BAE
Bio-based and Applied Economics

AIEAA
ASSOCIAZIONE ITALIANA DI ECONOMIA AGRARIA E APPLICATA

OPEN ACCESS

Citation: E. Lamonaca, F.G. Santeramo, A. Seccia (2021). Climate changes and new productive dynamics in the global wine sector. *Bio-based and Applied Economics* 10(2): 123-135. doi: 10.36253/bae-9676

Received: September 5, 2020
Accepted: December 16, 2020
Published: October 28, 2021

Data Availability Statement: All relevant data are within the paper and its Supporting Information files.

Competing Interests: The Author(s) declare(s) no conflict of interest.

ORCID
EL: 0000-0002-9242-9001
FGS: 0000-0002-9450-4618
AS: 0000-0003-4549-6479

Climate changes and new productive dynamics in the global wine sector

Emilia Lamonaca*, Fabio Gaetano Santeramo, Antonio Seccia

University of Foggia, Italy
* Corresponding author. E-mail: emilia.lamonaca@unifg.it

Abstract. Climate change has the potential to impact the agricultural sector and the wine sector in particular. The impacts of climate change are likely to differ across producing regions of wine. Future climate scenarios may push some regions into climatic regimes favourable to grape growing and wine production, with potential changes in areas planted with vines. We examine which is the linkage between climate change and productivity levels in the global wine sector. Within the framework of agricultural supply response, we assume that grapevines acreage and yield are a function of climate change. We find that grapevines yield suffers from higher temperatures during summer, whereas precipitations have a varying impact on grapevines depending on the cycle of grapevines. Differently, acreage share of grapevines tends to be favoured by higher annual temperatures, whereas greater annual precipitations tend to be detrimental. The impacts vary between Old World Producers and New World Producers, also due to heterogeneity in climate between them.

Keyword: climate change, acreage response, yield response, Old World producers, New World producers.
JEL code: F18, Q11, Q54.

1. INTRODUCTION

In both academic research and policymaking agenda there is growing awareness that climate change and the agri-food sector are closely related, and that those links deserve investigation and understanding to analyse the evolution of global agriculture, and to anticipate future challenges such as climate change adaption and mitigation (Falco et al., 2019; Santeramo et al., 2021).

Agriculture, on which human welfare depends, is severely affected by climate change. Some adverse effects, already observed, are likely to intensify in the future, contributing to declines in agricultural production in many regions of the world, fluctuations in world market prices, growing levels of food insecurity (Reilly and Hohmann, 1993; Meressa and Navrud, 2020). Adaptation potential and adaptation capability to climate change may exacerbate differences between regions. In a globalised world, the macro-level impacts of climate change are driven by comparative advantage between regions (Bozzola et al., 2021). If impacts of climate change on productivity

Firenze University Press | www.fupress.com/bae

differ between regions, then adjustments through production patterns may dampen the adverse effects of climate change (Costinot et al., 2016; Gouel and Laborde, 2021). Although the agricultural sector is identified as the most sensitive and vulnerable sector to climate change (e.g., Deschenes and Greenstone, 2007), the effects of climate change on the wine sector and on different producing regions (i.e., Old World Producers, New World Producers) is still an open question. How do productivity levels react to changes in climate? Do climate change impacts on production patterns differ between Old World Producers and New World Producers?

As suggested by Mozell and Thach (2014), the narrow climatic zones for growing grapes may be severely affected both by short-term climate variability and long-term climate change. A vast majority of earlier studies on the impacts of climate change have analysed the effects on domestic markets, leaving underinvestigated the effects on world production (Reilly and Hohmann, 1993). In the wine-related literature, previous studies reveal that the impacts of climate change are likely to differ across producing regions of wine. Jones et al. (2005) suggest that, currently, Old World Producers (i.e., European regions) benefit of better growing season temperatures than New World Producers. However, future climate scenarios may push some regions into climatic regimes favourable to grape growing and wine production (Lamonaca and Santeramo, 2021). All in all, there is the potential for relevant changes in areas planted with vines due to changes in climate (Moriondo et al., 2013; Seccia and Santeramo, 2018).

Projected scenarios of future climate change at the global and wine region scale are likely to impact the wine market. In particular, spatial changes in viable grape growing regions, and opening new regions to viticulture would determine new productive scenarios in the wine sector at the global level.

Given this background, our contribution aims at understanding how productive patterns allow different producing regions (e.g., Old World Producers, New World Producers) to respond to changes in climate. Specifically, we examine the linkage between climate change and productivity levels in the global wine sector. In this regard, Rosenzweig and Parry (1994) argue that doubling of the atmospheric carbon dioxide concentration would lead to only a small decrease in global agricultural production. In addition, Reilly and Hohmann (1993) suggest that interregional adjustments in production buffer the severity of climate change impacts both at global and domestic level. From a methodological perspective, the study of agricultural supply response has traditionally decomposed it in terms of acreage and yield responses (e.g., Haile et al., 2016; Kim and Moschini, 2018). Our contribution examines how climate change affects acreage and yield response for grapevines. To this aim, we assume that land allocations are consistent with the choices of a representative farmer who maximises expected profit. We posit that cropland can be allocated between grapevines and all other crops. Because these two allocation choices exhaust the set of possible land allocations, total county cropland is assumed to be fixed. Thus, the decision problem can be stated as that of choosing acreage. We assume that the acreage shares are a function of expected per acre revenue, given by the product between the output price and expected yield, and of climate change. Investigating both the responsiveness of grapevine acreage and yield to climate change allows us to conclude on the global supply response. While our cross-countries analysis is informative on the production patterns in the wine sector at a global scale, it cannot conclude on the effects of climate change at the micro-level (e.g., grape growers, wine producers). Indeed, a country-level analysis does not capture differences within countries in terms of both grapevine yield and climate variability, particularly in geographically heterogeneous countries such as the United States, Canada, Russia, China (Kahn et al., 2019).

2. ESTIMATING THE RELATIONSHIP BETWEEN CLIMATE CHANGE AND GRAPEVINES PRODUCTION

2.1 Yield response equation

Following Kim and Moschini (2018), we postulate a simple linear equation for yield response. In detail, the expected grapevines yield of county i at time $t(y_{it})$ is modelled as:

$$y_{it} = \alpha + \alpha_i + \beta T_t + \boldsymbol{\gamma}'\boldsymbol{X}_{it,s} + \varepsilon_{it} \tag{1}$$

where α_i are country-specific intercepts; T_t is a linear trend variable and β the related parameter; the vector $\boldsymbol{X}_{it,s}$ includes climate variables specific for county i, time t, and season s (i.e. 30-years rolling average seasonal temperatures and precipitations, $Temp_{it,s}$ and $Prec_{it,s}$), we also posit a quadratic relationship between climate and yields (i.e. $Temp^2_{it,s}$ and $Prec^2_{it,s}$); $\boldsymbol{\gamma}'$ is the vector of parameter of interest[1]; α and ε_{it} are a constant and the error term. Following the climate literature (e.g.,

[1] It is worth noting that the parameter captures the climate sensitivity of grapevine yield without considering the implicit adaptation to climate change, differently from analyses based on the Ricardian model of climate change (e.g., Mendelsohn et al., 1994).

Kurukulasuriya et al., 2011; Massetti et al., 2016), we use a four-season model, assuming that seasonal differences in temperatures and precipitations are likely to impact grapevines productivity. However, we exclude climate normals of the winter season which is characterised by the dormancy of grapevines; in fact, the annual growth cycle of grapevines begins with bud break in the spring season and culminate in leaf fall in the autumn season.

We explore the relationship between grapevines yield and climate variables to estimate the potential effects of climate change using either ordinary least squares (OLS) or quantile regression (QR). The model in equation (1) is estimated in an OLS fashion on the whole sample and on subsamples of Old World Producers and New World Producers. The properties of QR have motivated its application in the context of agriculture and weather, mostly focusing on the impact of climate change on various crop yield distributions (Conradt et a., 2015). The QR facilitates a thorough analysis of the differential impact of climate change across the yield distribution; a QR approach is useful in such situations and for considering asymmetry and heterogeneity in climatic impacts (Barnwal and Kotani, 2013).

2.2 Acreage response equation

Total county cropland (A) is assumed to be fixed and land allocations are presumed to be consistent with the choices of a representative farmer who maximises expected profit. We posit that agricultural land can be devoted to two alternative uses, grapevines and all other crops. The decision problem can be stated as that of choosing acreage shares $s_k \equiv A_k / A$, where A_k is the acreage allocated to the k-th use (k = 1 for grapevines and k = 2 for all other crops). Because A is fixed, increased land allocation to any one crop is equivalent to an increase in its share s_k, maintaining the land constraint $s_1 + s_2 = 1$[2].

Empirically, observed acreage share of grapevines in county i at time $t(s_{it})$ is modelled as:

$$s_{it} = \lambda + \lambda_i + \theta T_t + \varphi s_{it\text{-}1} + \psi \hat{r}_{it} + \boldsymbol{\omega}'\mathbf{Z}_{it} + \nu_{it} \tag{2}$$

where the set of conditioning variables includes country-specific trend effects, λ_i; a time trend, T_t, capturing exogenous technological progress; expected per acre revenue, $\hat{r}_{it}$; past acreage shares, $s_{it\text{-}1}$, climate variables, $\mathbf{Z}_{it}$, which may directly affect planting decisions (i.e. 30-years rolling average annual temperatures and precipitations, $Temp_{it}$ and $Prec_{it}$, and their squares, $Temp^2_{it}$ and $Prec^2_{it}$). The term λ is a set constant terms; θ, φ, and ψ are parameters to be estimated, $\boldsymbol{\omega}'$ is the vector of climate-specific parameters; ν_{it} is the error term. The term $s_{it\text{-}1}$ allows us to account for the behaviour of producers that adjust their acreage when they realise that the desired acreage differs from the acreage realised in the previous year; it captures the dynamic effects on acreage allocation (Santeramo, 2014). Following Kim and Moschini (2018), we interact own output price and expected yields estimated in equation (1), to obtain the expected per acre revenue (i.e., $\hat{r}_{it} = p_{it} \cdot \hat{y}_{it}$). Since our study is a country-level analysis, consistent with Hendricks et al. (2014) we assume that the country-level expected prices are exogenous: this assumption allows us to deal with potential endogeneity of prices. In order to compute the expected per acre revenue variables for the acreage response equations, we rely on the OLS estimate of equation (1).

We follow an approach similar to Haile et al. (2016) and Kim and Moschini (2018) and estimate the model in equation (2) using a system generalised method-of-moments (GMM) estimator, based on a one-step estimation with robust standard errors. In fact, applying OLS estimation to a dynamic panel data regression model, such as in equation (2), results in a dynamic panel bias because of the correlation of the lagged dependent variable with the country-fixed effects (Nickell, 1981). Since current acreage is a function of the fixed effects (λ_i), lagged acreage is also a function of these country-fixed effects. This violates the strict exogeneity assumption, thus the OLS estimator is upward biased and inconsistent. A solution to this issue consists in transforming the data and removing the fixed effects. However, under the within-group transformation, the lagged dependent variable remains correlated with the error term, and therefore the fixed-effects estimator is downward biased and inconsistent. To overcome these problems, the GMM is a more efficient estimator that allows the estimate of a dynamic panel difference model using lagged endogenous and other exogenous variables as instruments. In particular, the system GMM technique transforms the instruments themselves in order to make them exogenous to the fixed effects (Roodman, 2009).

[2] Due to a land constraint, a representative farmer may decide to allocate more (less) acreage to grapevine reducing (increasing) the share of acreage devoted to other crops to maximise expected profits. This may be a sort of implicit adaptation to climate conditions. For instance, due to warmer temperatures, acreages devoted to grapevine in Italy may increase to the detriment of acreage intended to other production (e.g., apple tree, pear tree). As suggested in Ricardian literature in climate change economics (e.g., Timmins, 2006; Kurukulasuriya et al., 2011; Bozzola et al., 2018).

Table 1. Descriptive statistics for key variables.

Variable	Unit	All producers	Old World Producers	New World Producers
Acreage	ha	303,640 (±347,791)	560,850 (±435,259)	160,745 (±162,051)
Share of acreage	-	0.01 (±0.02)	0.02 (±0.00)	0.001 (±0.001)
Yield	t/ha	10.50 (±4.59)	3.96 (±1.22)	12.09 (±1.13)
Price	USD/t	779.27 (±448.80)	528.60 (±40.70)	708.32 (±396.59)
30-years average temperature (annual)	°C	10.37 (±8.51)	10.86 (±1.87)	10.10 (±10.52)
30-years average temperature (spring)	°C	9.90 (±9.08)	9.70 (±1.54)	10.01 (±11.28)
30-years average temperature (summer)	°C	18.76 (±4.76)	18.26 (±2.54)	19.04 (±5.61)
30-years average temperature (autumn)	°C	10.92 (±8.21)	11.57 (±2.03)	10.55 (±10.12)
30-years average precipitation (annual)	mm	68.55 (±36.13)	71.89 (±17.46)	66.69 (±43.09)
30-years average precipitation (spring)	mm	62.35 (±34.87)	67.18 (±11.14)	59.66 (±42.50)
30-years average precipitation (summer)	mm	82.17 (±44.21)	61.95 (±19.52)	93.40 (±49.81)
30-years average precipitation (autumn)	mm	74.56 (±44.14)	82.93 (±24.25)	69.91 (±51.47)

Note: Average values and standard deviation in parentheses.

3. DATA SOURCES AND SAMPLE DESCRIPTION

The empirical analysis relies on a rich dataset of historical temperature and precipitation data (from 1961 to 2015) and historical trade flows data (from 1996 to 2015[3]) for 14 countries. The selected countries are Argentina, Australia, Brazil, Canada, China, France, Germany, Italy, New Zealand, Russian Federation, South Africa, Spain, the United Kingdom, the United States. They account for more than two-third of the volume of wine production (70% in 2016, Global Wine Markets, 1860 to 2016 database). This group of countries includes both Old Works Producers and New World Producers and countries belonging to Northern or Southern Hemisphere[4].

Table 1 provides descriptive statistics for key variables, also distinguishing between Old World Producers and New World Producers.

Historical country-specific monthly average temperature and precipitation data have been collected from the Climate Change Knowledge Portal World Bank (World Bank, 2018). Annual and seasonal climatologies (i.e., rolling 30-years averages[5]) of temperature (in °C) and precipitations (mm) have been constructed using historical weather data. As for seasonal climatologies, monthly data have been clustered into three-month seasons: December (of the previous year) through February as winter, March through May as spring, June through August as summer, and September through November as autumn. These seasonal definitions have been adjusted for the fact that seasons in the Southern and Northern Hemispheres occur at exactly the opposite months of the year.

The annual 30-years average temperature is 10.37 °C (table 1). Within this group, annual average temperatures are about 1 °C higher for Old World Producers than for New World Producers, reflecting the fact that New World Producers are mostly located to lower latitudes (figure 1). The difference in average temperatures between Old World Producers and New World Producers tends to be higher during winter (3.97 °C of Old World Producers and 0.77 °C of New World Producers; table 1).

The annual 30-years average precipitation is 68.55 mm and is about 5 mm greater in Old World Producers

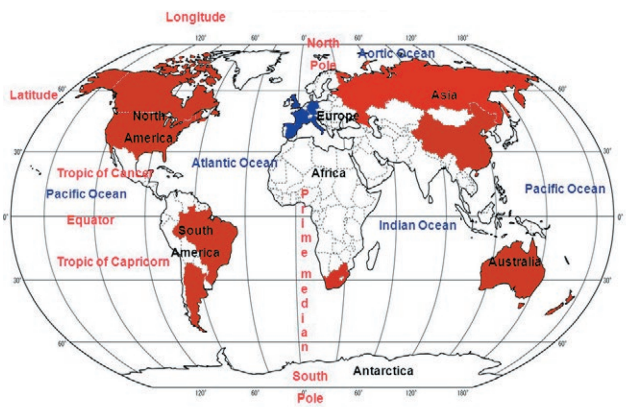

Figure 1. List of countries. Source: elaboration on Anderson and Nelgen (2015). Notes: Old World Producers in blue, New World Producers in red.

[3] The longer time period used for climate data allows to build climatologies (i.e. 30-years averages) of temperature and precipitations: in 1996 (the starting point of the final dataset) climate normal is based on a real 30-years average.

[4] The list of countries by group is presented in Appendix A.1.

[5] Differently from other studies that aggregated to data by weighting each information at the grid level by the amount of agricultural area the grid contains (e.g., Gammans et al., 2017), we use simple average of climate data aggregated at the country level.

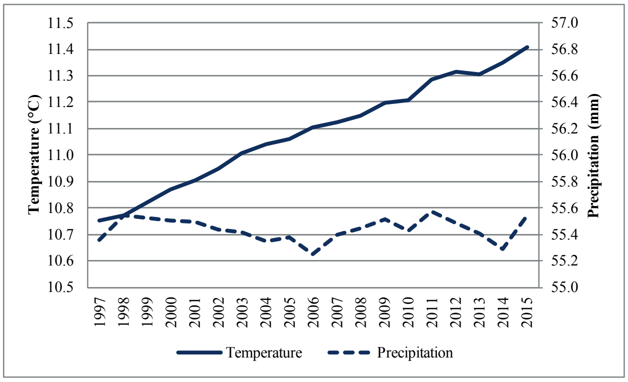

Figure 2. Median 30-years temperatures and precipitations in 1997-2015. Source: elaboration on data from CRU of University of East Anglia. Note: data refer to the sample of 14 major producers of wine.

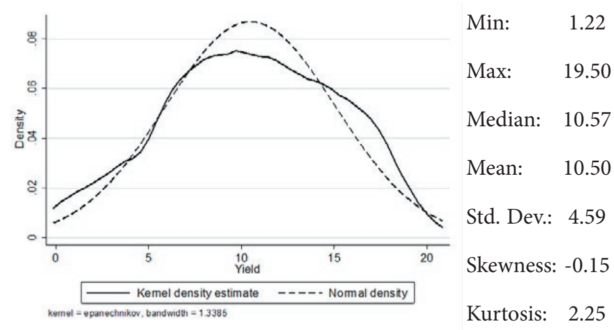

Figure 3. Distribution and descriptive statistics for grapevines yield.

than in New World Producers. However, seasonal differences are observed: during summer, the level of precipitations is much lower in Old World Producers than in New World Producers (table 1).

In our sample, we observe a 6% increase in median values of 30-years average temperature over twenty years (figure 2).

As suggested in Jones et al. (2005), Old World Producers benefit of better growing seasons as compared to New World Producers. It should be kept in mind, however, that the strength of seasonality varies significantly across the globe, with seasons being more homogenous around the Equator.

Country-specific annual data on areas planted with vines (in ha) and yields of areas planted with vines (in t/ha), collected from the FAOSTAT database, are described in table 1. The FAOSTAT database also provides country-level annual acres for agricultural land. Total agricultural land includes two components: i.e., cropland (arable land and land under permanent crops) and land under permanent meadows and pastures. In the methodological framework, we assume that agricultural land can be devoted to two alternative uses, grapevines and all other crops. The latter category should capture all acres that could have been not planted to grapevines. Hence, we obtain the category all other uses as the difference between total agricultural land and acres planted with vines. In our model, we also use country-specific annual price data for grapes (USD/t), collected from the FAOSTAT database. In order to obtain the reduced per acre revenue, we interact own output price and expected yields estimated in equation (1).

Within our sample, despite the expansion of areas planted with vines in New World Producers during the last decades, acres intended to grape growing are, on average, more than three times larger in Old World Producers (561 thousands ha with respect to 161 thousands ha, table 1). However, grapevines yields are much larger for New World Producers (12.09 t/ha) than for Old World Producers (3.96 t/ha).

Yields are often not normally distributed but are negatively skewed (e.g., Swinton and King, 1991). This is also what we find in the distribution of grapevines yield in our sample (figure 3). A distribution of yield different from a normal distribution may be associated with the frequent occurrence of outliers; for instance, yield realisations may not follow the pattern described by the majority of yield observations (Conradt et al., 2015).

It is worth noting that countries with grapevines yields within 25th percentile are Canada, Spain, France, United Kingdom, New Zealand, Russian Federation, whereas countries with yields of grape within 75th percentile are Argentina, Australia, Brazil, China, Germany, United States, South Africa.

4. RESULTS AND DISCUSSION

4.1 Yield response

The estimation results for the yield response, based on equation (1), are reported in tables 2 (OLS estimates)[6] and 3 (QR estimates). The results in table 2 show that the higher the average temperatures in producing countries during summer, the lower the grapevines yield. Greater precipitations are beneficial for yield during the early growing season (i.e., spring), but detrimental during the

[6] In a sensitivity analysis, we analyse the effects of annual climatic variables on grapevine yields. The results, reported in table A.2 in the Appendix, highlight differences between Old World Producers and New World Producers. While higher annual average temperatures are detrimental (up a certain threshold) for Old World Producers, New World Producers benefit of greater annual average temperatures and precipitations.

late growing season and the harvest time (i.e. summer and autumn). The relationship between summer climate and yields is nonlinear[7]. The overall effects are mostly driven by the impacts of climate change on grapevines yields of New World Producers. Differently, grapevines yield of Old World Producers seem not affected by climate change. The results are consistent with evidence from vine-related literature. In fact, Merloni et al. (2018) report that higher temperatures can have a negative impact on grapevines yield and quality. An increase in extreme high temperatures in summer may have adverse consequences on grapevines phenology (Briche et al., 2014). In addition, Ramos et al. (2008) suggest that seasonal distribution of precipitation matter, with larger rainfall levels being crucial for grapevines at the beginning of the growing season (i.e., spring) whereas more stable precipitations are desirable from flowering to ripening (i.e., summer and autumn).

The OLS approach is applied when the dependent variable is normally distributed, whereas QR is employed when the variable is not normally distributed (see figure 3). The QR (median) is more robust to outliers than mean regression (OLS)[8]. Furthermore, QR provides a clearer understanding of the data by assessing the effects of explanatory variables on the location and the scale parameters of the model (Conradt et a., 2015).

The results of the QR reported in table 3 mostly confirm the non-linear relationship between grapevines yields and average temperatures in producing countries during summer. No substantial differences are observed across different quantiles of the distribution of grapevines yields. Differently, the results reveal that lower yield realisations (i.e., within 25th percentile) tend to be most affected by greater precipitations during the harvest time (i.e., autumn). It is worth noting that countries with grapevines yields within 25th percentile are mostly cool climate wine regions such as Canada and Russian Federation. Cool regions tend to have also higher rainfall levels and yields tend to be lower on average, rising production costs (Anderson, 2017).

Table 2. Estimation results for grapevines yields, OLS.

Variables	Dependent variable: yield		
	All producers	Old World Producers	New World Producers
Temperature (spring)	1.4440	-9.5441	-1.4800
	(1.7044)	(12.7571)	(2.1761)
Temperature-squared (spring)	-0.3044***	0.3965	-0.2577**
	(0.0747)	(0.5755)	(0.1209)
Temperature (summer)	-16.3650**	-22.5187	-1.8786
	(7.1026)	(14.6183)	(11.2236)
Temperature-squared (summer)	0.4258**	0.4752	0.3047
	(0.1955)	(0.3634)	(0.3264)
Temperature (autumn)	0.6543	-0.6787	-0.5129
	(1.9410)	(12.3068)	(2.3252)
Temperature-squared (autumn)	0.0761	-0.0685	0.1321
	(0.0888)	(0.4882)	(0.1181)
Precipitation (spring)	0.5227*	0.4326	0.8057*
	(0.2795)	(0.7043)	(0.4339)
Precipitation-squared (spring)	-0.0041***	-0.0035	-0.0052***
	(0.0015)	(0.0048)	(0.0019)
Precipitation (summer)	-0.3230*	-0.0678	-0.0427
	(0.1906)	(0.3849)	(0.3922)
Precipitation-squared (summer)	0.0013	-0.0001	0.0005
	(0.0009)	(0.0022)	(0.0013)
Precipitation (autumn)	-0.3507**	-0.3838	-0.4272
	(0.1601)	(0.4282)	(0.3758)
Precipitation-squared (autumn)	0.0019**	0.0019	0.0019
	(0.0008)	(0.0020)	(0.0017)
Time trend	0.1392***	0.3459*	0.0109
	(0.0477)	(0.1756)	(0.1007)
Observations	280	100	180
R-squared	0.9314	0.9656	0.8930

Notes: OLS estimate of equation (1) on the whole sample (All producers) and subsamples of Old World Producers and New World Producers. All specifications include country-specific constants. Robust standard errors are in parentheses.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

[7] The results are robust also controlling for different combinations of fixed effects: the results are reported in tables A.3 and A.4 in the Appendix. We further detect a non-linear relationship between grapevine yield and summer precipitation controlling for time fixed effects (common to all countries) and country-specific fixed effects. Differently, we cannot conclude on the relationship between grapevine yield and detrended climate variables obtained from the yearly weather deviation from the long-run climate (30-year rolling average), as recently proposed by Khan et al. (2019). The result is not surprising: while detrended climate variables capture short-run changes in climate conditions (i.e., weather shocks), 30-year rolling average temperatures and precipitations inform on long-run changes in climate conditions: It is unlikely that weather shocks on a year-by-year basis affect the responsiveness of the viticultural sector, but long-run changes in climate capture structural changes in the sector and are more likely to influence production decisions of a multi-year crop. A comparison between short- and long-run analyses is reported in table A.5 in the Appendix.

[8] We conduct a multidimensional outlier detection analysis based on the 'bacon' algorithm, which identifies outliers based on the Mahalanobis distances (Billor et al., 2000, Weber, 2010). The algorithm allows the identification and removal of observations characterised by implausibly large or low entries of key variables. The results of the model estimated without outliers, reported in tables A.6 and A.7 in the Appendix, confirm the main results, although the effect of temperatures and precipitations on grapevine yields tend to be lower.

Table 3. Estimation results for grapevines yields, quantile regression.

Variables	Dependent variable: yield		
	25th percentile	50th percentile	75th percentile
Temperature (spring)	0.8721	0.7711	1.3070
	(1.9059)	(1.8734)	(2.3574)
Temperature-squared (spring)	-0.1418*	-0.2405***	-0.3368***
	(0.0756)	(0.0812)	(0.1073)
Temperature (summer)	-22.4737***	-27.0681***	-23.1306***
	(4.5501)	(7.0368)	(7.0902)
Temperature-squared (summer)	0.5454***	0.7064***	0.6102***
	(0.1219)	(0.1864)	(0.1763)
Temperature (autumn)	3.0239	1.9043	2.2129
	(2.1210)	(1.2873)	(2.4223)
Temperature-squared (autumn)	-0.1279	-0.0515	0.0525
	(0.0813)	(0.0611)	(0.0998)
Precipitation (spring)	0.2402	0.6707**	0.4740
	(0.2974)	(0.2899)	(0.2913)
Precipitation-squared (spring)	-0.0024	-0.0048***	-0.0035*
	(0.0018)	(0.0017)	(0.0018)
Precipitation (summer)	-0.2866	-0.0272	-0.1956
	(0.2024)	(0.1155)	(0.1925)
Precipitation-squared (summer)	0.0014	-0.0001	0.0011
	(0.0012)	(0.0006)	(0.0011)
Precipitation (autumn)	-0.3157*	-0.1921	-0.1535
	(0.1691)	(0.1477)	(0.1627)
Precipitation-squared (autumn)	0.0019**	0.0011*	0.0010
	(0.0008)	(0.0006)	(0.0007)
Time trend	0.1523***	0.1796***	0.1024*
	(0.0574)	(0.0534)	(0.0545)
Observations	280	280	280

Notes: QR estimate of equation (1) on the whole sample. All specifications include country-specific constants. Robust standard errors are in parentheses.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

Table 4. Estimation results for grapevines acreage, Old World Producers and New World Producers.

Variables	Dependent variable: acreage share		
	All Producers	Old World Producers	New World Producers
Lagged acreage share	0.995***	0.795***	0.953***
	(0.001)	(0.046)	(0.012)
Expected per acre revenue	-0.00003	-0.163	-0.0003
	(0.00003)	(0.109)	(0.001)
Temperature (annual)	0.107***	38.983*	0.131***
	(0.019)	(22.496)	(0.020)
Temperature-squared (annual)	-0.006***	-0.134	-0.008***
	(0.001)	(1.574)	(0.001)
Precipitation (annual)	-0.107***	18.447	-0.122***
	(0.033)	(11.384)	(0.028)
Precipitation-squared (annual)	0.001***	-0.120	0.001***
	(0.0002)	(0.081)	(0.0001)
Test for AR(1): p-value	0.096	0.106	0.239
Test for AR(2): p-value	0.238	0.326	0.266
Sargan test: p-value	0.134	0.592	0.926
Number of instruments	149	47	123

Notes: One-step generalised method-of-moments (GMM) estimate of equation (2) on the whole sample and on subsamples of Old World Producers and New World Producers. All specifications include a constant and a time trend. Coefficients and standard errors estimated are of the order of 10^{-6} for 'expected per acre revenue' and of 10^{-4} for climate variable. Observations are 198 for all producers, 47 for Old World Producers and 151 for New World Producers. Robust standard errors are in parentheses.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

4.2 Acreage response

Table 4 presents the estimation results under the acreage models. All dynamic models (All Producers, Old World Producers and New World Producers) are based on a one-step GMM estimator. The Arellano-Bond test for autocorrelation is used to test for serial correlation in levels. The test results indicate that the null hypothesis of no second-order autocorrelation in residuals cannot be rejected, indicating the consistency of the system GMM estimators. According to the Sargan test results, we fail to reject the null hypothesis of instrument exogeneity: the system GMM estimators are robust but weakened by many instruments.

We fail to find a significant acres-price relationship, which could imply that many grapevines' producers do not form their price expectations on the basis of information on expected per acre revenues.

More importantly, the estimation results reveal that higher annual temperatures in producing countries are beneficial for grapevines acreage share. This is true for both Old and New World Producers, despite the effects are much larger in Old World Producers. As suggested in Ruml et al. (2012), among the many climatic factors affecting wine production, temperature appears to be most important.

Differently, severe rainfall levels is significantly associated with less grapevines share. The negative effects of greater annual precipitations is entirely associated with New World Producers, whereas the Old World Producers seem not affected by changes in the rainfall levels.

5. CONCLUDING REMARKS

Climate change has the potential to impact the agricultural sector and the wine sector in particular (Mozell and Thach, 2014). Most of the previous studies analysing the impact of climate change on agriculture do not consider the effects of climate change on world production, markets and trade patterns (Reilly and Hohmann, 1993). Our analysis allowed us to understand if climate change is able to affect productivity levels of grapevines. Overall, we found that grapevines yield suffers from higher temperatures during summer, whereas precipitations have a varying impact on grapevines depending on the cycle of grapevines. In particular, we observed that greater precipitations are beneficial during the early growing season (spring), but detrimental during the late growing season and the harvest time (summer and autumn). Differently, acreage share of grapevines tends to be favoured by higher annual temperatures, whereas greater annual precipitations tend to be detrimental. The impacts however vary between Old World Producers and New World Producers, also due to heterogeneity in climate between them: the effects of temperatures are less pronounced for New World Producers, whereas precipitations have no effects for Old World Producers. As suggested in previous studies (e.g., Jones et al., 2005), Old World Producers benefit of better growing season, but climate change may push New World Producers into more favourable climatic regimes.

The opening of new regions, benefiting of better climatic regimes, to viticulture would determine new productive scenarios and, as a result, new trade dynamics (Macedo et al., 2019). New productive scenarios are likely to favour the production of varietal wines from autochthonous grapes whose quality is strongly related to microclimatic and pedological conditions (Seccia et al., 2017). In addition, changes in trade regulations, that have largely influenced the agri-food market, are modifying also global trade of wine (Santeramo et al., 2019; Seccia et al., 2019). Such dynamics should not be neglected. Future research should be intended to examine how climate change could affect global trade of wine and to understand how importers and exporters could react to new trade dynamics, due to climate change, in terms of trade regulations.

ACKNOWLEDGMENT

The research has been supported by a Research Grant funded by the International Organisation of Vine and Wine (OIV).

The authors are grateful to Dr. Martina Bozzola for collection and organisation of climate data, to Tatiana Svinartchuk, Tony Battaglene, and to the seminar audiences at the 9th AIEAA Conference and the EGU General Assembly 2021 for helpful comments.

REFERENCES

Anderson, K. (2017). How might climate changes and preference changes affect the competitiveness of the world's wine regions? *Wine Economics and Policy* 6(1): 23-27.

Anderson, K., and Nelgen, S. (2015). Global Wine Markets, 1961 to 2009: A Statistical Compendium. University of Adelaide Press.

Barnwal, P., and Kotani, K. (2013). Climatic impacts across agricultural crop yield distributions: An application of quantile regression on rice crops in Andhra Pradesh, India. *Ecological Economics* 87: 95-109.

Billor, N., Hadi, A.S. and Velleman, P.F. (2000). BACON: Blocked adaptive computationally efficient outlier nominators. *Computational Statistics & Data Analysis* 34: 279-298.

Bozzola, M., Lamonaca, E., and Santeramo, F.G., (2021). *On the impact of climate change on global agri-food trade*. Working Paper.

Bozzola, M., Massetti, E., Mendelsohn, R., and Capitanio, F. (2018). A Ricardian analysis of the impact of climate change on Italian agriculture. *European Review of Agricultural Economics* 45(1): 57-79.

Briche, E., Beltrando, G., Somot, S., and Quénol, H. (2014). Critical analysis of simulated daily temperature data from the ARPEGE-climate model: application to climate change in the Champagne wine-producing region. *Climatic Change* 123(2): 241-254.

Conradt, S., Finger, R., and Bokusheva, R. (2015). Tailored to the extremes: Quantile regression for index-based insurance contract design. *Agricultural Economics* 46(4): 537-547.

Costinot, A., Donaldson, D., and Smith, C. (2016). Evolving comparative advantage and the impact of climate change in agricultural markets: Evidence from 1.7 million fields around the world. *Journal of Political Economy* 124(1): 205-248.

Deschenes, O., and Greenstone, M. (2007). The Economic Impacts of Climate Change: Evidence from Agricultural Output and Random Fluctuations in Weather. *The American Economic Review* 97(1): 354–85

Falco, C., Galeotti, M., and Olper, A. (2019). Climate change and migration: Is agriculture the main channel? *Global Environmental Change* 59: 101995.

Gammans, M., Mérel, P., and Ortiz-Bobea, A. (2017). Negative impacts of climate change on cereal yields:

statistical evidence from France. *Environmental Research Letters* 12(5): 054007.

Gouel, C., and Laborde, D. (2021). The crucial role of domestic and international market-mediated adaptation to climate change. *Journal of Environmental Economics and Management* 106: 102408.

Haile, M.G., Kalkuhl, M., and von Braun, J. (2016). Worldwide acreage and yield response to international price change and volatility: a dynamic panel data analysis for wheat, rice, corn, and soybeans. *American Journal of Agricultural Economics* 98(1), 172-190.

Hendricks, N.P., Smith, A., and Sumner, D.A. (2014). Crop supply dynamics and the illusion of partial adjustment. *American Journal of Agricultural Economics* 96(5): 1469-1491.

Jones, G.V., White, M.A., Cooper, O.R., and Storchmann, K. (2005). Climate change and global wine quality. *Climatic Change* 73(3): 319-343.

Kahn, M.E., Mohaddes, K., Ng, R.N.C., Pesaran, M.H., Raissi, M., and Yang, J-C. (2019). *Long-term macroeconomic effects of climate change: A cross-country analysis*. National Bureau of Economic Research Working Paper.

Kim, H., and Moschini, G. (2018). The dynamics of supply: US corn and soybeans in the biofuel era. *Land Economics* 94(4): 593-613.

Kurukulasuriya, P., Kala, N., and Mendelsohn, R. (2011). Adaptation and climate change impacts: a structural Ricardian model of irrigation and farm income in Africa. *Climate Change Economics* 2(2): 149-174.

Lamonaca, E., and Santeramo, F.G. (2021). Climate changes and Dynamics of the Agricultural Productions in the Mediterranean Region. EGU General Assembly 2021, online, 19–30 Apr 2021, EGU21-1104, https://doi.org/10.5194/egusphere-egu21-1104, 2021.

Macedo, A., Rebelo, J., and Gouveia, S. (2019). Export propensity and intensity in the wine industry: a fractional econometric approach. *Bio-based and Applied Economics* 8(3): 261-277.

Massetti, E., Mendelsohn, R., and Chonabayashi, S. (2016). How well do degree days over the growing season capture the effect of climate on farmland values? *Energy Economics* 60: 144-150.

Meressa, A.M., and Navrud, S. (2020). Not my cup of coffee: Farmers' preferences for coffee variety traits–Lessons for crop breeding in the age of climate change. *Bio-based and Applied Economics* 9(3): 263-282.

Merloni, E., Camanzi, L., Mulazzani, L., and Malorgio, G. (2018). Adaptive capacity to climate change in the wine industry: A Bayesian Network approach. *Wine Economics and Policy* 7(2): 165-177.

Mendelsohn, R., Nordhaus, W., and Shaw, D. (1994). The impact of global warming on agriculture: a Ricardian analysis. *American Economic Review* 84: 753–771.

Moriondo, M., Jones, G.V., Bois, B., Dibari, C., Ferrise, R., Trombi, G., and Bindi, M. (2013). Projected shifts of wine regions in response to climate change. *Climatic Change* 119(3-4): 825-839.

Mozell, M.R., and Thach, L. (2014). The impact of climate change on the global wine industry: Challenges & solutions. *Wine Economics and Policy* 3(2): 81-89.

Nickell, S. (1981). Biases in dynamic models with fixed effects. *Econometrica* 1417-1426.

Ramos, M.C., Jones, G.V., and Martínez-Casasnovas, J.A. (2008). Structure and trends in climate parameters affecting winegrape production in northeast Spain. *Climate Research* 38(1): 1-15.

Reilly, J., Hohmann, N. (1993). Climate change and agriculture: the role of international trade. *The American Economic Review* 83(2): 306-312.

Roodman, D. (2009). How to do xtabond2: An introduction to difference and system GMM in Stata. *The Stata Journal* 9(1): 86-136.

Rosenzweig, C., Parry, M.L. (1994). Potential impact of climate change on world food supply. *Nature* 367(6459): 133-138.

Ruml, M., Vuković, A., Vujadinović, M., Djurdjević, V., Ranković-Vasić, Z., Atanacković, Z., Sivčev, B., Marković, N., Matijašević, S., and Petrović, N. (2012). On the use of regional climate models: implications of climate change for viticulture in Serbia. *Agricultural and Forest Meteorology* 158: 53-62.

Santeramo, F.G. (2014). *On the estimation of supply and demand elasticities of agricultural commodites*. Intl Food Policy Res Inst.

Santeramo, F.G., Miljkovic, D., and Lamonaca, E. (2021). Agri-food trade and climate change. *Economia agro-alimentare/Food Economy* 23(1), [In press].

Santeramo, F.G., Lamonaca, E., Nardone, G., and Seccia, A. (2019). The benefits of country-specific non-tariff measures in world wine trade. *Wine Economics and Policy* 8(1): 28-37.

Seccia, A., and Santeramo, F.G. (2018). Impacts of climate change on the wine sector in Italy and mitigation and adaptation strategies. In R. Compés López, V. Sotés Ruiz: *El sector vitivinícola frente al desafío del cambio climático. Estrategias públicas y privadas de mitigación y adaptación en el Mediterráneo*. Cajamar Caja Rural, pp. 91-115. ISBN-13: 978-84-95531-92-6.

Seccia, A., Carlucci, D., Santeramo, F.G., Sarnari, T., and Nardone, G. (2017). On the effects of search attributes on price variability: An empirical investigation on quality wines. *BIO Web of Conferences* 9, 03014.

Seccia, A., Santeramo, F.G., Lamonaca, E., and Nardone, G. (2019). On the effects of bilateral agreements in world wine trade. *BIO Web of Conferences* 12, 03009.
Swinton, S.M., and King, R.P. (1991). Evaluating robust regression techniques for detrending crop yield data with nonnormal errors. *American Journal of Agricultural Economics* 73: 446-451.
Timmins, C. (2006). Endogenous land use and the Ricardian valuation of climate change. *Environmental and Resource Economics* 33: 119–142.
Weber, S. (2010). Bacon: An effective way to detect outliers in multivariate data using Stata (and Mata). *The Stata Journal* 10(3): 331-338.
World Bank (2018). *Metadata of the Climate Change Knowledge Portal*.

APPENDIX

Table A.1. List and description of countries in the sample.

Country	ISO 3	Wine producer	Hemisphere	30-years annual average temperature (°C)	30-years annual average precipitation (mm)
Argentina	ARG	New World Producer	Southern	14.44	49.16
Australia	AUS	New World Producer	Southern	21.76	40.47
Brazil	BRA	New World Producer	Southern	25.14	148.20
Canada	CAN	New World Producer	Northern	-6.47	38.77
China	CHN	New World Producer	Northern	6.94	48.29
Germany	DEU	Old World Producer	Northern	9.28	61.12
Spain	ESP	Old World Producer	Northern	13.84	50.92
France	FRA	Old World Producer	Northern	11.41	71.61
United Kingdom	GBR	Old World Producer	Northern	8.94	103.42
Italy	ITA	Old World Producer	Northern	12.51	78.70
New Zealand	NZL	New World Producer	Southern	10.06	145.83
Russia	RUS	New World Producer	Northern	-5.43	36.64
United Stated	USA	New World Producer	Northern	7.50	55.57
South Africa	ZAF	New World Producer	Southern	18.13	40.89

Source: Wine producer classification follows Anderson and Nelgen (2015).

Table A.2. Estimation results for grapevines yields, OLS.

Variables	Dependent variable: yield		
	All producers	Old World Producers	New World Producers
Temperature (annual)	1.3078	-22.4180***	5.2902***
	(1.4604)	(7.5813)	(1.8500)
Temperature-squared (annual)	-0.0215	0.6741***	0.0892**
	(0.0344)	(0.1969)	(0.0423)
Precipitation (annual)	0.1755	0.3731	1.1522**
	(0.4226)	(0.9870)	(0.4877)
Precipitation-squared (annual)	-0.0021	-0.0025	-0.0058**
	(0.0022)	(0.0052)	(0.0026)
Time trend	0.0400	0.2498	-0.0490
	(0.0479)	(0.1578)	(0.0593)
Observations	280	100	180
R-squared	0.9148	0.9626	0.8758

Notes: OLS estimate of equation (1) on the whole sample (All producers) and subsamples of Old World Producers and New World Producers. All specifications include country-specific constants. Robust standard errors are in parentheses.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.

Table A.3. Estimation results for grapevines yield: controlling for different combinations of fixed effects.

Variables	Our results	Sensitivity analysis
Temperature (spring)	1.4440	2.2203
	(1.7044)	(1.8717)
Temperature-squared (spring)	-0.3044***	-0.3176***
	(0.0747)	(0.0794)
Temperature (summer)	-16.3650**	-16.1260**
	(7.1026)	(7.4473)
Temperature-squared (summer)	0.4258**	0.4022**
	(0.1955)	(0.2013)
Temperature (autumn)	0.6543	0.0276
	(1.9410)	(2.3118)
Temperature-squared (autumn)	0.0761	0.1007
	(0.0888)	(0.0948)
Precipitation (spring)	0.5227*	0.5692**
	(0.2795)	(0.2844)
Precipitation-squared (spring)	-0.0041***	-0.0041***
	(0.0015)	(0.0015)
Precipitation (summer)	-0.3230*	-0.3870*
	(0.1906)	(0.2034)
Precipitation-squared (summer)	0.0013	0.0015*
	(0.0009)	(0.0009)
Precipitation (autumn)	-0.3507**	-0.3009*
	(0.1601)	(0.1607)
Precipitation-squared (autumn)	0.0019**	0.0017**
	(0.0008)	(0.0008)
Country fixed effects	Yes	Yes
Time trend	Yes	No
Time fixed effects	No	Yes
Country-time fixed effects	No	No
R-squared	0.9314	0.9386

Notes: OLS estimate of yield response equation. Observations are 280. Robust standard errors are in parentheses.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

Table A.4. Estimation results for grapevines acreage: controlling for different combinations of fixed effects.

Variables	Our results	Sensitivity analysis
Lagged acreage share	0.995***	0.995***
	(0.001)	(0.002)
Expected per acre revenue	-0.00003	0.002
	(0.00003)	(0.003)
Temperature (annual)	0.107***	0.095***
	(0.019)	(0.021)
Temperature-squared (annual)	-0.006***	-0.006***
	(0.001)	(0.001)
Precipitation (annual)	-0.107***	-0.133***
	(0.033)	(0.047)
Precipitation-squared (annual)	0.001***	0.001***
Country fixed effects	Yes	Yes
Time trend	Yes	No
Time fixed effects	No	Yes

Notes: One-step generalised method-of-moments (GMM) estimate of acreage response equation. Coefficients and standard errors estimated are of the order of 10^{-6} for 'expected per acre revenue' and of 10^{-4} for climate variable. Observations are 198. Robust standard errors are in parentheses.
*** Significant at the 1 percent level.

Table A.5. Estimation results for grapevines yield: controlling for detrended climate variables.

Variables	Our results (Long-run analysis)	Sensitivity analysis (Short-run analysis)
Temperature (spring)	1.4440	0.1500
	(1.7044)	(0.1418)
Temperature-squared (spring)	-0.3044***	0.0164
	(0.0747)	(0.0900)
Temperature (summer)	-16.3650**	0.1692
	(7.1026)	(0.2820)
Temperature-squared (summer)	0.4258**	-0.2140
	(0.1955)	(0.1384)
Temperature (autumn)	0.6543	0.2483
	(1.9410)	(0.1584)
Temperature-squared (autumn)	0.0761	-0.1644**
	(0.0888)	(0.0820)
Precipitation (spring)	0.5227*	-0.0050
	(0.2795)	(0.0088)
Precipitation-squared (spring)	-0.0041***	-0.0002
	(0.0015)	(0.0005)
Precipitation (summer)	-0.3230*	0.0039
	(0.1906)	(0.0093)
Precipitation-squared (summer)	0.0013	-0.0005
	(0.0009)	(0.0003)
Precipitation (autumn)	-0.3507**	0.0071
	(0.1601)	(0.0056)
Precipitation-squared (autumn)	0.0019**	0.0002
	(0.0008)	(0.0002)
R-squared	0.9314	0.9177

Notes: OLS estimate of yield response equation. Observations are 280. Detrended climate variables in the sensitivity analysis are obtained from the yearly weather deviation from the long-run climate (30-year rolling average). All specifications include country-specific constants and the time trend. Robust standard errors are in parentheses.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

Table A.6. Multidimensional outlier detection analysis.

	5^{th} percentile	10^{th} percentile	15^{th} percentile
Total number of observations	280	280	280
BACON outliers	0	0	20
Non-outliers remaining	208	208	260

Table A.7. Estimation results for grapevines yields: OLS with and without outliers and QR.

Variables	OLS		QR		
	All observations (A)	Observations w/out outliers (B)	25th percentile (C)	50th percentile (D)	75th percentile (E)
Temperature (spring)	1.4440	1.6527	0.8721	0.7711	1.3070
	(1.7044)	(1.7917)	(1.9059)	(1.8734)	(2.3574)
Temperature-squared (spring)	-0.3044***	-0.3114***	-0.1418*	-0.2405***	-0.3368***
	(0.0747)	(0.0765)	(0.0756)	(0.0812)	(0.1073)
Temperature (summer)	-16.3650**	-14.7502*	-22.4737***	-27.0681***	-23.1306***
	(7.1026)	(7.7445)	(4.5501)	(7.0368)	(7.0902)
Temperature-squared (summer)	0.4258**	0.3653*	0.5454***	0.7064***	0.6102***
	(0.1955)	(0.2163)	(0.1219)	(0.1864)	(0.1763)
Temperature (autumn)	0.6543	0.2605	3.0239	1.9043	2.2129
	(1.9410)	(2.1218)	(2.1210)	(1.2873)	(2.4223)
Temperature-squared (autumn)	0.0761	0.1037	-0.1279	-0.0515	0.0525
	(0.0888)	(0.0967)	(0.0813)	(0.0611)	(0.0998)
Precipitation (spring)	0.5227*	0.5162*	0.2402	0.6707**	0.4740
	(0.2795)	(0.2777)	(0.2974)	(0.2899)	(0.2913)
Precipitation-squared (spring)	-0.0041***	-0.0041***	-0.0024	-0.0048***	-0.0035*
	(0.0015)	(0.0015)	(0.0018)	(0.0017)	(0.0018)
Precipitation (summer)	-0.3230*	-0.3643	-0.2866	-0.0272	-0.1956
	(0.1906)	(0.2388)	(0.2024)	(0.1155)	(0.1925)
Precipitation-squared (summer)	0.0013	0.0013	0.0014	-0.0001	0.0011
	(0.0009)	(0.0009)	(0.0012)	(0.0006)	(0.0011)
Precipitation (autumn)	-0.3507**	-0.3302**	-0.3157*	-0.1921	-0.1535
	(0.1601)	(0.1629)	(0.1691)	(0.1477)	(0.1627)
Precipitation-squared (autumn)	0.0019**	0.0019**	0.0019**	0.0011*	0.0010
	(0.0008)	(0.0008)	(0.0008)	(0.0006)	(0.0007)
Observations	280	260	280	280	280
R-squared	0.9314	0.9037			

Notes: OLS and QR estimate of yield response equation. Robust standard errors are in parentheses.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.