	-0.2755	0.2339	-0.0782	-0.3026	0.1463
Population density	0.0341	-0.0326	0.1008	0.0365	-0.0779	0.1509	0.0117	-0.0612	0.0847	-0.0281	-0.1169	0.0607

Notes: 95% confidence intervals are calculated using province-clustered standard errors corrected for heteroskedasticity. Estimates in ***bold*** *= CI does not include 0.*

Table C - 2: Regression results of the ZADR model

	No irrigation			Surface irrigation			Sprinkler irrigation			Drip irrigation		
	Estimate	95% CI		Estimate	95% CI		Estimate	95% CI		Estimate	95% CI	
(Intercept)	**-1.5911**	-2.7832	-0.3990	**-2.6695**	-5.1658	-0.1732	**-4.8735**	-6.0663	-3.6807	**-3.0833**	-4.2914	-1.8752
Mean growing season degree days	-0.0058	-0.7044	0.6927	-0.9406	-2.1528	0.2716	**2.2291**	1.6905	2.7676	-0.2958	-1.5137	0.9222
Growing season degree days trend	0.0456	-0.7165	0.8077	0.0048	-2.0573	2.0670	0.1160	-0.3212	0.5532	0.2285	-0.0574	0.5144
Mean growing season precipitation	0.1383	-0.6175	0.8940	0.1812	-0.7992	1.1615	-0.0917	-0.4445	0.2610	-0.2596	-1.6968	1.1775
Growing season precipitation trend	0.3014	-0.2563	0.8592	-0.7425	-1.8294	0.3445	0.6968	-0.9857	2.3793	-0.0844	-0.5471	0.3784
Frost days	-0.6907	-1.4289	0.0474	-1.4029	-3.1501	0.3444	**3.2936**	2.7490	3.8381	0.2012	-0.3712	0.7737
Age	0.1263	-0.5084	0.7610	0.0966	-0.6056	0.7987	-0.0447	-1.7860	1.6965	-0.0868	-0.7942	0.6206
Family	0.1458	-0.8992	1.1908	0.4330	-0.3240	1.1899	-0.4475	-0.9256	0.0306	-1.3860	-3.2741	0.5022
Off-farm income	0.2703	-0.3146	0.8552	-0.0719	-4.4596	4.3157	-0.3724	-1.1152	0.3703	-0.1372	-2.4397	2.1653
Organic farming	0.1946	-1.1008	1.4900	-0.1440	-1.0506	0.7627	-0.5143	-1.7943	0.7657	0.2094	-0.2090	0.6278
Less-favoured area	0.0067	-1.2761	1.2894	-0.3431	-1.0875	0.4013	-0.0738	-0.6292	0.4816	0.5011	-0.3942	1.3964
Rented	-0.0407	-0.7321	0.6507	0.0893	-1.5087	1.6873	0.1489	-0.2932	0.5910	0.0821	-0.9570	1.1212
Water source (base = groundwater)												
Consortium water	-0.3007	-0.9094	0.3080	0.9465	-0.0755	1.9685	0.2450	-0.2888	0.7788	-0.8834	-1.8401	0.0734
Surface water	-0.2609	-0.7447	0.2229	0.0428	-8.0262	8.1117	**1.7527**	0.4858	3.0196	-3.0402	-23.4098	17.3295
Farm size	0.0716	-0.5204	0.6635	0.0967	-0.4693	0.6628	0.0592	-0.2213	0.3397	-0.5184	-1.8901	0.8532
Perennial crops	-1.4495	-3.5204	0.6214	-0.1050	-0.8868	0.6768	-0.6250	-1.4648	0.2148	2.1907	-0.7210	5.1023
Livestock farming	0.1963	-1.7253	2.1178	0.2440	-0.6873	1.1754	0.4151	-0.7531	1.5832	-2.8547	-11.5717	5.8623
Soil (base = loose texture)												
Limy-clayey texture	0.2196	-0.5679	1.0072	0.2615	-4.0271	4.5501	0.2396	-3.0786	3.5578	-0.7825	-4.4311	2.8660
Medium texture	0.0449	-0.8488	0.9387	-0.0414	-1.2950	1.2122	0.4724	-0.1721	1.1168	-0.5534	-2.2282	1.1214
Available water-holding capacity	0.1198	-0.4053	0.6448	0.0750	-0.9146	1.0645	0.0405	-0.8980	0.9791	0.1942	-0.7084	1.0969
Slope (base = flat)												
Sloping	0.4659	-0.7439	1.6757	-0.1758	-3.9885	3.6369	**-0.9207**	-1.6599	-0.1814	-0.2807	-1.1210	0.5596
Steep	0.8222	-0.0124	1.6568	-0.3641	-4.7551	4.0269	-1.0459	-3.0872	0.9955	-0.4879	-3.6923	2.7166
Altitude	0.0977	-0.4530	0.6485	0.3436	-1.0230	1.7101	**-0.5397**	-0.8238	-0.2556	-0.1590	-1.9020	1.5840
Water cost	-0.7899	-1.8387	0.2588	0.2744	-1.2265	1.7753	**0.4958**	0.2099	0.7816	0.2273	-0.3761	0.8308
Electricity cost	0.0033	-0.7978	0.8043	-0.3748	-2.5384	1.7887	**0.2733**	0.0128	0.5338	0.0455	-0.2124	0.3035
Labour cost	0.4590	-1.0169	1.9349	-0.4839	-1.3326	0.3648	0.3173	-0.5847	1.2192	0.2459	-0.2621	0.7538
GDP per capita	0.6121	-0.2074	1.4316	-0.3081	-2.7352	2.1190	-0.1651	-1.0323	0.7021	-0.2644	-0.9157	0.3870
Population density	0.0001	-0.7080	0.7081	0.0017	-0.8297	0.8332	0.0587	-0.6486	0.7660	-0.1865	-0.6797	0.3067
Generalised residuals	**2.6210**	0.7520	4.4899	1.2930	-4.1883	6.7743	5.5212	-0.4841	11.5266	**3.7238**	0.3145	7.1330

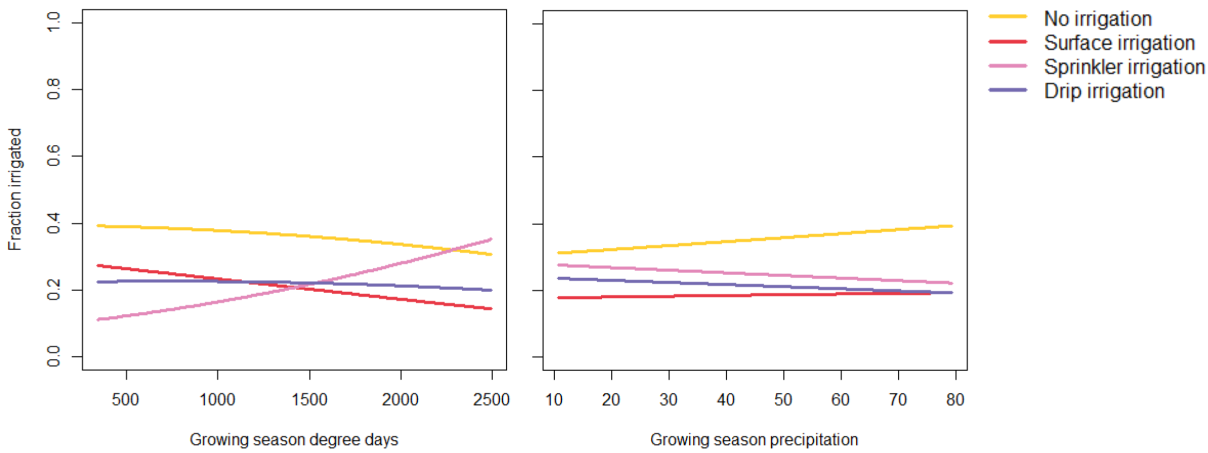
Notes: 95% confidence intervals are calculated using province-clustered standard errors (Jackknife SE (Hansen, 2022)). Estimates in ***bold*** *= CI does not include 0.*

Appendix D: Alternative estimations

In this additional section, we compare our results to the results of two simpler one-step approaches: a Dirichlet regression model with (0,1)-transformed data and a multinomial logit model with discretised data. Both these approaches can be applied to the full dataset, i.e., 5,876 observations.

For the first alternative, we use the DirichletReg package in R (Maier, 2014). This package first transforms the data from the [0,1] interval to the (0,1) interval using the 'lemon squeezer' proposed by Smithson and Verkuilen (2006). As such, it treats the zero values as erroneous rather than structural. The model is then estimated by maximising the log-likelihood presented in Appendix A. The results of this approach are similar to those of our two-step model: rainfed farming and sprinkler irrigation increase with temperature, surface irrigation decreases and drip irrigation remains relatively stable. Although these general trends are the same, the standard Dirichlet regression appears to be more moderated (figure D - 1). For the current climate, the Dirichlet model predicts fractions between 8.3% and 60.1% for all four irrigation options, the ZADR model predicts fractions between 0% and 94.8% and the combined approach with the multivariate probit models between 0 and 100%. This is likely caused by the transformation of the data to the (0,1) interval.

Figure D - 1: Irrigation response to degree days (left) and precipitation (right) estimated with Dirichlet regression. Model run on the full sample (5,876 observations)



For the second alternative, we transform the compositional data into a discrete variable. This categorical variable is the irrigation option which is used for the largest part of the farm's surface area. We then use this categorical variable as the outcome of a multinomial logit model. Multinomial logit models applied to farmers' adaptation behaviour have frequently been used in Structural Ricardian models, such as by Seo and Mendelsohn (2008) who studied switching between livestock species and Kurukulasuriya and Mendelsohn (2008) who studied switching between crop types. These studies do not take into account that a farmer can opt for a combination of different types, rather than just one predominant one. The alternative model we use here follows the same assumption. The vertical axis in figure D - 2 is thus not the estimated fraction of land treated with each irrigation option, it is the probability of choosing each irrigation option as their predominant irrigation option. We find that the responses predicted by this model are very different from those predicted by the other two approaches: the probability of choosing surface irrigation increases with temperature and the probability of choosing sprinkler irrigation decreases with temperature. These results are very different, likely because the discretised data looks very different from the compositional data. For example, in the discretised data, surface irrigation becomes the most frequent category (38% of farms have surface irrigation as their major irrigation option), whereas area-wise surface irrigation is the least used option (11% on average) (Table D - 1). Although this does not confirm our previous findings, it does confirm that the restriction of discrete choices generates very different results than when allowing farmers to choose a combination of different options. The interpretation of both approaches is very different, meaning that one cannot be compared with or preferred to the other. This clearly shows the relevance of the developed and applied method.

Figure D - 2: Irrigation response to degree days (left) and precipitation (right) estimated with MNL regression. Model run on the full sample (5,876 observations)

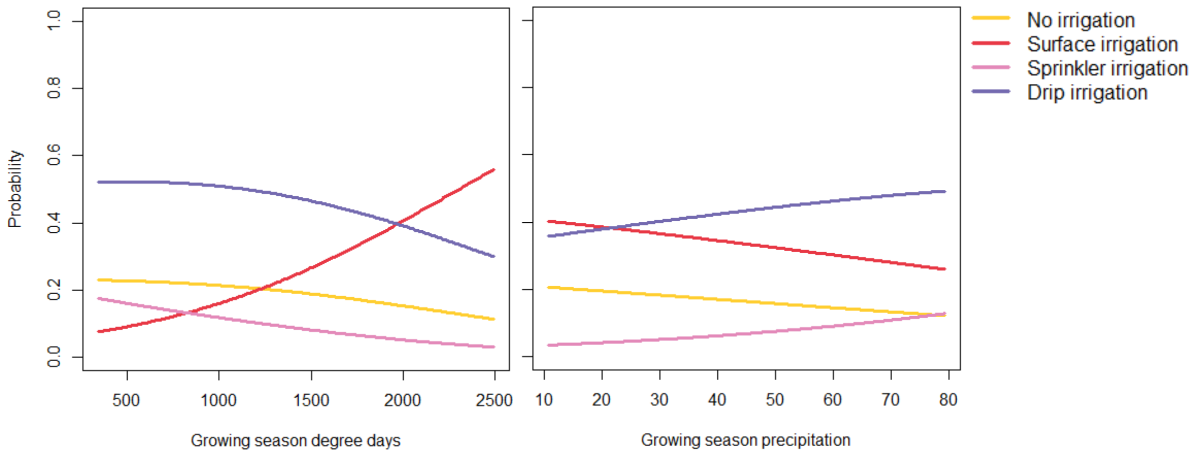


Table D - 1: Compositional irrigation data versus discrete irrigation data for the full sample (5,876 farms)

	Compositional data: mean % surface area	**Discretised data: % of farms**
No irrigation	38.9%	21.6%
Surface irrigation	11.1%	38.4%
Sprinkler irrigation	28.0%	11.5%
Drip irrigation	22.0%	28.6%