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On-farm adoption of irrigation technologies in two irrigated valleys in Central Chile: The effect of relative abundance of water resources

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ABSTRACT

This paper examines the adoption of irrigation technologies and the underlying diversity in terms of intensity of adoption in 2 irrigated valleys in Central Chile. Results show a low and narrow range of adoption, with only 30 % of farmers adopting technologies. Through a Latent Class Analysis, 2 types of farmers were identified, a small group comprising moderate to intensive users, and a second one consisting of the majority of farmers mostly constrained in natural capital. Furthermore, the econometric analysis indicates that education, diversification, continuous access to water, and perception of water reliability increase the adoption. Conversely, higher water-land ratios, presence of community reservoirs, and earthen canals reduce the uptake. Overall, the dominance of fruit and horticulture production, access to agricultural credits, and full irrigation of the farm are the main drivers of adoption. The latter is a critical factor, indicating a relative abundance of water resources, which, alongside contextual characteristics, discourages farmers from implementing technologies. The low adoption rate, as well as the hindering factors, will challenge public and private organizations to design and implement policies aiming to improve water reliability and management. To generate incentives and increase awareness on the scarcity of the resource in the light of the predicted reductions in water availability because of climate change will be crucial as well.

1. Introduction

Water availability and management have become a limiting factor and a challenge in various parts of the world, especially in countries with more scarce water resources. The agricultural sector is responsible for more than 70 % of water withdrawals for consumptive use (Grafton et al., 2018; Siebert et al., 2010), and irrigation constitutes an essential practice for agricultural production (Levidow et al., 2014). Given population growth and the increasing demand for fiber and food, the agricultural water usage is foreseen to increase (Mancosu et al., 2015).

Irrigation technologies (IT)[1] bring a series of benefits, allowing a better agricultural and water management, especially in water-resource scarce areas (Levidow et al., 2014), improvements in water use efficiency, increases in agricultural productivity, and shifts to more profitable crops (Adeyemi et al., 2017; Perry et al., 2017; Taylor and Zilberman, 2017). Farmers often apply or combine more than one technology, according to the expected profits (Foster and Rosenzweig, 2010; Green et al., 1996), easiness of use, or low maintenance requirements (Pokhrel et al., 2018). Because of the benefits of IT, their adoption has been a matter of study, especially in identifying determinants of adoption. Among these are environmental or producers characteristics (Fleischer et al., 2011; Green et al., 1996), their effect on production risk and uncertainty (Foudi and Erdlenbruch, 2012; Koundouri et al., 2006), their water-saving capacity (Jara-Rojas et al., 2012; Molle and Tanouti, 2017; Zhang et al., 2019), and water use efficiency (Chaudhry, 2018; Speelman et al., 2008). More recently, research also has been focusing on the role of irrigation as a climate change adaptation strategy (Bryan et al., 2013; Deressa et al., 2009; Iglesias and Garrote, 2015; Mendelsohn, 2012; Smit and Skinner, 2002; Varela-Ortega et al., 2016).

Besides, the literature on IT adoption reveals multiple factors influencing the decision to adopt IT. Socioeconomics characteristics of farmers such as age, education, family size, and experience as well as factors like financial constraints, access to credits and information are found to affect this decision (Bjornlund et al., 2009; Caswell and Zilberman, 1985; Engler et al., 2016; Wang et al., 2016). Likewise,

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[1] Although there are a variety of technologies at on-farm and off-farm level, in this paper irrigation technologies refer to those technologies intended to improve water delivery at the on-farm level (Perry, 2017), allowing for improvements in water-efficiency and economic benefits as well as reducing environmental burdens (Levidow et al., 2014).

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adoption of IT is determined by farm attributes (i.e., farm size, location, land or soil quality, growing crops) and environmental characteristics (precipitation, temperature) (Caswell and Zilberman, 1985; Green et al., 1996). Furthermore, policy interventions such as support services, subsidies, provision of information and pricing have shown to affect the adoption of IT (Caswell et al., 1990; Green et al., 1996; Zhang et al., 2019).

Despite the benefits of IT and the extensive literature regarding adoption in different irrigation settings, most of the research on this topic has focused either on specific technologies, e.g., on the decision to irrigate, or the application of drip or sprinkler irrigation. Other linked choices are often omitted (Huang et al., 2017; Pokhrel et al., 2018). Nowadays, complementary technologies and practices such as land leveling, irrigation scheduling, soil moisture monitoring, or tailwater recovery systems strengthen water management, thereby improving the performance of the irrigation systems (Huang et al., 2017; Montoro et al., 2011; Pokhrel et al., 2018; Zhang et al., 2019). Moreover, even though there are scholars who have studied the intensity of adoption of technologies, such as precision agriculture technologies (Barnes et al., 2019; Isgin et al., 2008; Paxton et al., 2011) or modern rice technologies (Mariano et al., 2012), the evidence on IT is still scanty, with some exceptions (Jara-Rojas et al., 2012; Pokhrel et al., 2018; Wang et al., 2016).

On the other hand, irrigation decisions may be influenced by either collective arrangements or because of neighbors' decisions, especially in irrigation systems with poor control, withdrawal infrastructure, and conveyance. As members of an irrigation system, farmers share some environmental context as well as socioeconomic and infrastructural characteristics such as reservoirs or watercourses (Chaudhry, 2018). System characteristics receive an increasing interest, considering their effects on agricultural production (Manero et al., 2019; Song et al., 2018; Zhang et al., 2013), adaptation to climate change (Tang et al., 2016) as well as input usage, and irrigation efficiency (Chaudhry, 2018).

Understanding the drivers shaping this technology adoption is required for further planning and strategic dissemination of farm technologies (Mariano et al., 2012), allowing policymakers and water managers to know the extent of policy interventions (Wang et al., 2016). In this regard, aiming to contribute to the literature of technology adoption in irrigated agriculture, the present article considers 2 irrigated valleys in Central Chile. Irrigation in Chile holds a long tradition, with private water users associations established since colonial times (Meza et al., 2012), and roughly 1,1 million hectares of irrigated lands (Jara-Rojas et al., 2012). Due to climate characteristics, irrigation is a central factor in agricultural production (Oyarzún et al., 2008). Moreover, the region in central Chile under consideration currently suffers the most extensive period of water shortage ever recorded (Garreaud et al., 2017; Garreaud et al., 2019). Because of this setting of relative scarcity, Chile has set irrigation as a primordial matter in the agricultural policy over the past 4 decades[2] (Martin and Saavedra, 2018), following a mostly hard-path approach through improvements in on and off-farm efficiency, as well as in infrastructure for water storage (Clarvis and Allan, 2014; Meza et al., 2008; Vicuna et al., 2014). Despite this long-standing irrigation history, the stimulus and support for adoption of IT, evidence concerning farmers' decisions in irrigation adoption is relatively new, with few exceptions (Engler et al., 2016; Jara-Rojas et al., 2012; Roco et al., 2016; Salazar and Rand, 2016) Thus, in order to better understand the adoption of IT, this article has two objectives. First and foremost, the research aims to estimate the level of adoption of IT in Central Chile, and examine the drivers of such adoption. The second goal, based on IT, consists in identifying and classifying farmers according to their adoption decisions. In order to do so, the article continues as follows. The next section introduces and describes the study area, the survey conducted, and provides an outline of the methods employed. Subsequently, the main results are analyzed and discussed. Finally, a conclusion and a policy implications section will conclude the research.

2. Methods and materials

2.1. Study area

In Chile, irrigation water management, as well as water management of other productive sectors, is governed through the Water Code of 1981 (WC81). The WC81 declares water as an economic good based principally on a complete separation of water from land, and defines private and permanent property rights on water (WR), allowing the free transferability of this resource. Another central feature of WC81 is the orientation towards private management, thereby reducing the capacity of regulation and intervention by the state (Vergara and Rivera, 2018). In terms of irrigation, the Code states that owners of WR are responsible for water management through three different levels of organization. At natural source level, management is organized by the Vigilance Committees (Juntas de Vigilancia, JV). For artificial sources, WR owners gather either in Comunidades de Agua (Water Communities, WC) which are in charge of secondary infrastructure (canals), or Asociacion de Canalistas (Canal Users Associations, CA), responsible for the administration of main infrastructure such as reservoirs and primary canals (Martin and Saavedra, 2018; Valdés-Pineda et al., 2014). These different water associations have some common responsibilities, such as conveying and delivering water to users according to WR ownership, conflict resolution, and collection and management of water fees (Donoso, 2014).

This research considers two sub-watersheds of the Maule River Basin in Central Chile: the Ancoa and the Achibueno river valleys (Fig. 1). Central Chile has a Mediterranean climate with a heterogeneous distribution of water availability throughout the year. Most of the rain occurs in periods in which agricultural production is less intensive with lower demand for irrigation; determining an imbalance between water demand and supply, and a relative scarcity for agricultural production (Vicuna et al., 2014; World Bank, 2011). The region receives, on average, 870 mm of rainfall, with June and July as the rainiest and coldest months, whereas January, February, and December are the driest and warmest months with median temperatures around 18 °C (AGRIMED, 2017).

The study area consists of the valleys irrigated by the Ancoa and the Achibueno rivers, which are managed by the Ancoa and Achibueno JV's. Under each JV, there are a series of autonomous WC. In this case, 31 WC's are part of Ancoa, holding 7.418,0 ($l*s^{-1}$), providing water to circa 10.000 ha (CNR, 2013). On the other hand, 22 WC's are under JV Achibueno, administrating 20.767,2 $l*s^{-1}$, and irrigating 25.000 ha (CNR, 2013). Moreover, since 2014, the area benefits from a header-reservoir with a storage capacity of 78,3 hm-3, allowing storage and better distribution of the water rights, and with the adverse effects of the drought affecting Central Chile since 2010 (Garreaud et al., 2017; Garreaud et al., 2019). This part of Chile is appropriate for a multiplicity of crops, and in the region, cash crops coexist with self-consumption agriculture, thereby all farm sizes are found as well. (Fernández et al., 2019; Jara-Rojas et al., 2012). Specifically, corn, rice, blueberries, raspberries, and perennials, such as apple and cherry trees, are the main crops cultivated (Jara-Rojas et al., 2012).

2.2. Data collection

The data were gathered in the Chilean summer, between December and February of 2018/19. The primary source of information utilized to select the sample comes from the Ancoa and Achibueno JV's. Each JV

[2] Irrigation became more relevant since 1985, when the Chilean state promulgated Law 18.450 of Irrigation and Drainage. This act states a clear focus on increasing the irrigated land areas, rather than water-saving purposes.

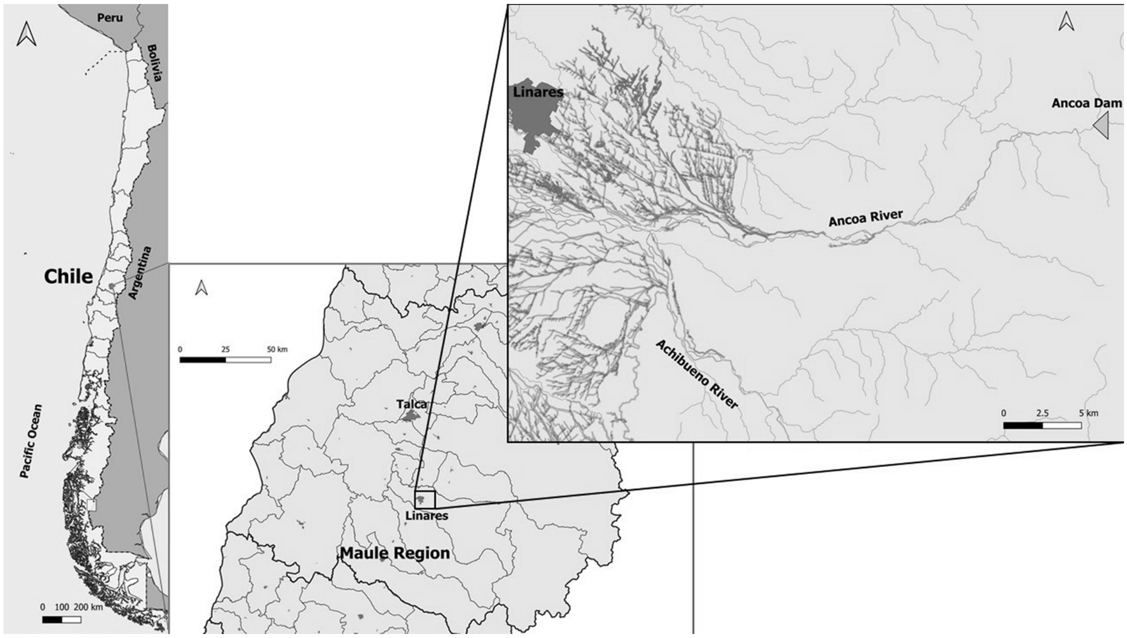

Fig. 1. Ancoa and Achibueno irrigated valleys in Central Chile.

keeps a list of farmers (and their water shares) because they pay annual fees for conveyance from the primary canal to the water intake point[3] . Unfortunately, the JV's and the WC's do not maintain detailed and updated records about their members. In most of the cases, they have lists of farmers and their water shares, yet lack the spatial location of water withdrawals and farms as well as telephone numbers.

In terms of agricultural policy regarding the sampled farmers, Chilean farms are divided into 3 main categories: small, medium, and large farms (Martínez et al., 2014; OECD, 2008), which define the type of subsidies and the technical support they receive[4] . This research entails information on the whole spectrum of farms, the sole requirement being a member of a WC. In total, 335 farmers of 26 WC's from both JV's were surveyed. The sampling followed a 2stage strategy, centered on water rights. First, farmers were divided into two groups (JV), according to the number of individuals of each JV. Afterwards, irrigators of main canals of each JV were selected through a proportional sampling, keeping the weight of each canal in the area.

The data comprises personal, social, and farm characteristics, as well as info on natural capital (land and water shares), IT, practices and crops, and some physical and contextual characteristics of the canals. In order to register the applied IT, a prior selection was made based on the existing literature (Bjornlund et al., 2009; Huang et al., 2017; Levidow et al., 2014; Perry et al., 2017) and previous studies carried out in Chile and neighboring areas (Engler et al., 2016; Jara-Rojas et al., 2012; Roco et al., 2014, 2016), taking into account the technologies funded by the government (CNR, 2013) and in consultation with the members of JV's and some WC's. After a pre-test period, where a low adoption range and rate of IT were found, farmers were required to enumerate and describe their IT, classified into 9 technologies. An important remark is that this study focuses on technologies (and techniques) that allow farmers to improve irrigation, but practices routinely applied to receive water rights, such as weed control in on-farm canals, withdrawal works, etc., were excluded. In addition, in order to characterize farmers' context and environment within each canal, self-reported data on their location and physical infrastructure characteristics were also gathered.

2.3. Methods

To meet the objectives of the article, a methodological approach consisting of 2 parts is applied. In the first part, the determinants affecting the number of irrigation technologies adopted is estimated. The second part is oriented towards disentangling the most applied combinations of IT implemented at the field level.

2.3.1. Econometric analysis

Regression analysis is utilized to model and estimate determinants influencing technology adoption.

Since the variable of interest is a non-negative count, the most appropriate approach is a count data model. The usual way to deal with count data is assuming that y follows a Poisson distribution, with a probability density function (Long and Freese, 2006; Wooldridge, 2010):

$$\Pr(Y = y/x) = \frac{e^{-\mu}\mu^{y}}{y!},\ with\, y = 0,\ 1,\ \ldots, m;\ and\, i = 1,\ \ldots, \mathrm{n} \tag{1}$$

and

$$Var(y/x) = E[y/x] = \mu = e^{X\beta} \tag{2}$$

With μ = expected mean = variance= (y/x), where y is the count data variable, and $x$and β are vectors of independent variables and parameters to estimate respectively.

The Poisson Model (PRM) accounts for observed heterogeneity (observed differences among sample members) by specifying the rate y as a function of observed X's. However, in practice, the PRM seldom fits well due to two issues: overdispersion (underdispersion), and the presence of an excess of zeros (Wooldridge, 2010). *Overdispersion*[5] means the variance exceeds the mean, *i.e.,* $Var(Y_i)/E(Y_i) > 1$, violating the Poisson assumption (Eq. 2), implying that PRM underestimates the dispersion of the outcome (Cameron and Trivedi, 2010; Long and Freese, 2006). If overdispersion exists and is ignored, PRM estimates

[3] Although each canal keeps an updated list for fees collection, some WC's have delegated this action to JV's hands, facilitating farmers payments to both JV and WC, as well as preventing high levels of indebtedness.

[4] In Chile, small farms are distinct in two aspects: they own less than 12 hectares of irrigation units (HBU), and their income must come primarily from agricultural production.

[5] Underdispersion goes on the opposite way, that is, the variance is lower than the conditional mean.

Table 1
Descriptive statistis for each dependent variable specification.

Variable	Description	Mean	Variance	Min	Max	Var/Mean ratio
Y_1	Number of IT implemented by farmers	0,47	0,75	0	5	1,6
Y_2	Number of IT implemented, grouping scheduling technologies in an unique category	0,45	0,68	0	4	1,5
Y_3	Number of IT's accumulating implementation per crop	0,65	1,42	0	6	2,2

will be consistent but inefficient, with standard errors biased downward, although the model might include the correct variables. To overcome this problem, a Negative Binomial Regression Model (NBRM) can be used instead (Isgin et al., 2008; Loeys et al., 2012; Long and Freese, 2006). In that case, the probability mass function of NB is:

$$\Pr(Y = y/\mu, \alpha) = \frac{\Gamma(\,y + \alpha^{-1})}{y!\Gamma(\alpha^{-1})}\left(\frac{\alpha^{-1}}{\alpha^{-1}+\mu}\right)^{\alpha^{-1}}\left(\frac{\mu}{\alpha^{-1}+\mu}\right)^{y} \tag{3}$$

Where Γ is gamma distribution, α is the variance parameter of the gamma distribution, and μ is the intensity or rate parameter (Cameron and Trivedi, 2010; Paxton et al., 2011). The second issue is the excess of zeros in the data set. In many empirical cases, the Poisson model (or NB) fails to estimate zeros. As an alternative, a zero-inflated model (ZI) allows dealing with both overdispersion and the excess of zeros. ZI's are mixture models, with two separate components representing the outcome distribution: the first modeling the probability of excess of zeros ("false or not always zeros"), and the second accounting for the non-excess of zeros ("true or always zeros") and non-zero counts (Barnes et al., 2019; Isgin et al., 2008; Loeys et al., 2012).

Bearing this in mind, a PRM was run as the initial model, testing for overdispersion and excess of zeros. This was done by simultaneously running an NBRM model. The variance of an NBRM is:

$$Var(Y/x) = E[Y/x] = \mu + \alpha * \mu^2 \tag{4}$$

Where α is the dispersion parameter, and with (Eq.3) reducing to (Eq.2) when α = 0. Overdispersion was tested by the generalized likelihood-ratio test (LLR), and if it exists (α ≠ 0), the NBRM model must be selected (Cameron and Trivedi, 2010; Long and Freese, 2006). The excess of zeros in the sample is tested by the modified versions of the Vuong test, corrected by the Aikake Information Criterion (AIC) and the Bayesian Information Criterion (BIC) (Desmarais and Harden, 2013; Wilson, 2015).

a Explicatory Variables

This section gives details on the dependent and explicatory variables. The conceptual model is:

$$Y = f(X,\ R,\ C,\ P) \tag{5}$$

Where Y is the number of IT implemented by irrigator i, with $y = 1, \ldots$, N; X is a vector of farmers' characteristics, and R comprises natural resources variables; C is a vector containing farmer contextual and physical variables within a WC; and finally, P is a set of perceptual variables. Given that irrigators apply a total of 9 different technologies (Table 2),3 different specifications of the dependent variable were constructed (Table 1). First, Y_1 represents the total number of IT, considering each different technology. For Y_2, those technologies related to scheduling, namely *scheduling*, *meteorological stations*, and *programming tools* are grouped in a single category. Finally, as some farmers use the same IT for irrigating more than one crop, this peculiarity is captured by Y_3, accumulating the total number IT, including the totality of efficient irrigation systems.

The explanatory variables include a set of regressors usually applied in the agricultural technology adoption literature (Caswell and Zilberman, 1985; Green et al., 1996; Isgin et al., 2008; Jara-Rojas et al., 2012; Mariano et al., 2012; Pokhrel et al., 2018; Tang et al., 2016). Table 1 of Annex 1 in the Supplemental material provides a complete explanation as well as descriptive statistics for the full set of variables.

Regarding households characteristics (HH), *Age* corresponds to the age of the HH head; Gender refers to the sex of the respondent (0 if Female and 1 if Male); *Education* corresponds to the level of schooling (years) of the HH head, and *Experience* denotes the years of farming and irrigation by the HH head. For farm variables, *Owner* refers to whether the farmer owns the plot (0 if yes, 1 if other). *Social capital* states if the farmer participates in social organizations (1 if yes, 0 otherwise); *Non-farm* income (*NA_income*) indicates whether a farmer gets income from non-agricultural activities or not, and *Agricultural advisor* considers whether a farmer receives recommendations from external people, either public or private. The last variable of this subset is *Access to Agricultural Credits (Credits)*, taking 1 if a farmer states that he is subject to apply for credits for agricultural activities (purchase of inputs, irrigation infrastructure, etc.).

The subset of natural capital includes *Farm size* (ha), *water shares* (*ws*), and a diversification index. The land size and water shares represent proxies of farmers' wealth. One *ws* in Ancoa is equivalent to 1, and in Achibueno it is 1,5 $l{*}s^{-1}$. To get a standard measurement, the *ws* in Achibueno were therefore multiplied with 1,5. *Crop diversification* is measured through the Herfindahl index (HI *index*) (Roco et al., 2017; Wuepper et al., 2017),

$$HI = \sum_{n=1}^{N} (x_n)^2 \tag{6}$$

Where x_n is the proportion of area for the *n-th* crop respecting the total area under production. The index is a continuous measure of diversification, ranging from 0 (complete diversification) to 1 (whole specialization). For a better understanding of the level of diversification, a variant of the index (*1-HI*) yielding the opposite results is applied, meaning 1 for a fully diversified farmer (Roco et al., 2017).

Moreover, a set of binary variables capturing the productive emphasis of each farmer is introduced, according to the predominant crop. Thus, 5 variables, cereals (C) fruit (F), annual crops(C), vegetable (V), and forage production (Fo), were included.

Contextual or environmental characteristics capture the fact that farmers share some characteristics in certain settings such as socio-economic and infrastructure context (Chaudhry, 2018; Wang et al., 2018). In irrigation systems, farmers may share a watercourse, a water delivery system, or reservoirs. From the set of characteristics that members could share, this article focuses on infrastructure variables, intended to increase the reliability and certainty with which farmers receive their water shares. This article uses lining, location, presence of a water community reservoir, organization for water withdrawal, water fees, and canal extension as contextual variables. When *lining* water conveyance is improved, water losses are reduced. Farmers were asked about the canal lining in the section close to their water intake. Hence, *Lining* is a binary variable taking the value of 1 if a farmer reports a section fully or partially lined, and 0 if it is an earthen canal (Tang et al., 2016). The variable *water community reservoir* (*wcr*) describes if a WC owns an off-farm reservoir, receiving a value of 1 if affirmative, and 0 otherwise. Although such infrastructure does not produce extra water, it allows for storage and use when required. The organization of *water withdrawal* (*ww*) refers to irrigator's access to water. WW is a dummy variable: 1 if withdrawal is continuous and permanent, and 0 if it is organized in turns[6] . *Type of canal* (*canal*) captures the position or location of a farmer in the canal network within a particular waterway.

Canal is 1 if a farmer gets water from the central canal, and 0 if he gets it from a secondary or tertiary level canal.

Annual fees is a binary variable with the value of 1 if a farmer pays more than average annual fees across the 26 canals, and 0 otherwise. When having to pay expensive fees, farmers might take care of their water, using it more efficiently. *Canal Extension (Extension)* is a variable that considers the length of each primary canal. *Canal Extension* takes 1 if the extension surpasses the average length for the 26 canals (km), and 0 otherwise. Also, *wua* is a dummy variable referring to the JV, with 0 for Ancoa and 1 for Achibueno. This variable is capturing the distinctive features of each *wua*, such as governance or operation rules.

Finally, since 2010 Central Chile has endured the most extensive drought ever recorded (Aldunce et al., 2017; Garreaud et al., 2019), encompassing most of the territory where irrigated agriculture thrives. Recent research in adjacent areas has shown that farmers perceive changes in rainfall (decreasing) and temperatures (increasing) as well as more frequent drought periods (Roco et al., 2015). Given the connection between climate and water supply for irrigation, 4 perception questions related to the availability and struggles for water use during the agricultural season were asked. These questions were listed as follows: a) How do you qualify your access to water rights? (*accessibility*); b) Does your water withdrawal enable you to irrigate your farm fully? (*full irrigation*); c) How do you value your irrigation skills? (*se-irrigation*), and d) Do you have any problems with getting your water? (*problems*). The variables were measured on a 5 point-Likert scale ranging from 1 (Very negative) to 5 (No negative, no problem perception). For each question, 4 dummy variables were set, taking 1 if the answer was over the average, and 0 otherwise.

2.3.2. Latent class analysis

The second objective of the paper is to analyze the underlying diversity of IT within the sample and to determine types of farmers in the study area. To that end, the IT forming the dependent variables in the regression analysis are used as the inputs variables for segmenting irrigators. Thus, this research assigns farmers in homogeneous classes of technologies instead of grouping them according to the characteristics of the observations. To accomplish the former, a Latent Class Analysis approach (LCA) was employed, a method applied extensively in social sciences, but not much in agricultural research, with some exceptions such as the adoption of improved agro-technologies (Bizimungu and Kabunga, 2018), and perception of farmers to climate change (Arbuckle et al., 2014; Barnes et al., 2013).

LCA is a method which, by a statistical procedure, identifies class-membership probabilities for a set of observations by using the responses of a set of observed or “manifest” variables (Barnes et al., 2013; Linzer and Lewis, 2011). The goal is to determine the smallest number of “latent classes” sufficiently explaining the unobserved associations among the set of manifest variables (Magidson and Vermunt, 2004).

The key characteristic of this method is that both the latent and the observed variables are categorical (Linzer and Lewis, 2011; Skrondal and Rabe-Hesketh, 2007). An LCA is a model-based clustering technique similar to cluster analysis, given the fact that both methods group individuals into homogenous classes (Vermunt and Magidson, 2002). However, LCA shows some advantages, since it is based on a statistical model, the selection of the number of clusters (classes) is defined based on statistical tests, and techniques to handle missing data are also available (Arbuckle et al., 2014; Kaufman and Rousseeuw, 2009; Vermunt and Magidson, 2002).

Formally, LCA is fitted as follows. First, let Y_{ijk} denote the observed value of the j manifest (observed) variable, for individual i who gives the *k-th* response to the *j-th* variable. In this case, j are the irrigation technologies, and k, the possible outcome is binary; thus, Y_{ijk} can take values of 1 or 0. In addition, π_{jrk} is the class-conditional probability that an observation i belongs to a class r, with $r = 1, \ldots, R$, yielding the k-*th* outcome for the *j-th variable.* Within each class,

$$\sum_{k=1}^{K_j} \pi_{jrk} = 1 \tag{6}$$

According to Linzer and Lewis (2011), and assuming mutual independence of responses within each class, the probability that an individual i in a specific class r yields a particular j set of outcomes is the product of:

$$f(Y_i, \pi_r) = \prod_{j=1}^{J} \prod_{k=1}^{K_j} (\pi_{jrk})^{Y_{ijk}} \tag{7}$$

The probability density function across the classes is the weighted sum;

$$P(Y_i, \pi, p) = \sum_{r=1}^{R} p_r \prod_{j=1}^{J} \prod_{k=1}^{K_j} (\pi_{jrk})^{Y_{ijk}} \tag{8}$$

Thus, the model parameters p_r, and π_{jrk} are estimated by the latent class model. The posterior probability $\widehat{P}(r_i \backslash Y_i)$ for an individual belonging to a specific class is estimated by Bayes' theorem as follows:

$$\widehat{P}(r_i \backslash Y_i) = \frac{\widehat{p}_r f(Y_i\ \hat{\pi}_q)}{\sum_{q=1}^{Q} \widehat{p}_r f(Y_i\ \hat{\pi}_q)} \tag{9}$$

where $\widehat{p}_r$ and $\hat{\pi}_q$ are the estimates of p_r, and π_{jrk}, by the Expectation-Maximization algorithm (EM), which proceeds in an iterative way. Firstly, the E-step creates a function for the expectation of the log-likelihood evaluated using the current estimate for the parameters (p_r and π_{jrk}). Then, the M-step computes parameters maximizing the expected log-likelihood found on the E step. The estimates for p_r and π_{jrk} are used to determine the distribution of the latent variables in the next E-step. Finally, the model selection is based on the Bayesian Information Criterion (BIC), and the Aikake Information Criteria (AIC), opting for the model that minimizes the values of *AIC* and *BIC* (Barnes et al., 2013; Linzer and Lewis, 2011).

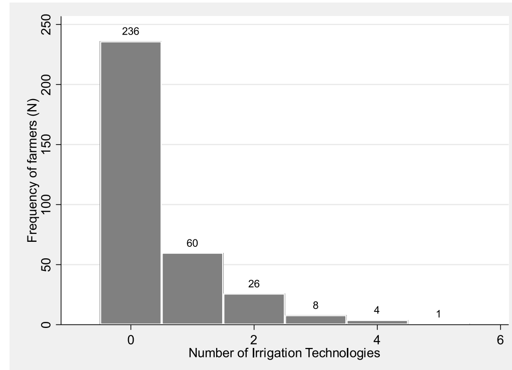

Fig. 2. Number of ITs and farmers' currently applying those technologies.

3. Results

3.1. The technological level of adoption of irrigation technologies

Fig. 2 shows the total number of IT implemented by irrigators in the study area. In the sample, 70 % of farmers have not implemented any technology intended to manage their water rights, and only around 11 % have put in place 2 or more practices. In terms of area, 26 % of the production land is irrigated by an efficient irrigation system (EIS).

At the farm level, EIS is the most utilized IT, representing 39 % of those farmers implementing at least one practice, but only reaching 18

[6] Although water rights are defined as continuous and permanent by the Chilean Water Code of 1981, some canals apply turn systems for some particular reasons, like land subdivision (and subsequently the water rights).

Table 2
Description, and percentage of IT adopters.

Technology	Description	Adopters (N)	Adopters (%)	Percentage of the total	Number of Irrigation Technologies				
					1	2	3	4	5
Efficient irrigation systems (EIS)	Drip, sprinkler, pivot, and lateral move irrigation systems.	60	61	18	28	20	7	4	1
On-farm reservoir	Storage infrastructure of water rights	12	12	3,6	26	13	6	4	0
Well	Well used to complement water for irrigation in dry years.	49	49	15	3	6	2	1	0
Solar panels	Use of solar panels for reducing electricity consumption	3	3	0,8	0	1	1	1	0
Scheduling	Irrigation programming based in technologies or advisor schedule, use of sensors for measuring soil humidity	11	11	3,3	0	4	4	2	1
Land Leveling	Leveling, smoothing and shaping the field surface for more efficient irrigation	8	8,1	2,4	2	3	0	2	1
Humidity retention	Organic matter, conservation agriculture, mulching, other.	9	9,1	2,6	1	4	2	1	1

% of the sample (Table 2). EIS constitutes 47 % for farmers adopting 1 IT, and 39 % from those applying 2 IT. Wells are behind EIS, with 15 % of adoption. Moreover, wells constitute 43 % for a single technology, and jointly with EIS, both represent 90 %, and 65 % of 1 and 2 adopted IT, respectively. On the other hand, scheduling is marginally adopted, with only 3,3% of the farmers within the sample using it. In addition, it is always adopted jointly with other IT. Humidity retention techniques are also minimally implemented by only 9 (2,6%) of the farmers.

Regarding the adoption level of the set of IT currently in use, the results show a low extent of adoption for each IT. When comparing with adoption rates in Chile, the results are higher than those found by Roco et al. (2016), who in nearby areas detected rates of adoption of the on-farm infrastructure of 3 %. The results differ, however, with adoption rates in more scarce regions in Chile such as the findings of Engler et al. (2016), who found an adoption rate of 43 % for drip irrigation, and 23 % of scheduling instruments for wine producers. They also differ with the findings of Molinos-Senante et al. (2016) in the semi-arid north of Chile, where the adoption rate of EIS was 94 %. Finally, the results differ with adoption rates in other countries where some technologies have been supported such as Spain (Alcon et al., 2011) and the U.S. (Pokhrel et al., 2018; Sears et al., 2018; Taylor and Zilberman, 2017).

3.2. Determinants of the intensity of adoption of irrigation technologies

The second part of the analysis looks for factors influencing the adoption of IT, utilizing a count data modeling approach. First of all, for the set of variables included in the regression analysis, both pairwise correlations and variance inflation factors (VIF) were tested to make sure there was no severe multicollinearity. The results for the correlations and VIF's(no higher than 5) determine no problems of collinearity (O'brien, 2007; StataCorp, 2017) (see Table 2 and 3 in Supplementary data for more details).

The count data models were estimated for the 3 dependent variables defined in 3.3.1. At first, overdispersion and zero-inflation were tested. These tests indicate that for specifications (Y_1 and Y_2), the PRM is preferred, and for Y_3, the NBRM is a more appropriate model (See Table 4 in Annex 2 in Supplemental material). Once decided that PRM and NBRM models yield better results, the second step was to select the model with the best fit to facilitate the interpretation. The specification Y_2, shows the best goodness of fit measures, minimizing the values for AIC and BIC 532,82, and 612,92,12 each, and getting the highest PseudoR^2 = 0,224 Table 5 in A Supplementary data material displays the results for the 6 remaining specifications).

Table 3 displays the results for 3 PRM models with Y_2 as dependent variable (See Table 6 in Supplementary data for more details). PRM1 depicts the results, including land size and *ws* as regressors, whereas the second and the third use the variable *wl-ratio* (PRM2) and PMR3, incorporating the series of perceptual variables. *Wl-ratio* is derived from the *ws* and land size quotient, taking a 1 if the ratio exceeds the mean for the sample and 0 otherwise. To get a better understanding and interpretation, regression coefficients are depicted and analyzed as Incidence Risk Ratios (*irr*[7]), and the average marginal effects (Long and Freese, 2006; Mariano et al., 2012).

For the HH variables, none, except for *Education*, impact the number of IT for any specification of the dependent variable. These findings are not consistent with the technology adoption literature analyzed by count data models, like the results on precision agriculture (Barnes et al., 2019; Isgin et al., 2008), and on IT (Jara-Rojas et al., 2012; Pokhrel et al., 2018). *Education* is highly and positively significant, increasing the adoption by almost 10 % in terms of *irr*, but it results in

[7] IRR are also called factor change. For their estimation, each β_i is exponented, so IRR (β_i) = $e^{\beta i}$. The IRR's coefficient tells how a change in an *X* affects the rate at which *Y* occurs, while the average marginal effects determinines the impact of any covariate on the number of technologies.

Table 3
Regression results incident risk ratios (IRR) for Poisson Regression Models (PRM) under specification Y_2.

Variable	Poisson Models		
	PRM 1	PRM 2	PRM 3
Age	1,008	1,009	1,006
	(0,009)	(0,009)	(0,009)
Education	1,089 ***	1092 ***	1,100 ***
	(0,026)	(0,025)	(0,024)
Agr. Experience	0,994	0,996	1,000
	(0,007)	(0,007)	(0,008)
Gender	0,798	0,819	0,853
	(0,193)	(0,199)	(0,208)
Social Capital	0,956	0,893	0,887
	(0,224)	(0,182)	(0,191)
Technical support	1,197	1,165	1,120
	(0,278)	(0,242)	(0,227)
Non Agr. Income	1,043	0,965	0,956
	(0,185)	(0,170)	(0,165)
Owner	0,908	0,957	0,900
	(0,178)	(0,190)	(0,176)
Credits	2,242 ***	2,525 ***	2,459***
	(0,748)	(0,733)	(0,717)
HI index	1,881 *	2,012 **	1,956 *
	(0,660)	(0,690)	(0,680)
Fruit	2,567 ***	2,519 ***	2,454 ***
	(0,559)	(0,543)	(0,579)
Horticulture	2,838 ***	2,621 ***	2,576 ***
	(0,966)	(0,886)	(0,892)
Mixed	0,995	0,923	1,069
	(0,469)	(0,435)	(0,494)
Forage	0,726	0,791	0,920
	(0,560)	(0,527)	(0,487)
ww	1,567 **	1,554 **	1,455 ***
	(0,331)	(0,323)	(0,305)
wcr	0,616 **	0,627 **	0,672 *
	(0,163)	(0,161)	(0,165)
Lining	0,696 *	0,726	0,755
	(0,133)	(0,135)	(0,141)
Canal	1,071	1,068	1,126
	(0,206)	(0,203)	(0,214)
Fees	1,270	1,433 *	1,437 *
	(0,343)	(0,337)	(0,337)
Length	1,044	1,019	1,026
	(0,201)	(0,189)	(0,182)
wua	1,263	1,262	1,240
	(0,269)	(0,267)	(0,248)
Land size	1,005 *		
	(0,003)		
ws	0,998		
	(0,002)		
wl ratio		0,660 *	0649 *
		(0,149)	(0,144)
Problems			1,261
			(0,343)
Accessibility			1,983***
			(0,539)
Se-irrigator			1,096
			(0,263)
Full irrigation			0,484 *
			(0,191)
Constant	0,030 ***	0,033 ***	0,033***
	(0,020)	(0,023)	(0,026)
Pseudo R^2	0,222	0,224	0,242
Observations	335	335	335

***$p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Robust standard erros in parenthesis.

only a slight increase in the number of technologies. Farms with more educated heads tend to increase IT, perhaps because they are exposed to more information, thereby internalizing the benefits (and costs) of these technologies. This finding is in line with adoption literature, which states a positive relationship between human capital and the decisions to adopt modern technologies (Bjornlund et al., 2009; Koundouri et al., 2006).

Table 4
Marginal effects of independent variables on the number of technologies (model PRM3)[b].

Variable	Marginal Effect	Std. Errors [a]
Education	0,044 ***	0,010
HI index	0,304 *	0,158
Fruticulture	0,372 ***	0,090
Horticulture	0,403 **	0,192
ww	0,170 *	0,096
wcr	−0,180 *	0,111
Fees	0,164 *	0,105
wl ratio	−0,196 *	0,101
Accessibility	0,311 ***	**0,124**
Full irrigation	**−0,328 *****	**0,177**
Credits	**0,408*****	**0,135**

[a] Standard errors obtained through Delta-method.
[b] Average Marginal Effects for each covariate are displayed in Table 7 in Annex 2.

Access to *technical support* has a positive yet not significant impact on the range of specifications. For *ownership*, being a renter reduces the rate, though not significantly. Likewise, *Non-agricultural income* has no impact on farmers' decisions to adopt technologies. Having extra resources, and a more favorable financial capacity could lead to a more considerable utilization of these types of technologies. On the other hand, *Credits* is the variable with the most significant impact of the HH characteristics on the rate of IT adoption. The incremental change is roughly 150 % (0,41 technologies according to marginal effects) compared to those who do not have access. This is consistent with the results of Jara-Rojas et al. (2012). It is noteworthy that in Chile, access to credits implies a more robust financial backing as well as access to a broader range of agricultural services, mostly offered by private agents.

Regarding *ws* and *land size*, the results are depicted in two ways: as independent variables, and as the *wl-ratio*. In PRM1 it is shown that *ws* has a negative but non-significant impact on technologies, while *land size* slightly increases the rate to acquire an irrigation technology (0,5%), being consistent with the findings of Green et al. (1996); Isgin et al., 2008; Engler et al. (2016), and Feike et al. (2017). The *wl_ratio,* a sign of water availability per unit of land (ha), causes a significant but negative effect on IT, reducing on average with 33 % the rate of adoption. This translates, according to the average marginal effects (discrete change), in 0,19 fewer technologies for more efficient water management. The *diversification index* has a positive and significant impact, increasing the percentage to apply technologies. IT's enable farmers to a more diversified agricultural production (Hussain and Hanjra, 2004). Both valleys cover a wide range of agricultural production, hence requiring customized water management. For the set of dummies capturing the specificity of agriculture production, farms focused on fruit and horticulture have higher rates of technology usage compared to those cultivating annual crops. The coefficients (*irr*), along with *Credits,* are the largest for the set of variables, around 2,43 for *fruit*, and 2,58 for *horticulture*. Translated to number of technologies, these variables determine an increase in the number of technologies adopted of 0,36 and 0,39. This positive impact is consistent with the findings of Feike et al. (2017), who studied the adoption of wells and drip irrigation in China, and it is also in line with research on water management practices in Arkansas, US (Huang et al., 2017).

For the contextual variables characterizing watercourses infrastructure and water withdrawals, the models illustrate that *canal*, *extension,* and *wua* are not significant, but *wcr*, *ww*, *lining,* and *fees* yield significant impacts on the adoption of technologies. These results suggest that both proxies of location, with the plausible gains on certainty on water rights for farmers located in a primary or a shorter canal, are not triggering decisions to adopt IT. That confirms findings by Zhang et al. (2013), who did not find an effect of canal length on water productivity In China. Regarding location, Manero et al. (2019), working in

Table 5
Regression results and marginal effects for models including the interaction terms Credits-Full irrigation.

Variable	IRR	Marginal Effects[a]	IRR	Marginal Effects[a]	IRR	Marginal Effects[a]
HH characteristics	YES		YES		YES	
NNRR characteristics	YES		YES		YES	
Contextual characteristics	YES		YES		YES	
Perceptual characteristics	YES		YES		YES	
Accesibility	1,843	0,277 *				
	(0,501)	(0,125)				
Credits			2,489 ***	0,418 ***		
			(0,727)	(0,134)		
Full irrigation					0,484 *	−0,329 *
					(0,189)	(0,176)
Credit-No irrigation	0,795	−0,198				
	(0,405)	(0,444)				
No Credit-full_rrigation	0,200 ***	−0,775 **				
	(0,085)	(0,377)				
Credit-full-irrigation	0,593	−0,394				
	(0,275)	(0,419)				
Accessibility-No full Irrigation			1,971	0,553		
			(0,879)	(0,432)		
No ww-Full_irrigation			0,595	−0,230		
			(0,274)	(0,244)		
ww-Full irrigation			0,812	−0,106		
			(0,369)	(0253)		
Credit-No ww					2,008	0,218 *
					(0,943)	(0,132)
No Credit-ww					1,166	0,036
					(0,508)	(0,099)
Credit-ww					3,116 ***	0,459 ***
					(1,416)	(0,142)
Constant	0,075 ***		0,026 ***		0,039 ***	
	(0,057)		(0,023)		(0,033)	
Pseudo R^2	0,2499		0,2423		0,2421	
Observations	335		335		335	

*** p < 0,01, ** p < 0,05, * p < 0,1.
[a] Standard errors obtained through Delta-method.

Table 6
Farmers' membership probabilities for belonging to each class.

Technology	Class 1: Precarious	Class 2: Technological
EIS	0,062	0,688
On-farm reservoir	0,008	0,154
Well	0,087	0,401
Programming tools	0,000	0,175
Solar Panels	0,000	0,048
Soil Levelling	0,005	0,106
Humidity retention	0,000	0,143

small irrigation schemes in Tanzania, found a significant yet negative effect on agricultural production and income for farmers located in secondary canals.

On the other hand, *wcr* produces a negative effect, reducing the rate of adoption of technologies between 35 % and 52 % in terms of *irr* and 0,2 in the form of marginal effects. The stabilization of water supply produced by community reservoirs affects farmers' decisions concerning irrigation negatively rather than generating incentives, coinciding with the findings of Zilberman et al. (2011). On the contrary*, ww* positively influences IT usage. Continuous access to water increases the rate of adoption by 50 % (0,18 technologies) compared to the turn system, allowing a full exercise of their water rights, and, thus, to conduct investments oriented towards better management. Furthermore, *fees* produces a positive effect on two of the three model specifications, rounding an increase in the rate of 50 %(irr). If farmers pay higher fees, this can either be due to more expensive fees (CLP$*l*s^{-1}), to the use of larger volumes of water, or both. Bearing that in mind, it is possible to infer that higher water costs trigger the adoption of IT. Significant higher fees were also found significant by Jara-Rojas et al. (2012) working in neighboring areas but focusing on water conservation technologies. Finally, *lining* is also impacting the level of adoption, but not as expected (*irr* below 1). A better infrastructure reduces conveying losses, providing farmers a more reliable environment for receiving their water shares and conditions for investments. However, the effect of lining goes in the opposite direction, somehow disincentivizing farmers taking action in terms of irrigation investments. Although not expected, these results are somehow similar to those found by Tang et al. (2016) in China, who state that it seems as though good canal infrastructure is sufficient as a water-saving technology.

Furthermore, when introducing the perceptual variables on PRM3, *accessibility*, and *full irrigation* are significant, but *se-irrigation* and *problems* are not (Table 3). The *irr*'s for the rest of the variables retain the significance and magnitude with the same interpretation as described before. Insignificance for *se-irrigation* points out that regardless of other personal characteristics, irrigation skills are rated similarly, with 63 % of farmers rating themselves as good irrigators. However, most of the farmers (98 %) know neither total irrigation requirements nor the volume applied to crops each irrigation time.

A more reliable water supply is positively impacting farmers to implement technologies compared to those who perceive a more deficient availability. A similar effect, but not significant, of reliability of water on technology adoption was found by Adeoti (2008) in Ghana. On the other hand, Manero et al. (2019) found a positive impact of water reliability on yields in Tanzania. Conversely, *full irrigation* significantly decreases the rate of IT implementation by 50 % on average. Although in terms of *irr*, *ww* gets a bigger rate change, *full irrigation* yields the most significant effect on the number of technologies, according to the average marginal effects.

Examining the marginal effects more closely, *Credits*, *full irrigation*, and *accessibility* have the highest impacts for the personal and the contextual and perceptual variables, respectively. While access to agricultural credits increases the number of technologies by 0,4, *Full* *irrigation* reduces them by 0,33. *Accessibility,* on the other hand, increases the number by 0,32. These variables, in some way, represent the availability (or lack) of financial and natural resources and the incentives for farmers to adopt IT.

As these variables are binary, interactions among these 3 variables are introduced to PRM3, yielding relevant results (Table 5). Firstly, for the *Credits-Full irrigation* combination, the *irr's* are below 1, meaning that each combination reduces the rate to implement practices relative to the base category. However, only the interaction "*No credit-Irrigation*" is significant, depicting the largest reduction in proportion (80 %) and number (0,78) of technologies compared to the base, *No credit-No irrigation*, suggesting that irrigating the full land perception has a dominant effect, which represents the perception of sufficient water to irrigate.

Secondly, the interaction *full irrigation-accessibility* unexpectedly produces no significant results. Since both variables have opposite effects, it seems that the variables cancel out each other's individual effects. Finally, in terms of the last interaction between *credits* and *accessibility*, the figures show that both variables complement each other, increasing the *irr*'s with positive marginal effects. However, only *credit-accessibility* is significant, with a factor change of 0,47 more technologies.

As it was stated before, it seems that the statement of full irrigation generates a dominant effect on the adoption of technologies, which may be interpreted as a relative abundance of the resource. According to the data, half of the farmers hold less than 1,3 $l{*}s^{-1}$, and 75 % of them are under the sample mean (1,86). When turned into a water-land ratio; however, only 28 % of farmers in the sample have less than 1 $l{*}s^{-1}{*}ha^{-1}$. Therefore, full irrigation could be explained by either capturing larger water applications respecting the water shares they own given the poor infrastructure and lack of control of water withdrawals or due to possible internal arrangements within each canal. This positive perception in terms of irrigation is strengthened by the head-reservoir, which allows for stabilization and better resource distribution and reducing farmers' exposure to water shortages, discouraging farmers' adoption of IT. This decreasing need for adopting risk-reducing measures due to improvements in water supply by dams coincides with those described by Biswo et al. (2018).

3.3. Latent class analysis results

Complementing the econometric analysis, an LCA was performed to identify the underlying diversity of IT in the study area, despite the figures showing a low rate of adoption. Table 2 depicts that the most utilized technology is *EIS* (18 %), followed by *wells* (15 %). Conversely, *humidity sensors,* and *solar panels* are the least used practices. To classify farmers, 4 LCA models were run, increasing the number of LC from 1 to 4, selecting the model that best disaggregates the data in homogenous classes while minimizing the AIC and BIC criteria. The results show that the model with 2 classes gets the best fit.[8] In this LCA, membership classes make up 88 % (C1), and 12 % (C2). C1 is the Non-technological, and C2 the Technological class. Table 6 depicts the average probability distribution of belonging to each class for each technology.

The Non-technological class comprises the vast majority of farmers (n = 295). The main feature of this group of farmers is that they have no technologies. This implies that the bulk of the farmers are technologically precarious. If they apply (59), it is only 1 technology (either EIS or wells) but with a low probability, around 9%. In figures, for this group, 28 irrigators use EIS, 26 utilize wells, and only 3 hold a reservoir, though not jointly. As a result, there is a clear preference for infrastructure technologies among farmers in this group. These 59 farmers overlap with the Technological irrigators class (n = 40), containing farmers' with the highest item responses for the set of technologies and practices (Fig. 3). C2 is distinct because farmers have installed EIS (32) and wells (23), but in addition to these technologies, C2 contains the totality of irrigators making use of irrigation programming tools.

C1 entails 80 % (236) of farmers with no technologies, implying water applications by surface irrigation methods, such as flood and furrow. By contrast, C2 comprises irrigators applying at least one technology, ranging from 1 to 5, with 2 (67,5%) and 3 (17,5%) the most applied. For those farmers using 2 technologies (n = 27), the most common “packages” are *EIS* and a well (n = 11); or an *EIS* plus a programming tool (n = 4).

Differences in characteristics conforming the two groups were tested through statistical analysis (Table 10 in Supplementary Data). Class 1 is less educated and has more farming experience, while Group2 receives more technical support and has a higher percentage of farmers with access to agricultural credits (significant at 10 % and 1 % respectively). In terms of natural resources capital, Group1 holds smaller plots, lower water rights dotation, and less area using EIS, all significant at 1%. However, they have a higher water-land ratio, 1,90 vs. 1,54 for C2 (Table 7). These figures contribute to explain the low rate of adoption, confirming the regression analysis results, i.e., access to credits and larger water-land ratios generate disincentives to invest.

In terms of agricultural production, both clusters entail irrigators growing the 4 main crop categories. More specifically, C2 is dominated by fruit production, with 68 % growing either raspberries, blackberries, blueberries, and apples, and cereals as the second-largest type of crop (8 farmers, 20 %). In C1 annual crops and fruit are the dominant crops, both comprising 88 % of the agricultural land under production for this class (38,3 % and 49 % each). One relevant issue makes up fruit production, which consists of 2 sub-segments. Class 1 focuses on small-scale production based on berries (raspberry and blackberry); meanwhile, Class 2 grows more extensive areas with apple, cherry-tree, or blueberries.

Out of the 431 plots cultivated in Class 1, 402 (93 %) are watered by flood or furrow. For Class 2, 52,3 % of crops are being cultivated using EIS, out of which 63 % makes up fruit and 44 % horticulture (both significant at 1 %). Pastures and forage are irrigated by surface irrigation in both classes.

Regarding contextual and infrastructural characteristics, C1 contains 40 % of irrigators who have access to water by turns, whereas 22 % in C2 do. Out of 126 irrigators declaring being on a turn regime, 93 % are in the non-technological class. Likewise, in C1 a higher proportion of irrigators is located at a secondary canal level (46 %) and pay fewer annual fees, with 85 % of farmers’ payments below average (both significant at 1 %). Finally, in terms of perception, the only distinctive difference is related to the perceived water availability (at 1 %), with Class1 giving a lower valuation (0,54, vs. 0,8 for Class2).

Despite the difference in grouping farmers, the classes detected for the LCA - the non-technological and technological types- present some similarities with other clustering studies. For instance, Takeshima (2016) found out that in Nigeria, for the less technological cluster, a minority (33 %) of farmers use irrigation to some extent. Robert et al. (2017), working in India, grouped farms into 3 groups, defining one group as the technological and more diversified. Lastly, Maton et al. (2005) in France found 2 types of irrigation strategies according to irrigation practices: intensive and extensive irrigators.

The results of the econometric and latent class analysis jointly allow for a better understanding of the low rate of adoption of IT, leading to a series of considerations for further developments regarding technology adoption and on-farm irrigation water management not only in this study area but for the wider agricultural irrigation in Chile as well as in similar environments.

For farmers adopting IT, there is a clear preference and tendency for the adoption of infrastructural technologies to the detriment of improved IT, such as scheduling or programming tools. Despite the well-known benefits of these techniques, the precise timing and amount of

[8] See table 9 in Annex 3 for the goodness of fit of each Latent Class model.

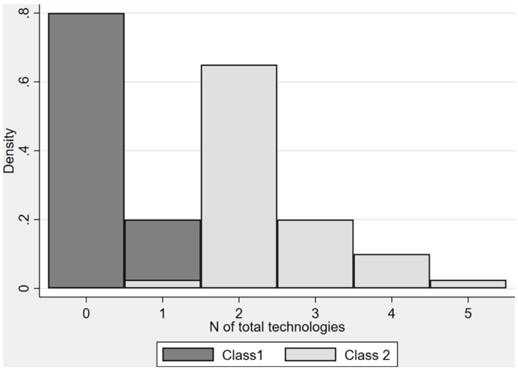

Fig. 3. Technology adoption scope for technological and non-technological classes.

water applied (Bjornlund et al., 2009; Montoro et al., 2011) and reducing the overall application and potential gains in efficiency and yields (Gleick, 2003), the results show a minimal usage of scheduling, being only applied in fruit production, which is the most profitable crop in the study area.

However, these results in terms of extent and type of adoption of IT are somehow expectable, since they match with technologies subsidized by public programs mostly through the act “Ley 18.450 de Fomento a la Inversion Privada en Obras de Riego y Drenaje”, which aims to foster the implementation of on-farm (and off-farm) irrigation infrastructure such as efficient irrigation systems and reservoirs. Excluded in this law are management techniques such as scheduling (Engler et al., 2016). The promotion of these type of technologies has been common in other countries such as the US, Spain (García-Mollá et al., 2019), India (Bahinipati and Viswanathan, 2019; Malik et al., 2018), Australia (Grafton and Wheeler, 2018) and China (Zhang et al., 2019), where programs have a water conservation focus and some of them also incentivize the adoption and implementation of scheduling (Sears et al., 2018). The Chilean program differs in explicitly orienting towards an expansion of the irrigated land (Engler et al., 2016), and improving the transparency and legal security of the water rights (Clarvis and Allan, 2014). However, recent research has shown that the implementation of EIS (drip irrigation) increases the adoption of scheduling, claiming for the inclusion of management tools to the current set of subsidized technologies (Engler et al., 2016).

It may be argued that the adoption of IT depends on means and incentives (Levidow et al., 2014). According to the results of our case study, credits and full irrigation are the main drivers influencing the adoption of IT, where the former may represent the availability (lack) of financial resources or means demonstrated to influence the adoption of IT (Alcon et al., 2011)- and full *irrigation* the availability of water giving incentives (disincentives) to adopt IT. Out of these incentives (disincentives), water availability (scarcity) has been shown to be a driver of the adoption of technologies (Olen et al., 2015; Taylor and Zilberman, 2017). Conversely, the relative abundance of surface water disincentives farmers to invest and adopt IT and reduce water usage (Mendelsohn and Dinar, 2003).

Nevertheless, in addition to these factors, it is possible to introduce a set of elements hindering the adoption of IT. Some institutional and policy factors have demonstrated to trigger the adoption of irrigation technologies. In this setting, policy instruments like water pricing have shown to boost the adoption of IT (Alcon et al., 2011; Berbel and Gómez-Limón, 2000; Zilberman et al., 2011). In this regard, the relative water abundance in the study area, next to some distinctive features of the allocation process and the characteristics of irrigation water rights –no cost for initial allocation, the full and permanent ownership on a certain amount of resources ($l*s^{-1}$), poor conveyance and control infrastructure at canal level - the current focus of the irrigation programs,

Table 7
Key characteristics of the 2 Classes detected by Latent Class Analysis.

Class	Household	Farming	Irrigation	Contextual	Perceptual
Nontechnological (295 farmers, 88 %)	Older and more experienced farms. A lower level of education and a higher proportion of HH having an extra source of income. 62 % of land ownership.	70 % farms < 5 ha, and 4 % > 50 ha, the coexistence of small-scale farming (limited in resources), and large scale agriculture, but not intensive. 66 % of the land of annual crops, 28 % fruit, (berries). Less diversified agriculture.	9 % fruit under EIS (blueberries), 4 % cereal (corn). 80 % do not apply irrigation technology. The only usage is EIS and well, but not jointly.	40 % under turns system, and 46 % in a secondary canal level	54 % with a positive valuation of water availability. 61 % of self-value that waters well. 88 % irrigates the whole land.
Technological (40 farmers, 12 %)	More educated, less experienced, as well a Non-Agricultural income. High access to agricultural advisors	25 % < 5 ha, and 20 % > 50 ha. Intensive agriculture in 68 % of plots. Focus on fruit (blueberries, apple, cherry tree), and 28 % annual crops.	33 % cereal (maize) 63 % fruit (blueberries 93 %) Use of EIS plus other technologies.	78 % of access to water continuously. Payment of higher fees.	80 % value positive water availability 75 % considers itself as a good irrigator

and the presence of a head-reservoir shape an unsuitable scenario to apply policies to increase willingness to adopt, such as pricing, and as a result, do not generate enough incentives to adopt IT.

However, for a better understanding of IT adoption and irrigation management in the study area, deeper comprehension of this stated relative abundance water is needed, especially given the divergence between this relative abundance, and the manifest water shortage scenario of central Chile in the last decade (Garreaud et al., 2019).

4. Conclusions and policy implications

This article examines the adoption of irrigation technologies and the underlying diversity in terms of intensity of adoption in 2 irrigated valleys of the Maule region in Central Chile, where a mixture of farming coexists. The results show a low level and range of technology adoption, with only 30 % of farmers adopting technologies and efficient irrigation systems and wells as more widespread practices. This conforms to the subsidies provided by the Chilean government over the past 4 decades.

This low level of adoption was disaggregated in 2 groups by a Latent Class Analysis. A small group was comprised of moderate to intensive users of technologies, while the second group gathered the majority of non-adopters, most of them restricted in terms of natural capital and financial barriers.

Econometric analyses showed that the adoption of technologies depends on a series of factors. Particularly education, diversification, and the dominance of fruit or horticultural production positively impact the number of technologies. Conversely, higher water-land rates, community reservoirs, and unlined canals reduce adoption. The relative abundance of water and accessing financial capital are the main factors influencing the adoption of technologies.

Although the results are case-study specific to these two irrigated valleys, they allow addressing some policy implications to both the public sector and private agents. To date, the irrigation policy in Chile focuses on improvements in efficiency and on and off-farm infrastructure, aiming at increments of agricultural productivity, and favoring projects with the largest increases in irrigated land. This policy does not incorporate technical support, and it is restricted to a limited type of technologies. Therefore, if the goal is to increase the rate of adoption, widening and facilitating access to public subsidies and relaxing entry barriers for those with limited resources, creating irrigation extension programs to support and spread the range of subsidized irrigation technologies, including management techniques, is required.

Given the low rate of adoption, programs incentivizing the implementation of irrigation technologies are still needed. Nevertheless, it is also crucial to consider a few other elements. The results show that contextual characteristics are hindering adoption rates, challenging the correct design of policy and programs. Moreover, efficiency-oriented policies can raise the pressure over water resources, leading to incremental water consumption and irrigated areas, instead of water-savings if control on water resources is absent (Perry et al., 2017; Sears et al., 2018). Switching from less to more efficient irrigation causes changes in the demand of water, and such improvements may also be a source of adverse spillover effects for those placed downstream (Grafton et al., 2018; Vicuna et al., 2014). Moreover, those improvements do not uniquely depend on individual efforts, but demand collective decisions in many situations, requiring financial and technical capacity as well as a suitable environment and governance, at both canal and basin level.

Finally, irrigation technologies are considered essential in dealing with water shortages, as well as in developing long-term adaptation strategies in light of climate change. Reductions in water availability are expected for central Chile, challenging public and private organizations to design suitable policies and programs, increasing reliability, generating incentives, and raising farmers' awareness for better water resources management.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary material related to this article can be found, in the online version, at doi:https://doi.org/10.1016/j.agwat.2020.106147.

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