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The Impact of Climatic Change Adaptation on Agricultural Productivity in Central Chile: A Stochastic Production Frontier Approach

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Abstract: Adaptation to climate change is imperative to sustain and promote agricultural productivity growth, and site-specific empirical evidence is needed to facilitate policy making. Therefore, this study analyses the impact of climate change adaptation on productivity for annual crops in Central Chile using a stochastic production frontier approach. The data come from a random sample of 265 farms located in four municipalities with different agro-climatic conditions. To measure climate change adaptation, a set of 14 practices was used in three different specifications: binary variable, count and index; representing decision, intensity and quality of adaptation, respectively. The aforementioned alternative variables were used in three different stochastic production frontier models. Results suggest that the use of adaptive practices had a significant and positive effect on productivity; the practice with the highest impact on productivity was irrigation improvement. Empirical results demonstrate the relevance of climate change adaptation on farmers' productivity and enrich the discussion regarding the need to implement adaptation measures.

Keywords: climate change; adaptation; agricultural systems; productivity; technical efficiency; Chile

1. Introduction

Agriculture represents a relevant economic sector for the analysis of climate change, given that it is situated at the interface between ecosystems and society, and it is highly affected by changes in environmental conditions [1,2]. Climate change is affecting food prices, food security, land use [3] and raising uncertainty for crop managers [4]. According to Kahil [5], the severity of climate change impact depends on the degree of adaptation at the farm level, farmers' investment decisions and policy choices, and these factors are interrelated. Thus, it is necessary to recognize the effect that limitations in natural resources will have on agriculture to build resilience to climate change at the farm level [6].

On the other hand, as natural resources available for food production become more constraining, crop productivity is essential for fostering the growth and welfare of the agricultural sector [7]. To relax these constraints, farmers have been modifying their practices to cope with climatic variability for centuries; however, climate change is now threatening their livelihoods with increasing unpredictability, including frequent and intense weather extremes such as droughts, floods and frosts [8]. According to Zilberman et al. [9], adaptation is the response of economic agents and societies to major shocks such as climate change. Adaptation practices are adjustments intended to enhance resilience or reduce vulnerability to observed or expected changes in climate [10]. Nelson et al. [11] claim that adaptation is imperative for three reasons: (i) many future environmental risks are now more apparent and predictable than ever; (ii) even where risks are not quantifiable, environmental changes may be very significant; and (iii) environmental change, although often the outcome of multiple drivers, has indisputable human causes. Changes in food production affect all consumers; however, it is producers that need to adapt to insure adequate supplies and who bear the costs involved in improving efficiency [12].

There is a wide range of methodological approaches that have been developed over the years to generate multiple measures of productivity and efficiency [13]. A relevant measure of productivity for management recommendations is technical efficiency (TE) [14]. This indicator evaluates the difference between frontier or maximum attainable output and observed output given an input bundle and technology. Given that TE is an important component in overall productivity, the development and implementation of public policies can be more effective if the TE of any given farming system is known [15]. Several studies have investigated factors associated with agricultural productivity across the globe, but the literature linking TE with climate change adaptation is scanty. One exception is the study by Mukherjee et al. [16], which finds that heat stress in the southeastern U.S. has a significant and negative impact on milk production, while adaptation through a fairly simple cooling technology has a positive and significant effect on efficiency. In addition, in the same analysis, when climate change is factored into the production function (frontier) specification, the resulting estimates are more accurate, because they avoid possible parameter bias stemming from the omitted variable problem.

It is thus important to model the full range of interactions that might exist between productivity and climate change [17]. Most of the scientific information related to climate change and its effects on agriculture comes from case studies in developed countries. In developing countries, where there are high levels of uncertainty and vulnerability to climate change, there is need to target policy instruments to adapt the productive systems, particularly considering the lack of articulation between climate change adaptation and agricultural policy [18].

In this work, we investigate whether adaptive practices can increase productivity in different agricultural production systems based on annual crops in Central Chile. Major adaptation practices in farming systems include: conserving soil, using water efficiently, planting trees, changing planting dates and using improved varieties [19–23]. It is expected that farmers who are more aware of and better adapted to climate change will be able to make more efficient use of their resources and thus cope with any adversities. This study adds valuable information for agricultural policy design, as it provides evidence of the impact of alternative adaptation strategies to climate change. Additionally, farmer and agricultural system characteristics are linked to productivity to inform agricultural policy.

The rest of the paper is organized as follows: Section 2 gives a description of the study area, the methodological approach and the empirical models; Section 3 presents and discusses the empirical results; and Section 4 summarizes and concludes.

2. Materials and Methods

2.1. Study Area and Data

The study area covers 8,958 farms in four municipalities of the Maule Region, in Central Chile, a Mediterranean transition zone between the arid north and the rainy south. Projections for the study area comprise a decrease in precipitation of up to 40% and a rise in temperatures between 2 °C and 4 °C in the next 40 years [24,25]. This region is a major contributor to the agricultural output of the country and, despite rapid technological progress in recent years, the cultivation of annual crops, fruits and vegetables is not changing fast enough to counteract the predicted adverse effects of climate change [26,27]. Specific adverse effects expected in the near future concern losses in the quality of the environment for agricultural production [28].

The four municipalities selected for the study were: Pencahue, San Clemente, Cauquenes and Parral. Pencahue and Cauquenes are dryland areas; San Clemente is primarily composed of irrigated land near the Andes Mountains; and Parral is in the central irrigated valley. San Clemente has a total of 226,826 hectares (ha) dedicated largely to the production of forage, cereals and seeds. Cauquenes and Parral have 128,017 and 125,630 ha, respectively, with a significant area devoted to vineyards, cereals and forage. Pencahue is the smallest municipality, with 65,118 ha dedicated mostly to vineyards, orchards and cereals [26]. Table 1 presents some key characteristics of the four municipalities and the main cropping systems for each one.

Table 1. General information for the study area.

Municipality	Area	Rainfall (mm/Year)	Farms	Farms Interviewed	Main Crop System (%)				
					Wheat and Oat	Spring Crops [a]	Spring Vegetable [b]	Rice	Others Crops [c]
Pencahue	Irrigated dryland	709	1129	40	12.5	35.0	52.5	0.0	0.0
Cauquenes	Non-irrigated dryland	670	3026	81	97.5	2.5	0.0	0.0	0.0
San Clemente	Irrigated Andean foothill	920	2990	89	40.4	42.6	12.4	0.0	4.6
Parral	Irrigated central valley	900	1813	89	54.5	7.3	1.8	36.4	0.0
	Total		8958	265	56.6	77.4	12.5	7.5	1.5

[a] Spring crops are: maize, beans and potatoes. [b] Spring vegetables are: peas, onion, tomato, melon, watermelon, cucumber and squash. [c] Other crops are: tobacco and cabbage.

During August and November of 2011, a random survey was conducted that involved 274 interviews, representing 3.06% of the farmers in the study area. This survey targeted farmers that specialized in annual crops. The surveys with missing information were excluded from the analysis, leaving 265 valid surveys. Previous work in the study area inquired about the perception of and adaptation to climate change [24,26]; however, this article goes further by linking adaptation to climate change and productivity at the farm level.

Table 2 shows a description of the variables used in the study. The mean crop production value is US$66,383 (MM$31.2 where MM$ is equivalent to millions of Chilean pesos; and the prevailing exchange rate was 470 Chilean pesos per U.S. dollar when the data were collected). Farms range in size from 0.5–595 hectares, with a mean of 55.5 hectares. The average cultivated land area is 17.1 hectares. The mean value of purchased inputs (seeds, fertilizers, pesticides and hired machinery) is MM$11.4, and the mean investment in labor for crop production is MM$2.2. Crop diversification is measured using a variant of the Herfindahl index (H) calculated for each farm as: $H = \left(1 - \sum_{i=1}^{n} \left(\frac{c_i}{T}\right)^2\right) \times 100$, where c_i is the area under the i-th crop and T is the total cropped area [29]. The H index for the sample is 23.7%, ranging from 0–96.4%.

The average age for farmers is 55.5 years, while the average level of formal education is 7.2 years. The majority (82.6%) of farmers claimed that agriculture is their main income source, accounting, on average, for 62.1% of their total income. Eighty-one farms are in dryland areas. Meteorological information from the Internet and mass media (radio, TV and newspaper) is used by 93.2% of the farmers, and 52.4% of them participate in farmer associations. The mean distance from the farms to the city of Talca, the regional capital, is 77.4 kilometers.

Table 2. Description of the variables used in the stochastic production frontier (SPF) and inefficiency models. MM$, millions of Chilean pesos.

Variable	Name		Unit	Definition	Mean	SD
Production Function Variables						
y	Agricultural production		MM$	Crop production value in Chilean pesos [a]	31.2	14.0
L	Cultivated land		Ha	Hectares with crops	17.1	53.3
C	Capital		MM$	Value of seeds, fertilizers, pesticides and machinery contracted in Chilean pesos	11.4	51.7
W	Labor		MM$	Value of family and hired labor	2.2	6.8
D	Dryland		%	Dummy variable = 1 if the farm is located in a dryland area and 0 otherwise	30.6	46.2
H	Diversification		%	Crop diversification index	23.7	27.5
A_1	Climate change adaptation	Decision	%	Dummy variable = 1 if there are at least one practice adopted and 0 otherwise	56.6	49.7
A_2		Intensity	Number	Number of climate change adaptation practices adopted in the farm	1.8	2.2
A_3		Quality	%	Index of adaptation based on experts' opinion	12.6	15.4
Inefficiency Model Variables						
z_1	Age		Years	Age of the head of the farm in years	55.5	14.1
z_2	Schooling		Years	Years of schooling of the head of the farm	7.2	4.1
z_3	Dependence		%	Dummy variable = 1 if agriculture is the main source of income for the household and 0 otherwise	82.6	37.9
z_4	Specialization		%	Percent of total income that corresponds to income from crops	62.1	32.0
z_5	Use of meteorological information		%	Dummy variable = 1 if the farmer is a user of meteorological information and 0 otherwise	93.2	25.2
z_5	Membership		%	Dummy variable = 1 if the farmer is a member of an association and 0 otherwise	52.4	50.0
z_7	Farm size		Ha	Total farm size in hectares	56.4	122.3
z_8	Distance to market		Km	Distance to the regional capital city in kilometers	77.4	43.8

[a] Four hundred seventy Chilean pesos = US$1 for the study period.

2.2. Practices Considered for Climate Change Adaptation

In recent studies, adaptive practices are identified as investment in technologies such as irrigation, the use of drought- and heat-tolerant and early-maturing varieties [19,30] and the adoption of strategies such as changing planting and harvesting dates, crop diversification, agroforestry and soil and water conservation practices [20–22]. Tambo and Abdoulaye [23] highlight the relevance of adaptation and its intensity regarding climate change. The authors just mentioned use as a first hurdle the decision to adopt a drought-resistant variety of maize and then intensity as the degree to which they will invest in adaptation measured as the area cultivated with the resistant variety.

A panel of experts was consulted to determine the most appropriate climate change adaptation strategies for the farming systems of Central Chile. This expert panel was composed of 14 national experts in agricultural systems and climate change. These experts were asked to assign a score from 0–3, where 0 is no impact and 3 is high impact, to 14 practices according to the importance of each practice for adaptation. These practices, described in Table 3, fall into three main categories: (1) water and soil conservation practices (WSC); (2) changes in cropping schedule and varieties (Cr); and (3) improvement of irrigation systems (I). These practices have been used previously in the literature [19,20,31]. We used this list of practices in the producers' survey to learn about what practices are being used by them. In several quantitative studies, the adaptation to climate change has been measured as the adoption of strategies, practices and technologies to increase the capacity of a farm to cope with changing climate and variability ([19–23] and others), and in most studies, the adaptation variable is defined as a binary decision. To carry out a more comprehensive analysis of adaptation, we include alternative measures of adaptation, from a simple binary variable to a more complex adaptation quality index. Each measure accounts for different interpretations of adaptation described as follows:

- Binary decision: a dichotomous variable indicating that at least one practice was adopted (A_1). In this case, the aim is to analyze the impact of being able to carry out a basic strategy.
- Intensity: measured as the number of practices or technologies adopted on the farm (A_2). Compared to A_1, this measure analyzes the impact of passing the first hurdle, i.e., the decision to adapt.
- Quality: an index calculated as the sum of adaptation practices weighted by the experts' score (A_3). The objective here is to estimate the impact of adopted practices that are more effective to face climate change. The weights were estimated by normalizing the average scores (0–3) given by the panel of experts to each practice, to generate a scale. The quality adaptation index (A_3) was constructed considering the sum of all the practices on a given farm multiplied by the weight assigned by experts (W_{ij}), divided by the sum of all weights (W_i). The formula used is as follows: $A_{3_i} = \left[\frac{\sum_{j=1}^{14} W_{ij}}{\sum_{j=1}^{14} Wj}\right] \times 100$, where i are the farms (from 1–265) and j are the practices (from 1–14).) The value of A_3 ranges from 0–100% where 100% implies that the practice presents the highest valuation assigned by the experts.

The number of farmers who have decided to adopt at least one of the practices is 150, representing 56.6% of the sample. The intensity in the number of practices adopted by farmers ranges from 0–11, with a mean of 1.8. The quality of adaptation (average index) is 12.6%, ranging from 0–79.3% (as can be seen in Table 2).

Table 3. Climate change adaptation practices according to the recommendation by experts.

Practice	Type [a]	Weight %	Farmers (n = 265)	
			No. of Respondents	% of Total
Incorporation of crop varieties resistant to droughts	Cr	85.7	2	0.7
Use of drip and sprinkler	I	83.3	31	11.7
Incorporation of crops resistant to high temperatures	Cr	80.9	2	0.7
Changes in planting and harvesting dates	Cr	78.6	110	41.5
Afforestation	WSC	76.2	5	1.9
Zero tillage	WSC	69.0	3	1.1
Use of water accumulation systems	I	66.7	38	14.3
Use of green manure	WSC	66.0	33	12.4
Use of mulching	WSC	61.9	24	9.0
Use of cover crops	WSC	61.9	16	6.0
Other WSC practices	WSC	61.9	16	6.0
Use of hoses and pumps for irrigation	I	59.5	52	19.6
Implementation of infiltration trenches	WSC	57.1	19	7.1
Cleaning of canals	WSC	54.8	60	22.6

[a] Cr: changes in crops, I: improvement of irrigation systems, WSC: water and soil conservation practices.

2.3. Analytical Framework and Empirical Model

The stochastic production frontier (SPF) model developed by Battese and Coelli [32] was used to estimate the following Cobb–Douglas frontier:

$$lny_i = \beta_0 + \beta_1 lnL_i + \beta_2 lnC_i + \beta_3 lnW_i + \beta_4 D_i + \beta_5 H_i + \beta_6 A_i + (v_i - u_i) \quad (1)$$

where y_i is the value of agricultural production of the i-th farm, including the value of the output marketed, as well as the value of home consumption; L is the number of hectares assigned to annual crops by the farmer; C represents capital and is the sum of seeds, fertilizers, pesticides purchased and machinery contracted; W is the value of family and hired labor; D is a dichotomous variable that indicates if a farm is located in a dryland area and is thus expected to have lower production; H is the crop diversification index used to control for the intensity of agricultural activity and land use on the farm; A is the climate change adaptation measured as explained in Section 2.2; βs are the parameters to be estimated; and $v - u = \varepsilon$ is the composed error term.

The term v is a two-sided random error with a normal distribution (v~N $[0, {\sigma_v}^2]$) that captures the stochastic effect of factors beyond the farmer's control and statistical noise. The term u is a one-sided

($u \geq 0$) component that captures the TE of the producer; in other words, u measures the gap between observed production and its maximum value given by the frontier. This error can follow various statistical distributions including half-normal, exponential or gamma [33–35]. A high value of u implies a high degree of technical inefficiency; conversely, a value of zero implies that the farm is completely efficient. According to Battese and Coelli [32], the TE of the i-th farm is given by:

$$TE_i = exp(-u_i) \tag{2}$$

where u is the efficiency term specified in (1). TE for each farm is calculated using the conditional mean of $exp(-u)$, given the composed error term for the stochastic frontier model [36]. The maximum-likelihood method developed by Battese and Coelli [32] allows for a one-step estimation of u and v, and u can be expressed in terms of a set of explanatory variables Z_{nj} as:

$$u_j = \delta_0 + \sum_{n=1}^{k} \delta_n Z_{nj} + e_j \tag{3}$$

where δ_n are unknown parameters to be estimated.

The variables that affect technical inefficiency in our study (Table 2) are related to human capital (age, schooling, dependence, specialization and the use of meteorological information); social capital variables (membership in associations or organizations); and structural factors (distance to regional capital and farm size).

The adoption of climate change adaptation practices is a choice variable and, as in studies related to soil conservation adoption and credit access (e.g., [37–39]), might be correlated with the error term in Equation (1). Instrumental variables are commonly used to address endogeneity biases, and the Durbin–Wu–Hausman test (DWH) [40] is often the approach employed to statistically evaluate if this is indeed a problem. This test is based on the difference between the ordinary least square (OLS) and instrumental variables estimators [41]. The idea of the DWH test is to check whether the dissimilarity across these estimators is significantly different from zero given the data from the available sample. Under the null hypothesis that the error terms are uncorrelated with all the regressors against the alternative that they are correlated with at least some of the regressors, an F-test is performed [42]. The instrumental variables approach has been used in several recent studies of agricultural production analysis [43–47].

Therefore, to resolve the potential endogeneity of the variables A_1, A_2 and A_3, an instrumental variable approach was used to obtain their predicted values in a first-step regression, where A_1', A_2', and A_3' are the predicted values for A_1, A_2 and A_3, respectively. In the first step regression, the predicted values were generated as follows: A_1' was estimated using a logistic regression model; A_2' was assumed to have a zero-inflated negative binomial distribution; and for A_3', a truncated regression was applied. The models used to estimate the first step are shown in the Tables A2–A4, respectively.

To identify possible differences in TE across various technologies, we performed a Student's t-test comparing the mean of the expected TE for producers that did and did not adopt the following: (a) at least one irrigation improvement, (b) change in planting and harvesting schedule, and (c) at least two conservation practices. This simple procedure allows one to compare two independent groups by testing the null hypothesis of equal means.

3. Results and Discussion

3.1. Production Frontiers

Table 4 shows the estimations of the three SPF models. The parameter gamma is significant at the 1% level for the three models, with values of 0.42 for the Intensity model and 0.54 for the Decision and Quality models. In addition, the null hypothesis that sigma is equal to zero is rejected, confirming that the stochastic model is superior to the model that would result from using OLS. The presence of endogeneity is confirmed according to the DWH test implemented (as detailed in Table A1).

For the three models, the parameter for L, C and W are positive and statistically significant at the 1% level presenting also similar values across models. Capital (C) represents the most important production factor, with estimated coefficients around 0.60. Other studies reveal that capital is also important in the production function, with estimated parameters between 0.3 and 0.5 [39,48,49]. The size of the area under cultivation has an estimated parameter close between 0.23 and 0.29, consistent with those reported in other studies [50–52]. The lowest values are related to labor, L, around 0.11, consistent with the results from Rahman et al. [53] and Mariano et al. [52].

As expected, D is significant and negative, indicating that farms located in areas with lower quality soils and without irrigation are relatively less productive. Various agricultural production studies have shown that less-favored areas in terms of soil fertility or irrigation have lower productivity levels [52,54] and that this condition tends to be associated with high levels of inefficiency [48,49].

On the other hand, it is expected that crop diversification helps farmers to increase output, *ceteris paribus*, by allowing the continuous and more intensive use of the available soil and labor, and other resources. Crop diversification is one of the strategies used by farmers to minimize agricultural risk and to stabilize income [55]. Based on the H index, our results are consistent with expectations, revealing that higher diversification is positively associated with productivity. The Herfindahl index has been used in several studies to measure crop concentration or diversification [29,56]. Manjunatha et al. [57] incorporated this index in a production function for crops in India; Rahman [51] used it as a variable explaining crop efficiency in Bangladesh, demonstrating that crop diversification is associated with high levels of TE; and Kassali et al. [55] established a positive relation between crop diversification and efficiency among farmers in Nigeria.

The adoption of climate change adaptation technologies, for the three specifications (A_1, A_2, A_3) resulted in a positive and significant effect on productivity, evidencing the importance of adaptation in farming. As envisioned by Sauer et al. [58], over the next two decades, there will be pressing need for new agricultural responses in the face of population and economic growth, and these responses include increases in irrigated area and in water use intensity. Adaptation measures will need to play an increasingly important role to equilibrate food supply and demand in a global context [11,17].

The sum of the coefficients associated with L, C and W (partial elasticities of production) is close to one, an indication of nearly constant returns to scale for all models. This finding is consistent with those of Nyemeck et al. [48], Karagiannis and Sarris [50], Sauer and Park [59], and Reddy and Bantilan [49], but differs from that of Jaime and Salazar [60], who found increasing returns to scale in a sample of Chilean wheat farmers.

3.2. Technical Efficiency

Table 4 (bottom) shows that the average values of TE for the three models accounting for endogeneity are 67.8% (Decision), 76.4% (Intensity) and 72.3% (Quality). The mean TEs for models of decision are statistically the same. Table 5 shows that the range of TE for the 30% most efficient farms (the last three intervals) ranges from 53.9% to 74.1%. The average TE value is consistent with other studies done in Latin America using SPF models. Solís et al. [39] reported an average TE of 78%, and Bravo-Ureta et al. [14] reported a value of 70%. Table 5 also reveals high correlation coefficients between TE levels across the various models with values exceeding 0.95. In addition, Table 5 shows that the estimated TE values tend to be higher for models acknowledging endogeneity, indicating the relevance of considering this issue in the analysis.

Now we go back to Table 4 to examine the results concerning the Inefficiency Model. According to Gorton and Davidova [61], variables affecting farm efficiency can be divided into agency and structural factors. Agency factors, such as age, experience, education, specialization and training (i.e., human and social capital), represent the capacity of individuals to act independently and to make their own free choices. By contrast, structural factors, such as access to markets and credit, land tenure and farm size, influence or limit an agent in his or her decisions.

Table 4. Cobb–Douglas parameters for the stochastic production frontiers estimated considering endogeneity and three different specifications to measure climate change adaptation.

Variables	Climate Change Adaptation Measurement		
	Decision	Intensity	Quality
Constant (β_0)	4.1356 (0.9463) ***	4.7996 (0.9253) ***	4.7690 (0.9894) ***
Land (β_1)	0.2284 (0.0849) ***	0.2876 (0.0850) ***	0.2726 (0.0877) ***
Capital (β_2)	0.6184 (0.0739) ***	0.5950 (0.0710) ***	0.6041 (0.0779) ***
Labor (β_3)	0.1224 (0.0278) ***	0.1044 (0.0276) ***	0.1140 (0.0275) ***
Dryland (β_4)	−0.3485 (0.1303) ***	−0.4280 (0.1222) ***	−0.3882 (0.1350) ***
Diversification (β_5)	0.5670 (0.1312) ***	0.5933 (0.1373) ***	0.6074 (0.1361) ***
Climate change adaptation (β_6)	0.1092 (0.3012) ***	0.1656 (0.0546) ***	0.0075 (0.0052) *
Inefficiency Model			
Constant (δ_0)	0.2005 (0.6762)	0.3462 (0.6594)	−0.3082 (0.6554) ***
Age (δ_1)	0.0124 (0.0083) *	0.0171 (0.0080) **	0.0212 (0.0084) ***
Schooling (δ_2)	0.0200 (0.0175)	0.0147 (0.0270)	0.0107 (0.0296)
Dependence (δ_3)	−0.7099 (0.1738) ***	−0.8436 (0.1797) ***	−0.7310 (0.1800) ***
Specialization (δ_4)	−0.0085 (0.0034) ***	−0.0099 (0.0034) ***	−0.0112 (0.0031) ***
Use of meteorological information (δ_5)	−0.6258 (0.2770) **	−0.8279 (0.2463) ***	−0.7480 (0.2556) ***
Membership (δ_6)	0.2027 (0.1698)	0.2533 (0.1742) *	0.1915 (0.1884)
Farm size (δ_7)	−0.0036 (0.0008) ***	−0.0028 (0.0029)	−0.0035 (0.0026) *
Distance to market (δ_8)	0.0085 (0.0033) ***	0.0038 (0.0031) *	0.0057 (0.0031) **
Returns to scale	0.9692	0.9870	0.9907
Maximum Likelihood Function	−209.18	−209.60	−212.76
Sigma^2	0.4209 (0.0731) ***	0.4203 (0.0693) ***	0.4828 (0.0747) ***
Gamma	0.5363 (0.1043) ***	0.4247 (0.1111) ***	0.5411 (0.0989) ***
TE	67.8	76.4	72.3
TE difference with models without correcting endogeneity	ns	***	***

Climate change adaptation (A) is estimated through a logit regression (A_1′) in the model for Decision, a zero-inflated negative binomial regression (A_2′) in the model for Intensity and using a truncated regression (A_3′) in the model for Quality (see the Appendix A). Numbers in parentheses are standard errors. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$; ns: not significant. Estimations using Frontier Version 4.1 and STATA 11.1.

Most of the literature on TE uses human capital as the main source for explaining inefficiency [61]. Studies show that the relation of the age of farmers and TE levels varies according to geographic region and context. A negative and significant relation was described by Jaime and Salazar [60] for Chilean farmers; similar results were found by Mariano et al. [52] for rice producers in The Philippines and by Bozoğlu and Ceyhan [62] for vegetable farms in Turkey. Conversely, a positive relation is described by other authors [51,54,63]. In our study, the positive sign for age indicates that older farmers are less efficient.

It is expected that schooling has a negative effect on inefficiency levels, as noted by Jaime and Salazar [60], because education improves access to information, facilitates learning and the adoption of new processes and promotes forward-looking attitudes. Other studies support this conclusion [39,48,51,54,63–65]. However, in our study, schooling, measured by the number of years of formal instruction, has a negative, though not significant relationship with TE.

Our study found that the farmers who depend on agriculture as a primary source of income tend to be more efficient than those who do not. Similarly, Jaime and Salazar [60] report that the degree of dependence of Chilean wheat farmers on agriculture has a significant and positive relation with efficiency. Along this same line, Melo-Becerra and Orozco-Gallo [66] found that Colombian households that are dedicated exclusively to agricultural production are more efficient.

A similar relationship was found between specialization and TE; producers who specialize in crop production are more efficient than those who do not. Karagiannis et al. [67] showed that TE depends on specialization for both organic and conventional milk farms. Guesmi et al. [68], using the proportion of vineyard revenue to total agricultural revenue as a measure for specialization, also observed a positive relation between specialization and TE.

The use of meteorological information also shows a positive and significant relation with TE; farmers with access to meteorological information can be more alert about changes in weather and, in this way, minimize negative effects on productivity at the farm level. It is to be expected that access to information can have a positive effect on farm management and on the adoption of technologies related to farm productivity improvements. The use of meteorological information can represent a way to reduce uncertainty in productive operations. However, Lemos et al. [69] and Roco et al. [26] argue that the use of forecasts in decision-making is not straightforward and that much work is required to narrow the gap between producers and users of this kind of information.

Table 5. Distribution of TE and the correlation matrix for fitted models.

Interval TE		Farms in Interval (%)					
		Not-Correcting Endogeneity			Correcting Endogeneity		
		Decision	Intensity	Quality	Decision	Intensity	Quality
0–29		2.6	3.0	3.0	6.4	2.6	3.4
30–39		9.1	5.3	5.3	7.9	3.0	4.5
40–49		7.2	6.8	6.4	6.4	4.9	6.0
50–59		10.6	6.4	6.4	9.1	6.0	6.4
60–69		16.6	13.3	13.7	10.9	9.4	12.1
70–79		25.6	23.0	23.0	22.7	16.7	23.4
80–89		23.8	35.8	34.7	30.6	45.7	35.9
>90		4.5	6.4	7.5	6.0	11.7	8.3
Average TE		67.5	71.3	71.5	67.8	76.4	72.3
Correlation Matrix for TE Values							
Not-correcting for endogeneity	Decision	1	-	-	-	-	-
	Intensity	0.9872	1	-	-	-	-
	Quality	0.9876	0.9999	1	-	-	-
Correcting for endogeneity	Decision	0.9666	0.9779	0.9766	1	-	-
	Intensity	0.9532	0.9842	0.9841	0.9569	1	-
	Quality	0.9874	0.9967	0.9969	0.9741	0.9839	1

Social capital is another important factor to be considered in efficiency analyses. Membership in farmers' organizations can help to reduce inefficiency. Dios et al. [70] relate technical efficiency to innovation among farmers in Spain. Jaime and Salazar [60] note that in the Bío Bío Region in Chile, producers with higher levels of participation in organizations had higher levels of efficiency. Similar results were found by Nyemeck et al. [48] among producers in Cameroon. While in general, we found a positive relation between membership in organizations and TE levels, our results are not conclusive.

Intra- and inter-organizational arrangements are relevant for farm efficiency [61]. Our analysis, reveals a positive association between farm size and TE levels. There is evidence supporting the notion that large farms have higher levels of efficiency, due to advantages derived from economies of scale [49,53,54,60,63,66,71,72]. Considering the high percentage of small farms in the area under study, 28.6% according to ODEPA, which is the Chilean National Service for Agricultural Policy (the acronym stands for *Oficina de Estudios y Políticas Agrarias*) [72], this factor is likely a barrier to improve productivity levels in the region.

As expected, our results indicate that distance from the regional capital city has a negative and significant effect on TE levels. Proximity to markets, extension agencies and information coming from the regional capital tend to enhance farmers' TE. Tan et al. [54] claim that distance to a major city has a negative effect on TE levels for rice producers in China. Nyemeck et al. [48] highlight the importance of accessibility and find that TE is higher for farmers located near main roads.

In fact, Henderson et al. [73] found a strong and statistically-significant relationship between market participation and performance for crop-livestock smallholders in Sub-Saharan Africa.

3.3. Efficiency and Climate Change Adaptation

The analysis of efficiency in agriculture has been widely used to propose improvements in the management of farm systems. Areal et al. [74] argue that if the information received by policy makers concerning farm efficiency levels is harmonized with policy aims, policy measures may be targeted to support the targeted farms. This deserves further consideration given that the literature that links efficiency and climate change adaptation is limited.

Various *t*-tests were performed to relate efficiency levels and climate change adaptation (Table 6). We found a positive relation between TE and adopting at least one irrigation technology, i.e., farmers that adopt irrigation improvements exhibit a higher TE. In this regard, Yigezu et al. [75] argue that the use of modern irrigation methods yields an improvement of 19% in TE for wheat farmers in Syria.

However, a comparison across municipalities shows considerable geographical variability. In San Clemente, TE and the implementation of at least one irrigation alternative is evident regardless of the crops involved. For Pencahue, no differences are found between groups probably because most of the farmers in the sample (62.5%) have adopted at least one irrigation technology. In Cauquenes and Parral, we also find no significant difference and this is probably due to the low number of adopters. These results demonstrate the importance of climate change adaptation through the improvement of irrigation at the farm level to increase resource use efficiency. Kahil et al. [5] argue that water management policies, such as irrigation subsidies and efficient water markets, are key to face climate change in agriculture. Policy measures include supply enhancements to remove the threat of immediate water scarcity along with demand management measures and improved governance [76].

In general, changes in planting and harvesting dates show no relation with TE levels; however, in San Clemente, where the crops are highly diversified, farmers who have changed their planting calendars appear to have higher efficiency. Thus, it appears that this strategy that a priori could be expected to play a significant role for climate change adaptation, does not have a clear direct effect on efficiency. Additional information is required, to understand in a deeper way, the effects of a climate change practices portfolio on productivity and efficiency of agricultural systems.

The higher TE values detected for the groups who have more intensive adaptation strategies and with higher quality (number of practices and quality index) substantiate the importance of further research focusing on adaptation. It is not only necessary to adapt, but is also relevant to determine what and how much to adapt. Therefore, it is essential to foster effective adaptation and to improve the design of relevant programs to promote the adaptation capacity across farming systems. In Pencahue, 65% of the sample has adopted at least one adaptation practice, and 60% is above 25% in the adaptation index. In contrast, only 3.7% of the sample for Cauquenes has implemented at least one adaptation practice, and none of the farmers interviewed show an adaptation index over 25%. Based on this analysis, it seems clear that climate change adaptation in agriculture requires a complex set of actions including technical and managerial dimensions to reduce vulnerability and improve farmer productivity.

Table 6. *t*-tests for average TE levels grouped into various categories.

Average TE	Model	Grouping Criteria											
		Adoption of at Least One Irrigation Improvement			Changes in Planting and Harvesting Schedules			Adoption of at Least Two Adaptation Practices			Value of Adaptation Index $\geq$ 25%		
		Yes	No	Sig	Yes	No	Sig	Yes	No	Sig	Yes	No	Sig
Complete sample	Decision	73.5	65.3	***	64.9	70.0	**	81.4	65.1	***	86.5	65.4	***
	Intensity	80.9	74.4	***	75.1	77.3	ns	86.3	74.5	***	88.8	74.8	***
	Quality	77.5	69.9	***	70.9	73.3	ns	84.4	69.9	***	87.3	70.3	***
	%	*54.7*			*42.6*			*16.2*			*11.3*		
Pencahue	Decision	86.1	85.0	ns	85.7	85.7	ns	85.1	86.0	ns	86.0	85.2	ns
	Intensity	88.2	88.5	ns	87.8	88.7	ns	88.2	88.5	ns	88.1	88.5	ns
	Quality	86.7	86.7	ns	86.3	87.0	ns	86.8	86.6	ns	86.7	86.7	ns
	%	*62.5*			*37.5*			*65.0*			*60.0*		
Cauquenes	Decision	45.2	50.2	ns	47.2	50.9	ns	41.7	49.4	ns	-	-	
	Intensity	62.0	62.8	ns	62.0	63.3	ns	63.6	62.6	ns	-	-	
	Quality	55.7	58.2	ns	56.3	59.0	ns	59.6	57.6	ns	-	-	
	%	*21.0*			*48.1*			*3.7*			*0.0*		
San Clemente	Decision	82.2	77.0	***	83.3	77.1	***	81.6	78.2	ns	86.3	78.3	**
	Intensity	86.3	81.7	***	87.2	81.8	***	87.6	82.5	**	90.0	82.8	**
	Quality	83.2	77.4	***	84.4	77.6	***	85.0	78.4	**	87.8	78.9	**
	%	*31.5*			*24.7*			*13.5*			*4.5*		
Parral	Decision	66.5	64.1	ns	64.0	65.8	ns	79.5	64.0	*	93.1	63.5	***
	Intensity	80.0	76.3	ns	76.7	77.6	ns	89.0	76.6	*	94.5	76.4	**
	Quality	75.7	70.9	ns	71.2	71.6	ns	86.1	71.2	*	92.9	71.0	***
	%	*20.0*			*67.3*			*3.6*			*3.6*		

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$, ns: not significant.

4. Concluding Remarks

This study analyzes the impact of climate change adaptation in productivity and efficiency for producers of annual crops in Central Chile. We used three measures of adaptation: a binary choice of adopting at least one adaptation practice or technology; an intensity measure given by the number of practices or technologies adopted; and a quality index measure. A positive association between productivity and climate change adaptation was observed for the three measures. The fitted stochastic production frontier models revealed that climate change adaptation is endogenous. Incorporation of instrumental variables allowed us to check the robustness of our results and improved the TE estimations. The fitted models showed important levels of inefficiency, suggesting the potential for increasing crop production using the current level of inputs and available technology.

Our results also show that factors such as dependence on annual crop production for income and high levels of specialization in production are associated with elevated TE levels. The use of meteorological information is also positively related with TE. In addition, our results indicate that farm size is positively related to efficiency while distance to a major city exhibits a negative relationship.

Farmers who have adopted irrigation technologies have higher TE levels. These results suggest that climate change adaptation is significant for agricultural production, especially for the intensity of climate change adaptation. Our results validate the importance, of incorporating climate change adaptation in agricultural policies designed to promote productivity growth. Our analysis also sheds light on the relevance of using meteorological information by farmers given the positive link between the latter variable and technical efficiency.

The connection between productivity with the implementation of specific farm-level adaptive practices, as well as with actions that ease adoption barriers deserves additional analyses. These analyses are essential to generate information required by policy makers to formulate robust action plans across differing cultural, economic and agricultural environments.

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Appendix A

Table A1. Cobb–Douglas parameters for stochastic production frontiers estimated considering three different specifications for the measurement of climate change adoption and without considering endogeneity.

Variables	Climate Change Adaptation Measurement		
	Decision	**Intensity**	**Quality**
Constant (β_0)	4.0218 (0.9857) ***	4.6682 (0.9741) ***	4.6090 (0.9891) ***
Land (β_1)	0.2314 (0.0887) ***	0.2654 (0.0869) ***	0.2602 (0.0857) ***
Capital (β_2)	0.6828 (0.0764) ***	0.6206 (0.0754) ***	0.6255 (0.0758) ***
Labor (β_3)	0.1043 (0.0283) ***	0.1112 (0.0283) ***	0.1110 (0.0270) ***
Dryland (β_4)	−0.4204 (0.1334) ***	−0.3578 (0.1270) ***	−0.3614 (0.1314) ***
Diversification (β_5)	0.5990 (0.1381) ***	0.5957 (0.1357) ***	0.6054 (0.1349) ***
Climate change adaptation (β_6)	0.0331 (0.0735)	0.0035 (0.0017) ***	0.0046 (0.0024) **
Inefficiency Model			
Constant (δ_0)	0.2035 (0.6194)	0.2166 (0.5937)	0.1591 (0.7713)
Age (δ_1)	0.0189 (0.0072) ***	0.0177 (0.0075) ***	0.0185 (0.0096) **
Schooling (δ_2)	0.0097 (0.0250)	0.0129 (0.0259)	0.0130 (0.0262)
Dependence (δ_3)	−0.4878 (0.1697) ***	−0.7657 (0.1776) ***	−0.7480 (0.2117) ***
Specialization (δ_4)	−0.0099 (0.0031) ***	−0.0098 (0.0034) ***	−0.0099 (0.0032) ***
Use of meteorological information (δ_5)	−0.7010 (0.2326) ***	−0.7406 (0.2423) ***	−0.7420 (0.2981) ***
Membership (δ_6)	0.0877 (0.1701)	0.2591 (0.1773) *	0.2663 (0.1970) *
Farm size (δ_7)	−0.0040 (0.0026) *	−0.0035 (0.0010) ***	−0.0034 (0.0009) ***
Distance to market (δ_8)	0.0056 (0.0029) **	0.0053 (0.0029) **	0.0051 (0.0030) **
Returns to scale	1.0185	0.9972	0.9967
MLF	−218.13	−211.14	−211.51
Sigma^2	0.4588 (0.0611) ***	0.4516 (0.0652) ***	0.4493 (0.0725) ***
Gamma	0.5632 (0.0996) ***	0.5222 (0.1044) ***	0.5178 (0.1144) ***
TE	67.52	71.34	71.50
Endogeneity (F value)	4.868 ***	14.266 ***	13.012 ***

Climate change adaptation (A) is measured as: the adoption of at least one practice (A_1) in the model for decision; the number of practices adopted (A_2) in the model for intensity; the number of practices weighted according to experts' opinion (A_3) in the model for quality. Numbers in parentheses are standard errors. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Estimations using Frontier Version 4.1 and STATA 11.1.

Table A2. Logit regression estimation.

Variable Name	Description	Coefficient
A_1	**Dependent Variable**	
ExpAgIndep	Years of independent experience in agriculture.	−0.0153 * (0.0087)
SanClemente	Dummy variable = 1 if the farm is located in San Clemente and 0 otherwise	−0.9189 *** (0.2886)
TTPropia	Dummy variable = 1 if the farmer is owner and 0 otherwise	0.3590 (0.2821)
Internet	Dummy variable = 1 if the farmer has access to meteorological information principally form the Internet and 0 otherwise	0.9667 *** (0.3290)
Constant		0.5849 ** (0.3012)
	Log-likelihood	−170.73
	N	265
	Pseudo R^2	5.86
	Correctly classified values by Logit (%)	62.2

Numbers in parenthesis are standard errors. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table A3. Zero inflated negative binomial regression estimation.

Variable Name	Description	Coefficient
A_2	**Dependent Variable**	
ExpAgIndep	Years of independent experience in agriculture.	−0.0121 *** (0.0034)
RXP	Dummy variable = 1 if the farmer has adopted any irrigation improvement and the location is in Pencahue municipality and 0 otherwise	0.7731 *** (0.1324)
SupProd	Surface designated to production in hectares	0.0003 (0.0003)
Internet	Dummy variable = 1 if the farmer has access to meteorological information principally form the Internet and 0 otherwise	0.2233 * (0.1329)
Constant		1.0172 *** (0.1362)
	Log-likelihood	−411.76
	N	265
	Correlation of predicted values (A_1′) with A_1 (%)	53.51

Numbers in parenthesis are standard errors. * $p < 0.1$; *** $p < 0.01$.

Table A4. Truncated linear regression estimation.

Variable Name	Description	Coefficient
A_3	**Dependent Variable**	
ExpAgIndep	Years of independent experience in agriculture.	−0.2518 *** (0.0893)
RXP	Dummy variable = 1 if the farmer has adopted any irrigation improvement and the farm location is Pencahue and 0 otherwise	18.445 *** (4.2773)
SupProd	Surface designated to production in hectares	0.0173 * (0.0105)
Internet	Dummy variable = 1 if the farmer has access to meteorological information principally form the Internet and 0 otherwise	3.4477 (3.1870)
Constant		20.1456 *** (2.8415)
	Log-Likelihood	−574.27
	N	265
	Correlation of predicted values (A_2′) with A_2 (%)	51.35

Regression was truncated in values with 0 as the lower limit and 100 as the upper limit. Numbers in parenthesis are standard errors. * $p < 0.1$; *** $p < 0.01$.

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