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CLIMATE CHANGE AND ITALIAN AGRICULTURE: EVIDENCE FROM WEATHER SHOCKS

by Antonio Accetturo* and Matteo Alpino*

Abstract

We estimate the effect of weather shocks on corn, durum wheat, and wine grape yields based on two-way fixed effect models on annual Italian province-level panel data. Our estimates reveal substantial non-linearity in the effect of temperature on agricultural yields, in line with the literature. Grapevine, in particular, appears less sensitive to high temperatures than cereals. Combining our estimates with climate projections under the A1B scenario, we find that in 2030 the effects of climate change on crop yields will be non-negative. Corn crops appear the most exposed to the risk of reduced yield.

JEL Classification: Q10, Q54.
Keywords: temperature shocks, precipitation, agricultural yields, climate change.
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Contents

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1 Introduction[1]

Agriculture is the most exposed sector to the physical risk generated by climate change because temperature and precipitation are inputs in crop production (Deschênes and Greenstone, 2007). The sign and extent of this risk likely varies across crops and across regions, depending on crop-specific sensitivity to weather and on baseline climate (Schlenker and Roberts, 2009). Furthermore, farmers have the opportunity to engage in adaptation activities to mitigate this risk (Burke and Emerick, 2016).

In advanced countries agriculture accounts for a small share of value added, but it is more important than this crude statistic suggests for at least two reasons. First, agriculture often provides a large share of intermediate inputs to other importan industries (e.g. food and beverages, hotel and restaurant). Second, agriculture likely generates high consumer surplus. In fact, food prices are low, and so the GDP share in agriculture, thanks to massive productivity improvements occurred over the last decades (Jorgenson and Gollop, 1992; Taylor and Schlenker, 2021b). However, since the demand for food is quite inelastic due to the minimum caloric intake necessary to human life, a decrease in agricultural supply generated by climate change has the potential to have substantial detrimental impacts on consumer welfare by making food scarce. Moreover, agricultural products are essential inputs for other important sectors of the economy, such as food processing and restaurants; as a result, food scarcity may negatively impact the other industries through the supply chain.

The aim of this paper is to estimate the effects of climate change on Italian agriculture by 2030 using weather shocks.[2] First, we use annual panel data at the province level for the period 2006-19 to estimate crop-specific sensitivity of yield to temperature and precipitation, focusing on corn, durum wheat and grapevine. Second, we combine our estimates with three external province-level forecasts of future climate under the A1B scenario to project the effect over the period 2000-2030. The A1B scenario is

[1]The views expressed in this paper are our own and do not necessarily reflect those of the Bank of Italy. For comments we are grateful to Federico Cingano, Luca Citino, Marta Crispino, Guido De Blasio, Andrea Linarello and Salvatore Lo Bello.

[2]Climate is defined as the distribution of all possible weather, while observed weather is the realization from such distribution.

developed by the Intergovernmental Panel on Climate Change (IPCC) and is characterized by very rapid economic growth at global level, low population growth, and by a balanced use of fossil and renewable energy.

The empirical analysis uses panel data regressions of crop yield (from Istat - the Italian Statistical Office) on weather variables in the growing season (constructed from Agri4cast). The sample period is 2006-2019. In order to causally identify the effect of precipitation and temperature on crop yield, we include province time and fixed effects in all specifications. Inclusion of this set of fixed effects isolates year-to-year weather shocks, which are plausibly uncorrelated with inputs of production, chosen by farmers before weather is realized (Blanc and Schlenker, 2017; Dell et al., 2012). Furthermore, we model yield as non linear (production) function of temperature and precipitation, by using degree days variables as standard in the literature (Schlenker et al., 2006; Schlenker and Roberts, 2009). In doing that, we take specification selection seriously: among several estimated models with different shape of the production function, we choose the one that minimizes out-of-sample prediction error.

In line with agronomic studies and past econometric evidence, we find that yield is increasing in temperatures up to a certain threshold and then declining for higher temperatures. For cereals the threshold is lower than for grapevine (28-29° against 32°), and the decline that occurs at higher temperature much steeper. Our results also suggest that precipitation affects yields to a lesser extent. In order to test for adaptation over time, we also split the sample in two sub-periods and test whether estimates are significantly different between the two. We find evidence that this is the case only for grapevine, suggesting that this crop has become more heat resistant in the the period 2013-2019.

Our projections using climate forecast under the A1B scenario suggest that by 2030 the average yield for all crops will increase or remain stable as a consequence of the changing climate, depending on the climate model. The change relative to 2000 is estimated between -1 and 6 per cent for corn, 3 and 5 per cent for durum wheat, and 10 and 12 per cent for grapevine. Most projections display limited geographical heterogeneity: the majority of provinces display changes in line with the national average, although there are some differences across crops and across climate models. For example grapevine, which is farmed almost everywhere in Italy, is expected to display the largest increase in yield in the Alpine region, while most Southern provinces will not experience a drop.

Our paper contributes to the large empirical literature in economics that investigates the effect of climate change on agriculture. In particular, we provide evidence on corn, durum wheat and grapevine in the Italian context using panel data methods. Contrary to most existing studies in this literature, we focus on short-run effects (by 2030) and on a scenario of moderate global warming (A1B). Thus our predictions do not heavily rely on extrapolation outside the support of the data, and can shed light on the likely evolution of agricultural output in the immediate future.

Existing papers have found that climate change will negatively affect corn yield in the United States. Relative to the period 1960-89 the change by the period 2020-49 ranges between -20 and -30 per cent approximately (Schlenker and Roberts, 2009). Similar predictions are obtained using the long-difference approach to account for adaptation (Burke and Emerick, 2016). To the best of our knowledge, the existing literature did not apply panel data methods to study durum wheat and grapevine yields.

Available evidence on Italian agriculture relies on the Ricardian (or hedonic) approach, that estimates the effect of weather on farmland value using cross-section data. The approach, initially proposed by Mendelsohn et al. (1994), has come under severe scrutiny for three reasons (Auffhammer, 2018): a) it is prone to omitted variable bias (Deschênes and Greenstone, 2007; Ortiz-Bobea, 2020); b) it implicitly assumes costless adaptation, while switching to crops or varieties less sensitive to hot weather is likely to have some fixed cost; c) it assumes that only past weather is capitalized into farmland price, while nowadays farmers can also incorporate expectations of future climate (Severen et al., 2018). Using the Ricardian approach, Bozzola et al. (2018) find that irrigated Italian farms will lose between 8 and 25 per cent of their value in the period 2031-2060 relative to the period 1971-2000 in a low emission scenario (RCP 4.5), while rain-fed Italian farms will experience an increase in the range 0-20 per cent. Such estimates are heterogeneous across Italian regions, but the heterogeneity is not constant across climate models: in some models damages are concentrated in the North, while in others in the South. In a similar paper that covers most European countries and focuses on long-run effect in a high-warming scenario (A2) (Van Passel et al., 2017), Italy is the country that experiences the largest drop in farmland value (between -60 and -80 per cent in 2071–2100 relative to 1961–1990) together with Spain, Greece and, to a lesser extent, France.

It is hard to systematically compare our estimates of future damages with those in the literature, due to differences in the time horizon, in the underlying scenario, and in the climate models. However, we argue that our results are not necessarily inconsistent with previous evidence, because the effect of weather on agricultural output is highly non-linear. As warming increases, the effects are positive at first, but eventually become negative after temperature increases above a tolerance threshold. Our estimates suggest that in the next ten years increasing temperature will be on average beneficial for corn, durum wheat and grapevine farmed in Italy; this results does not exclude that in later decades, as the upward trend in temperature continues, the effects will become negative and more than offset the initial gains.[3]

In interpreting our estimates, the reader must also keep in mind some caveats. First, greenhouse gases emissions do not affect agricultural output only via climate change. In particular the stock of CO2 in the atmosphere positively affects photosynthesis and thus vegetation growth, a process known as *CO2 fertilization*; the effect is stronger for C3 crops (e.g. wheat, rice, trees) than for C4 crops (e.g. corn). Most studies in economics, including the present one, abstract from CO2 fertilization, but in a recent contribution, Taylor and Schlenker (2021a) provides causal evidence that this process is responsible for very large shares of the productive improvements recorded

[3]To fully appreciate this point, it is useful to remind the reader that climate change is a function of the *stock* of greenhouse gases, not of its *flow*; thus, reducing greenhouse gas emissions will not stop global warming immediately.

in corn and wheat production in the US since 1940. Second, climate change does not only affect the average level of temperature and precipitation, but also their variability, both within and across years. As in most previous studies, our empirical analysis based on degree days only captures mean temperature shifts from one year to the next, but does not allow for heterogeneous effects that depends on the exact week where hot days occur, or on the cumulative effects of several hot days in a row. However, in a recent contribution Miller et al. (2021) show that models that takes such heterogeneity into account predict that climate damages in agriculture may be 5–10 times larger than estimated by previous models. Third, our only outcome variable is yield, but weather can also affect crop quality, and thus its value. Using micro data on apple prices in Switzerland, Dalhaus et al. (2020) show that quality can be much more sensitive to weather relative to yield. Quality is likely less important for commodity cereals, but more for wine. Using data on Bordeaux wine over the period 1800-2009, Chevet et al. (2011) find that over time the effect of weather on yield has decreased, while the effect on prices has increased. In a recent review, Ashenfelter and Storchmann (2016) conclude that climate change will likely improve quality of wine produced in continental Europe, and harm quality of wine produced in the Mediterranean region. Fourth, our analysis does not take into account adaptation, but farmers can adopt several strategies to make yields less sensitive to weather. Our simple test of adaptation can only provide suggestive evidence, considering the short length of our time series (14 years). Estimating adaptation is particularly challenging and represents the current frontier of research in this field.

The rest of the paper is organized as follows: Section 2 provides background information on the Italian agriculture; Section 3 illustrates the empirical strategy and the data; Section 4 presents the results; Section 5 concludes.

2 Italian agriculture

Like many in advanced economies, the direct role of the agricultural sector in Italy is quite limited. The value added generated by the primary sector accounts for roughly

2 per cent, a percentage that has slightly increased in the last 15 years.

Despite such limited share, Italian agriculture has played a relevant role as a stabilizing factor for the economy. Between 2007 and 2019 the agricultural value added has slightly increased (+1 per cent) while GDP has shrank by -5 per cent due to the combined effects of the financial and the sovereign debt crises; export performance showed a similar pattern: the value of exported agricultural goods has increased by almost 40 per cent while sales abroad by other sectors registered a rise by slightly more than 30 per cent. The resilience of the agricultural sector proved substantial even during the recent Covid-19 crisis: in 2020 the drop of the primary sector value added (-6.3 per cent) was more limited in comparison the overall economy (-8.9 per cent).

Italian agriculture has also an important role in providing intermediate goods for other crucial sectors. Domestically produced agricultural products account for more than 70 per cent and almost 100 per cent of all primary sector inputs in, respectively, the agroindustrial and hotel and restaurants industries. The agroindustry sector accounts for 3 per cent of the Italian GDP and 9 per cent of total exports; hotel and restaurants is a crucial industry for the Italian touristic sector (6 per cent of total GDP).

Finally, agricultural products account for a large share (more than 80 per cent) of final consumption of agricultural goods by households. This implies that fluctuations in quality, quantity, and prices for Italian agriculture have a direct impact on the welfare of final consumers.

The most important crops in terms of quantity produced are shown in Table 1.

In this paper we focus on three main crops (Corn, Durum Wheat, Grapevine) due to their heterogeneities in terms of growing conditions and representativeness in the geographical distribution of crops.

Corn requires relatively high temperatures and abundant water, especially in summer. These conditions are more frequently met in rainy areas, or where irrigation is available at low cost, with relatively warm summers. For this reason, in Italy, corn production is concentrated in the North, especially in the Po Valley (figure 1).

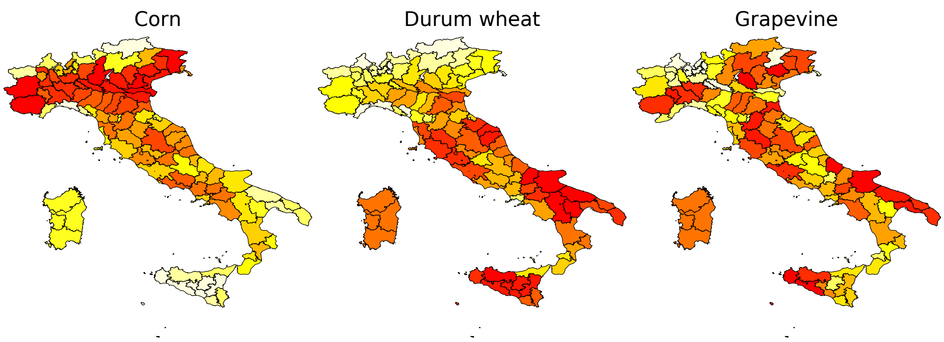
Table 1: Top ten crops in terms of quantity produced (average 2006-19)

Crop	Production
Corn	81.1
Wine grape	66.6
Open air tomato	51.7
Durum wheat	42.5
Sugar beet	32.7
Soft wheat	30.9
Olive	29.8
Apple	23.0
Orange	20.5
Rice	15.2

Source: Istat.
Note: millions of tons.

Durum wheat requires warm conditions but suffers when temperatures above 30°with dry winds. For these reasons, it is mostly farmed in the South of Italy.

Figure 1: Farmed surface (average 2006-2019)



Note: sixteen quantiles. Darker areas have more absolute surface devoted to the specific crop.

Grapevine is able to grow under very heterogeneous conditions but it generally requires fresh springs and not particularly hot summers. Water requirements can also be very variable depending on type. For these reasons, it can be cultivated almost everywhere in Italy.

3 Empirical strategy and data

Our approach estimates the effect of weather on a crop by crop basis. As explained in the previous section, we focus on Corn, Durum wheat, and Wine grape, which are the most relevant Italian agricultural products; they are also characterized by different growing conditions and, as a consequence, they are also likely to be affected in an heterogeneous way by climate change. In order to analyze the impact of temperature and rain shocks on yields, we estimate the following equation:

$$\begin{aligned} y_{it}^c = \mu_i + \lambda_t + \beta_1 GDD_{it} + \beta_2 KDD_{it} + \\ + \gamma_1 Rain_{it}^{above} + \gamma_2 Rain_{it}^{below} + \gamma_3 Rain_{it}^{above} \times I_i + \gamma_4 Rain_{it}^{below} \times I_i + \varepsilon_{it} \quad (1) \end{aligned}$$

where i and t indicate, respectively, the geographical area of analysis (Italian NUTS3 regions; i.e. provinces) and time (year). We estimate our specification via weighted lest squares (WLS), with the time-invariant weights being equal to the average surface devoted to the crop under investigation. This kind of weighting is common in the literature (Burke and Emerick, 2016) and allows to recover the effect of climate change on the Italian agriculture as a whole when we extrapolate the estimates in to the future. We cluster our standard errors to account for arbitrary spatial correlation with a spatial cut-off of 300 kilometers (Conley, 1999; Colella et al., 2019).

3.1 Variables and data

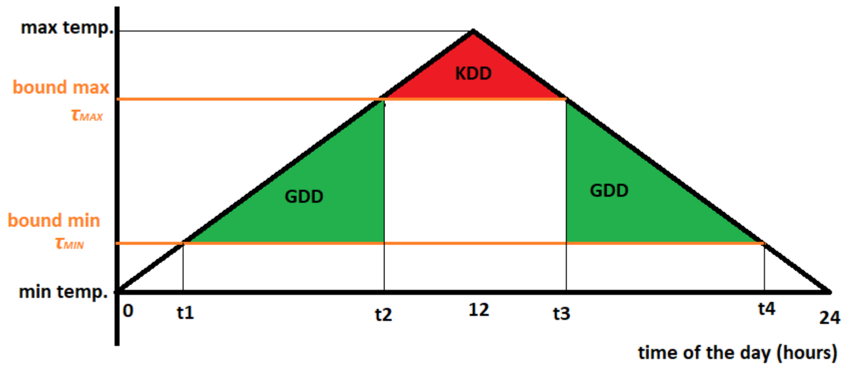
We download crop-specific data on total production and farmed surface from Istat (Italian Statistical Bureau) to construct the dependent variable. Data is at the annual frequency and the level of disaggregation is province. The outcome variable y_{it}^c is the log yield:

$$y_{it}^c = \ln\Big(\frac{Production_{it}^c}{Land_{it}^c}\Big), \quad (2)$$

where both numerator and denominator refer to a specific crop c (e.g. corn).

GDD_{it} (growing degree days) and KDD_{it} (killing degree days) are variables that approximate the impact of temperature on yields (Schlenker and Roberts, 2009; Burke and Emerick, 2016; Blanc and Schlenker, 2017). Degree days are constructed from daily readings of minimum and maximum temperature. We assume that at the beginning of the day the temperature is at its minimum, and then it grows linearly until midday, when it reaches its maximum; after that, we assume it decreases back to the minimum at the same rate. The within day distribution of temperature is depicted in figure 2, where time of the day is on the horizontal axis, and temperature on the vertical axis.

Figure 2: Construction of degree days for one example day



Note: temperature on the vertical axis, and time of the day on the horizontal axis. The black line is the assumed within-day temperature distribution, constructed from the observed minimum and maximum temperatures of the day. Here the value of τ_{min} and τ_{max} is picked just for illustrative purposes.

To define our degree days, we must pick two temperature thresholds for each crop: bound min τ_{min} and bound max τ_{max} (more on how we select the bounds in Section 3.2). We assume that when the temperature is below bound min or above bound max, the weather is too cold or too hot for the crop and so it is detrimental for its growth; such a negative effect is stronger the more the temperature deviates from the bounds. When instead the temperature is between the two thresholds, the weather is appropriate for the crop and makes the plants grow; in particular, it is the more favorable the higher the temperature, conditional on being below bound max.

GDD_{it} is calculated for each day as the green area in Figure 2; the horizontal side of the triangles measures the temporal exposure to the good temperature, while the vertical side measures the intensity of the exposure. The annual GDD is calculated as the sum of all green areas over the entire growing season. KDD_{it} is the variable that captures the negative effects from hot temperature, and corresponds to the red area.

The effect of precipitation on agricultural yields depends crucially on the availability of irrigation (Schlenker et al., 2005). We download information on the availability of irrigable land (e.g. due to underground water, river, aqueduct etc.) from the 2010 Agricultural census and construct a dummy I_i equal to one if more than half of agricultural land (all crops) is irrigable. Availability of irrigation is not uniform: highly irrigable provinces are located in the North in the vicinity of the Po river, and they record on average 26 per cent more precipitation than the rest of the provinces. We will allow for the effect of precipitation to be different in high vs. low irrigable provinces. Note that, contrary to actual irrigation, availability of irrigation is fixed in the short run, because it depends on the presence of rivers, lakes, basins, wells, canals or other natural or artificial infrastructure.

The effect of precipitation on agricultural yields is captured by $Rain_{it}^{above}$ and $Rain_{it}^{below}$. The two variables are constructed as follows:

$$Rain_{it}^{above} = Precipitation_{it} \times \mathbb{1}(Precipitation_{it} > \pi) \tag{3}$$

$$Rain_{it}^{below} = Precipitation_{it} \times \mathbb{1}(Precipitation_{it} < \pi) \tag{4}$$

where π is a chosen threshold and $Precipitation$ is the total precipitation in province i over the growing season in year t. This formulation allows the estimated relationship to have a different slopes on the two sides of the threshold, and thus can accommodate positive effects of additional rain when precipitations are low, and null or even negative effects when precipitations are high.

The source of our weather data is the JRC Agri4cast MARS Meteorological Database, a gridded database with 25×25 km cells which covers the European Union and neighboring countries. It contains daily observations on precipitation and minimum and maximum temperatures.

In order to map cells into Italian provinces, we first aggregate our degree days variables and the precipitation variable at the cell-year level, restricting the dataset to the growing season of each crop. Since provinces typically span over more than one cell, we proceed as follows. First, we superimpose a finer 8.3×8.3 km grid, and assign the centroid of each sub cell to the province where it lies. Second, for each variable we construct its weighted average using values of all cells that intersect the province territory; the weights are the number of sub cell centroids from the same cell, and are thus proportional to the portion of province territory that belongs to that cell.

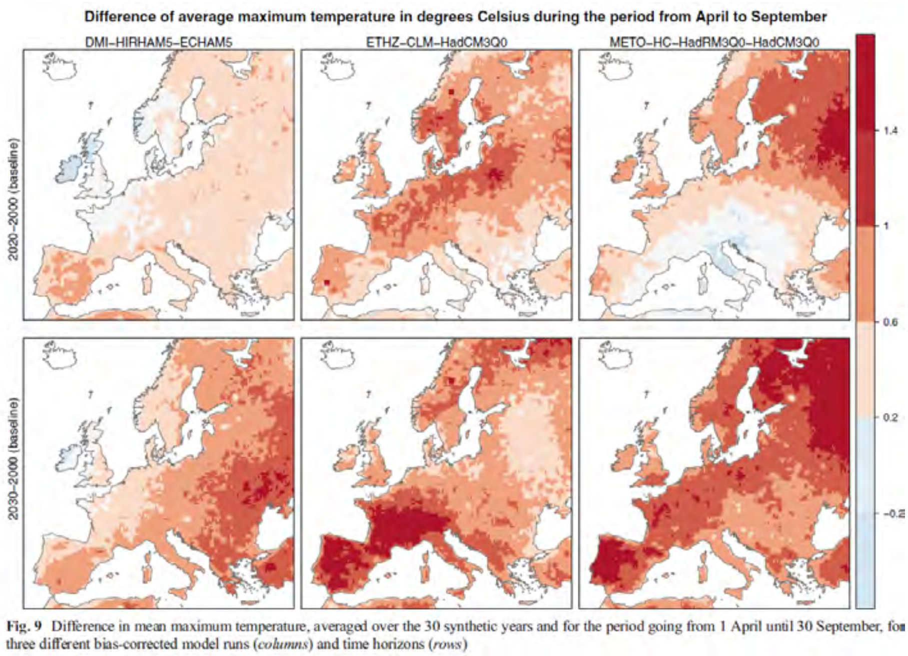
From the same source, we download data on model-based future weather in 2000 (the benchmark year used for validation) and 2030 under the A1B scenario, which assumes very rapid economic growth at global level, low population growth, and a balanced use of fossil and renewable energy (Duveiller et al., 2017). The dataset features 30 synthetic years drawn from the statistical distribution of meteorological variables in 2000 and 2030, as predicted by the climate models. In particular, the dataset contains predictions from three climate models: DMI-HIRHAM5-CHAM5, ETHZ-CLM-HadCM3Q0 and METO-HC-HadRM3Q0-HadCM3Q0. For each synthetic year, the data has the same frequency and geographical format as the actual weather data, and thus we are able to use the same procedure to aggregate our variables of interest at the province-synthetic year level. The bottom panel in Figure 3 shows the increase in maximum temperature between 2000 and 2030 predicted by the three different climate models; in Italy the increase is more limited compared to countries like Spain and France, and it is below 1°everywhere in two models (side panels), and below 1.4 in one (central panel).

3.2 Identification and model selection

Our baseline specification eq. (1) is a two-way fixed effects (TWFE) model that includes year fixed effects, province fixed effects and the weather variables.

The causal interpretation of the results crucially rests on the presence of province fixed effects, whose inclusion effectively demean the outcome and the weather variables. In this way, the specification identifies the effect of year-to-year weather variation (shocks) (Blanc and Schlenker, 2017). These shocks are plausibly uncorrelated with

Figure 3: Difference of average maximum temperatures (°) in April-September



Source: Duveiller et al. (2017).

inputs of production controlled by farmers; in fact, these inputs are chosen in the plantation season, well before weather in the growing season is realized (Dell et al., 2012). Furthermore, province fixed effects control for time-invariant characteristics that are correlated both with yield and with average weather, such as the availability of irrigation or soil quality.

Year fixed effects control for the presence of aggregate shocks, such as changes in national crop prices or institutional reforms. This set of fixed effects ensure that the effect of weather is not identified by identical shocks that occur everywhere in the same year. However, year fixed effects are not essential for identification because our identifying assumption is not a parallel trend assumption like in a difference-in-differences. On the contrary, we assume that weather shocks are orthogonal to other inputs of production, and this only requires inclusion of province fixed effects, as explained above.

TWFE models can be biased in case of treatment effects that are heterogeneous over time (dynamic effects) or across units (de Chaisemartin and D'Haultfœuille, 2020). In our application, we do not expect that weather shocks have dynamic effects because we analyze crops characterized by a vegetation cycle that begins and ends within 12 months. Weather shocks are unlikely to affect yields in subsequent years, which effectively shuts down one of the source of bias in the TWFE model identified by the recent econometric literature. We can expect instead that weather shocks have heterogeneous effects across provinces, since Italian NUTS3 regions are well known to be characterized by large differences in terms of baseline climate, irrigation availability, firm structure, etc.

To cope with the potential bias of TWFE model, we propose an *ad hoc* approach uniquely available in this context. The economic literature on the effects of climate change have advocated for the use of out-of-sample prediction tests for model validation (Schlenker and Roberts, 2009; Blanc and Schlenker, 2017). We do the same here, by comparing the relative forecasting performance of the TWFE model and of the model with only province fixed effects. If the former model has lower prediction error, we conclude that the gain from controlling for nation-wide year shocks is larger than the bias due to the potential cross sectional heterogeneity. Note also that, to the best of our knowledge, most solutions proposed in the literature to cope with the TWFE bias are not readily applicable in our context, characterized by several continuous endogenous regressors.

In studying the effect of temperature on output, selecting the correct functional form is often more challenging than finding a plausibly exogenous source of variation (Newell et al., 2021). In fact, weather shocks are plausibly random, but their effect on output is non linear in a non trivial way (Schlenker et al., 2006). In our case, selecting the functional form amounts to choosing the thresholds τ_{min}, τ_{max} and π. In order to do that, we perform a comparison of different models in terms of out-of-sample forecasting accuracy against a benchmark that only includes time and year fixed effects. Following Blanc and Schlenker (2017), for all years we drop one year at the time from the estimating sample, predict that year, and then calculate the mean squared error across all years. Note that in this setting the use of both previous and later years to estimate the coefficients is not problematic because the agricultural cycle is such that weather shocks can not affect yields in subsequent years.

Finally, extrapolation of future damages is as follows. First, we construct degree days and precipitation variables for each synthetic year. Second, we take the average over synthetic years for 2000 and 2030. Third, for each variable we calculate the difference between 2000 and 2030. Fourth, we use the estimated coefficients of our preferred specification to project these differences in to changes in log yield.

4 Results

4.1 Thresholds selection

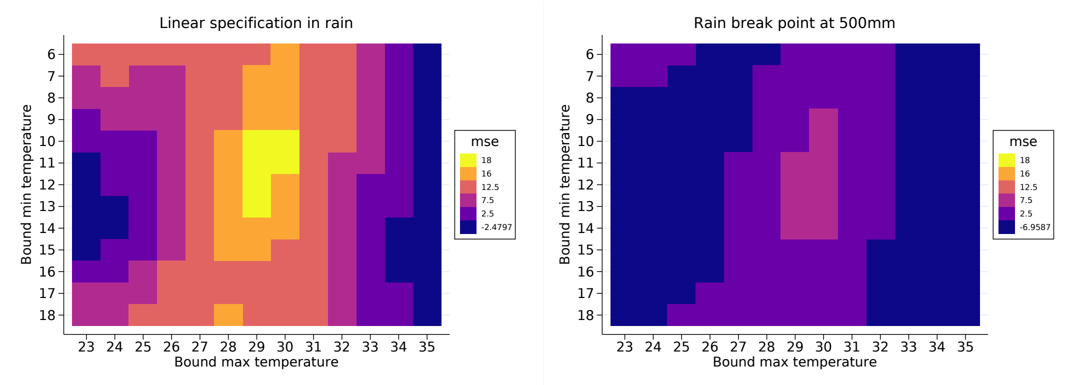
Corn. In Italy, the growing season for corn goes from May to mid September. According to agronomists, corn does not grow if temperature is below 10°and suggest to start sowing when average soil temperature is around 12°. Temperature above 32°is particularly harmful for the crop. Abundant water, especially in summer, is essential to reach maximum yield: the optimal amount is approximately $25mm$ per week. The available econometric evidence is consistent with agronomic studies: for the United States, Schlenker and Roberts (2009) find that $\tau_{min} = 10°$, $\tau_{max} = 29°$ and $\pi = 635mm$.

We test the out-of-sample prediction performances of different models against a benchmark model with only time and province fixed effects. We focus on parameters in a neighborhood of the optimal values found in the agronomic and econometric literature. In particular, we consider the following temperature ranges: $\tau_{min} = \{6°, 18°\}$ and $\tau_{max} = \{23°, 35°\}$. Since in our data, the 99th percentile of precipitation in low-irrigable provinces is equal to $610mm$, that is very close to the optimal value identified in the literature, we consider $\pi = 500mm$ against a fully linear specification.

Results, reported graphically in Figure 4, are consistent with the existing literature. The best performing models (yellow squares) are those with $10° \leq \tau_{min} \leq 13°$, and $29° \leq \tau_{min} \leq 30°$, and without break point in precipitation.[4]

[4]The coefficients on the two sides of the precipitation threshold are statistically indistinguishable from one other.

Figure 4: Out-of-sample prediction performance for corn yield



Note: each square correspond to a different model. Colors are assigned based on the percentage change in MSE relative to a benchmark that only includes time and province fixed effects. MSE are calculated on out-of-sample predictions obtained by leaving one year out in every estimation step.

Durum Wheat. The growing season for dumum wheat goes from December to May. According to agronomists, the minimum growing temperature is 0°, but at least 2-4°are needed for the growing process to occur quickly. As we said before, temperatures above 30°, especially when coupled with dry winds, can be very detrimental for the crop and for the related yield. Durum wheat is more resistant to high temperatures compared to soft wheat. The optimal amount of rain is between 450 and 650mm per season.[5]

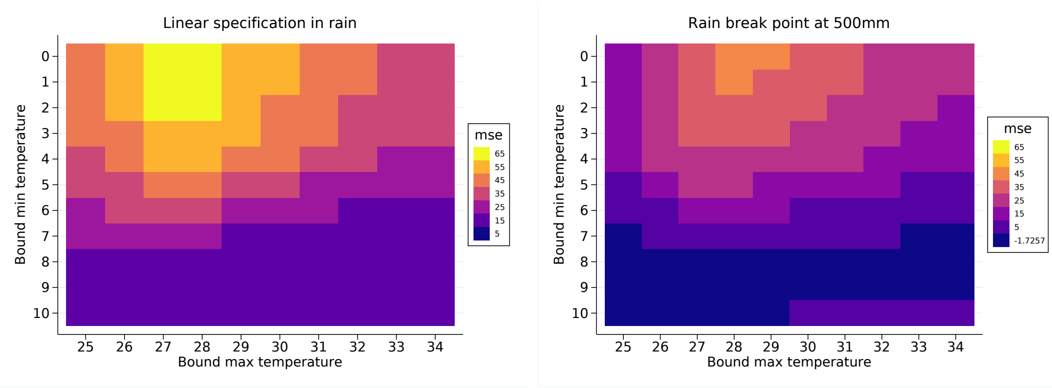
We proceed as before and consider the following temperature ranges: $\tau_{min} = \{0°, 10°\}$ and $\tau_{max} = \{25°, 34°\}$. Since in our data, the 99th percentile of precipitation in low-irrigable provinces is equal to 726mm, that is very close to the optimal value identified in the literature, we consider again $\pi = 500mm$ and also a fully linear specification without break point.

Results, reported graphically in Figure 5, are broadly consistent with the information from agronomic studies. The best performing models (yellow squares) are those with $0° \leq \tau_{min} \leq 2°$, and $27° \leq \tau_{min} \leq 29°$, and without break point in precipitation.[6] The forecasting performance is quite high relative to the benchmark.

[5]https://www.fao.org/land-water/databases-and-software/crop-information/wheat/en/

[6]Note that since negative temperature are not very frequent, GDD variables with $\tau_{min} \leq 2°$ are highly correlated (in the order of 98 per cent). For this reason, it makes no sense to expand the search for better prediction performance to $\tau_{min} < 0$.

Figure 5: Out-of-sample prediction performance for durum wheat yield



Note: each square correspond to a different model. Colors are assigned based on the percentage change in MSE relative to a benchmark that only includes time and province fixed effects. MSE are calculated on out-of-sample predictions obtained by leaving one year out in every estimation step.

Grapevine. The growing season varies depending on the area and type of grape; for our purposes we consider weather in the period April-September. According to agronomists, fast development of shoots starts when mean daily temperatures reach l0°. High temperatures might become detrimental when above 30°approximately. Total water requirements vary between 500 and 1200 mm, depending mainly on climate and length of growing period.

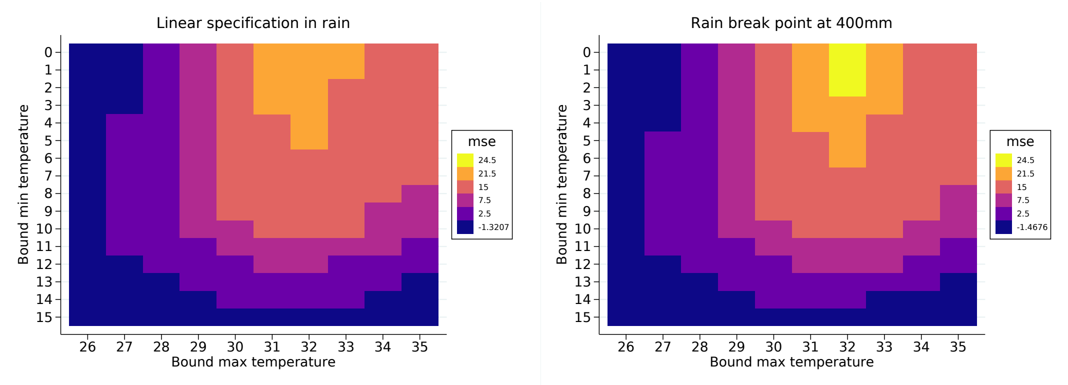
As before, we test the out-of-sample prediction performances of different models against a benchmark model with only time and province fixed effects, restricting our focus on the following temperature ranges: $\tau_{min} = \{0°, 15°\}$ and $\tau_{max} = \{26°, 35°\}$. We also experiment with models where precipitation enters linearly or with break points in the range $\pi = \{300, 700\}$.

The out-of-sample forecasts, reported graphically in Figure 6, are broadly consistent with the agronomic values. The best performing models (yellow squares) are those with $0° \leq \tau_{min} \leq 4°$, and $31° \leq \tau_{min} \leq 33°$; in terms of precipitation, the models with a linear function and with break point at $400mm$ have similar performances.

4.2 Effect of weather shocks

Corn. Table 2 reports the estimated coefficients of four specifications with $\tau_{min} = 12°$, $\tau_{max} = 29°$, and no break point in precipitation. Column (4) refers to our pre-

Figure 6: Out-of-sample prediction performance for grapevine yield



Note: each square correspond to a different model. Colors are assigned based on the percentage change in MSE relative to a benchmark that only includes time and province fixed effects. MSE are calculated on out-of-sample predictions obtained by leaving one year out in every estimation step.

ferred specification that include province and year fixed effects. The coefficient on the degree days variables have the expected sign, but the coefficient on KDD is imprecisely estimated.[7] The effect of precipitation is positive in provinces where the availability of irrigation is low, but equal to zero elsewhere; in the former, a 1cm increase in rain leads to a 0.4 per cent increase in yield. The results are very similar in column (2) when year fixed effects are not included the model, suggesting that the bias produced by the TWFE estimator in case of heterogeneous effects is minimal in this case.

In order to interpret the effect of temperature shocks, it is useful to use the estimated coefficients to construct a mapping from minimum and maximum temperature into yield. The left panel of Figure 7 plots the relationship between minimum temperature and yield: the slope is positive, and become steeper above 12°. The right panel plots the relationship between maximum temperature and yield: the slope is positive below 29°and become negative beyond that point; the negative part of the spline is steeper, suggesting that high temperature quickly become very detrimental for the crop.[8]

Next we implement a simple test for adaption in the spirit of Roberts and Schlenker

[7]The standard errors become smaller when reducing the radius used to construct the clusters or provinces, or when clustering at the province level.

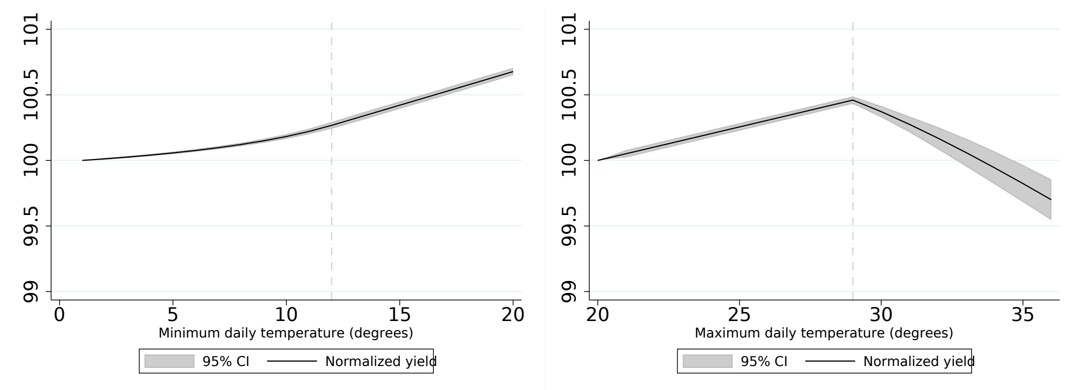
[8]Note that this line has a unique peak at 29°by construction. The true relationship might be smoother, but the literature has found that the approximation used here is very close to what would be estimated by more flexible models. (Schlenker and Roberts, 2009)

Table 2: Effect of weather on log corn yield

	Log corn yield			
	(1)	(2)	(3)	(4)
GDD 12-29°	0.069**	0.108***	0.091***	0.102***
	(0.030)	(0.022)	(0.027)	(0.029)
KDD >29°	-0.425*	-0.210	-0.340	-0.313
	(0.254)	(0.245)	(0.282)	(0.291)
Rain (cm)		0.010***		0.004*
		(0.003)		(0.002)
Rain (cm) X irrigable (0/1)		-0.004		-0.004
		(0.003)		(0.003)
Prov. FE	X	X	X	X
Year FE			X	X
N Obs.	1269	1269	1269	1269
R2	0.11	0.18	0.06	0.07

Note: Estimation via weighted linear regression; weights equal to the average surface devoted to corn. Conley standard errors (radius 300 km) in parentheses. The sample include 99 Italian provinces over the period 2006-2019.

Figure 7: Effect of temperature on corn yield



Note: the left panel plots the relationship between minimum temperature and corn yield (normalized to 100 at 1°), keeping maximum temperature fixed at 22°; the right panel plots the relationship between maximum temperature and corn yield (normalized to 100 at 20°), keeping minimum temperature fixed at 16°. Shadow areas are 95 per cent confidence intervals.

(2011). We estimate a new model where all explanatory variables are also interacted with a dummy equal to one for the years 2013-2019. We thus allow weather shocks to have different effects in the period 2006-2012 vs. the period 2013-2019. If adaptation is at work, we should find that the estimated relationship between weather shocks and yield become flatter over time, as farmers learn how to protect crops from the changing climate. As reported in the appendix, the coefficients on the interaction terms are small and not statistically significant at conventional levels, suggesting that there is no evidence of adaptation in corn production over this short period of time.

Durum wheat. Table 3 reports the estimated coefficients of four specifications with $\tau_{min} = 2°$, $\tau_{max} = 28°$, and no break point in precipitation. Column (4) refers to our preferred specification that include province and year fixed effects. The coefficient on the degree days variables have the expected sign. The effect of precipitation is approximately equal to zero both in provinces where the availability of irrigation is low, that is in the areas where the production of durum wheat is concentrated, and where irrigation is more diffuse.

Comparing columns (2) and (4) we notice that the estimated coefficients are somewhat sensitive to the inclusion of year fixed effects. In particular, the coefficient on GDD_{it} is equal to zero when year fixed effects are included, while the coefficient on KDD_{it} is larger in absolute value. Since these results might suggest the presence of bias in the TWFE model due to the presence of heterogeneous effects (de Chaisemartin and D'Haultfœuille, 2020), we perform a comparison of the two models in terms of out-of-sample predictive performance in order to pick the most accurate. The results (not reported) indicate that the TWFE model is up to 4 times more accurate than the model without time fixed effects, suggesting the importance to control for year-level shocks in this application.

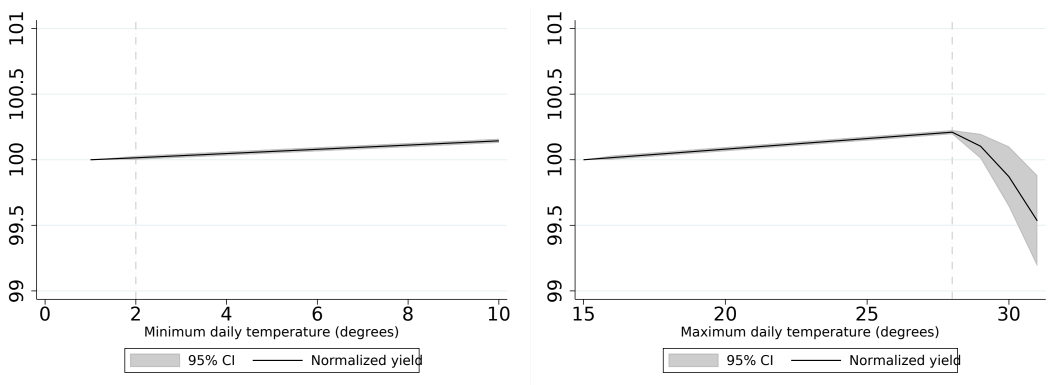
The left panel of Figure 8 plots the linear positive relationship between minimum temperature and yield. The right panel plots the relationship between maximum temperature and yield: the slope is positive below 28°and become negative beyond that point; the negative part of the spline is much steeper, suggesting that high temperature quickly become highly detrimental for the crop. However, the last day of the growing season is May, thus maximum temperatures do not raise often much above the turning point under the current climate.

Table 3: Effect of weather on log durum wheat yield

	Log durum wheat yield			
	(1)	(2)	(3)	(4)
GDD 2-28°	0.001	-0.000	0.034*	0.032**
	(0.017)	(0.017)	(0.017)	(0.016)
KDD >28°	-3.945***	-3.893***	-2.285	-2.465*
	(1.359)	(1.350)	(1.398)	(1.380)
Rain (cm)		-0.001		-0.000
		(0.001)		(0.001)
Rain (cm) X irrigable (0/1)		-0.003		-0.004
		(0.003)		(0.003)
Prov. FE	X	X	X	X
Year FE			X	X
N Obs.	1187	1187	1187	1187
R2	0.05	0.05	0.02	0.02

Note: Estimation via weighted linear regression; weights equal to the average surface devoted to durum wheat. Conley standard errors (radius 300 km) in parentheses. The sample include 99 Italian provinces over the period 2006-2019.

Figure 8: Effect of temperature on durum wheat yield



Note: the left panel plots the relationship between minimum temperature and corn yield (normalized to 100 at 1°), keeping maximum temperature fixed at 14°; the right panel plots the relationship between maximum temperature and corn yield (normalized to 100 at 15°), keeping minimum temperature fixed at 12°. Shadow areas are 95 per cent confidence intervals.

Grapevine. Table 4 reports the estimated coefficients of six specifications with $\tau_{min} = 2°$ and $\tau_{max} = 32°$; for grapevine we present results from models with no break point in precipitation and with break point at 400, because their out-of-sample forecasting performance is comparable. Columns (5) and (6) refer to our preferred specifications that include province and year fixed effects. In both cases, none of the coefficients on the precipitation variables is statistically different from zero. In model (5) the coefficients on precipitation is small and positive both in areas with high irrigation and in areas with low irrigation. In model (6), in low irrigable provinces the effect of rain is positive (0.2 per cent for each additional cm) below 400 mm, and becomes equal to zero for higher values; in the other provinces, the effect is also positive (0.4 per cent per 1 more cm) below the threshold and negative (-0.3 per cent) above. Thus the non-linear pattern (consistent with the idea that more rain is good when there is little precipitation, but eventually it becomes useless or even counterproductive) is qualitatively similar in areas with high and low availability of irrigation. This is consistent with the fact that in Italy irrigation is used in grape making only in case of severe heat stress (*irrigazione di soccorso*), and to this extent is likely to be available everywhere for a valuable crop such as grapevine.

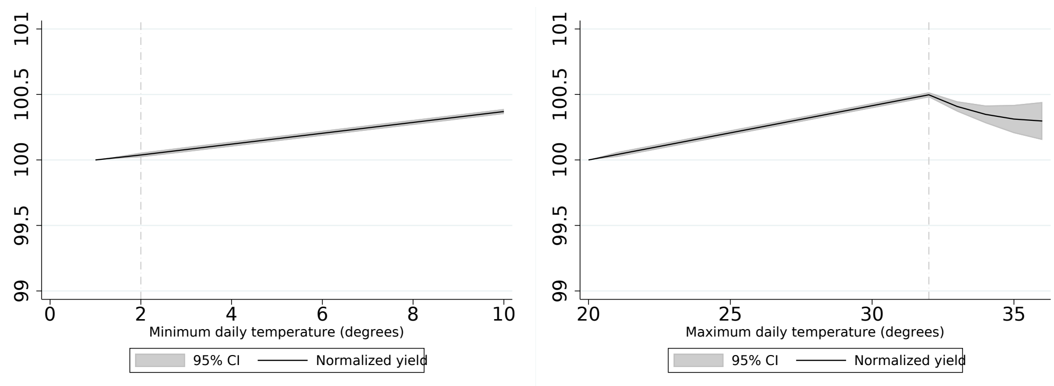
The coefficients on GDD and KDD are similar irrespective of the way we model precipitation. The coefficient on GDD is positive, large, and quite precisely estimated; the coefficient on KDD is positive but very imprecisely estimated and not statistically significant. Interpreting these coefficients in isolation is hard, since the standard *ceteris paribus* interpretation used in regression analysis is misleading here: KDD can not change while GDD remains fixed, because they are both functions of the maximum temperature. Thus we use coefficients to create a mapping from temperatures to yield, as we did for other crops. Figure 9 shows a positive relationship for maximum temperature below 32°. For higher temperatures, the relationship becomes negative, but the decline in yield is moderate, convex and flattens out quickly. The change of sign in the graph is generated by the drop in GDD that occurs when the maximum temperatures exceeds 32°, since the coefficient on KDD is also positive. Additional analyses show that in order to obtain a negative coefficient on KDD (and thus a function which is strictly increasing below the cutoff and strictly decreasing above) it is necessary to increase the threshold τ_{max} to at least 34°. The most important takeaway is that the data, irrespective of the exact specification, supports the idea that grapevine yield in Italy is on average quite resistant to heat.

Table 4: Effect of weather on log grapewine yield

	Log grapevine yield					
	(1)	(2)	(3)	(4)	(5)	(6)
GDD 2-32°	0.036**	0.045***	0.045***	0.078***	0.083***	0.084***
	(0.015)	(0.015)	(0.015)	(0.017)	(0.019)	(0.019)
KDD >32°	-0.328	-0.151	-0.122	0.320	0.366	0.385
	(0.430)	(0.420)	(0.419)	(0.479)	(0.519)	(0.525)
Rain (cm)		0.003**			0.001	
		(0.002)			(0.002)	
Rain (cm) X irrigable (0/1)		0.000			0.001	
		(0.003)			(0.002)	
Rain above (cm)			0.001			0.000
			(0.002)			(0.002)
Rain above (cm) X irrigable (0/1)			-0.003			-0.003
			(0.007)			(0.006)
Rain below (cm)			0.004*			0.002
			(0.002)			(0.002)
Rain below (cm) X irrigable (0/1)			0.004			0.004
			(0.004)			(0.004)
Prov. FE	X	X	X	X	X	X
Year FE				X	X	X
N Obs.	1390	1390	1390	1390	1390	1390
R2	0.04	0.04	0.05	0.04	0.04	0.04

Note: Estimation via weighted linear regression; weights equal to the average surface devoted to corn. Conley standard errors (radius 300 km) in parentheses. The sample include 99 Italian provinces over the period 2006-2019.

Figure 9: Effect of temperature on grapevine yield



Note: the left panel plots the relationship between minimum temperature and grape wine yield (normalized to 100 at 1°), keeping maximum temperature fixed at 14°; the right panel plots the relationship between maximum temperature and corn yield (normalized to 100 at 20°), keeping minimum temperature fixed at 15°. Shadow areas are 95 per cent confidence intervals.

The results for GDD and KDD are quite different in columns (2) and (3) when year fixed effects are not included in the model; however, the out-of-sample forecasting performance of these specifications are approximately equal to the benchmark model with only time and province fixed effects, and thus sensibly worse than the models in columns (5) and (6).

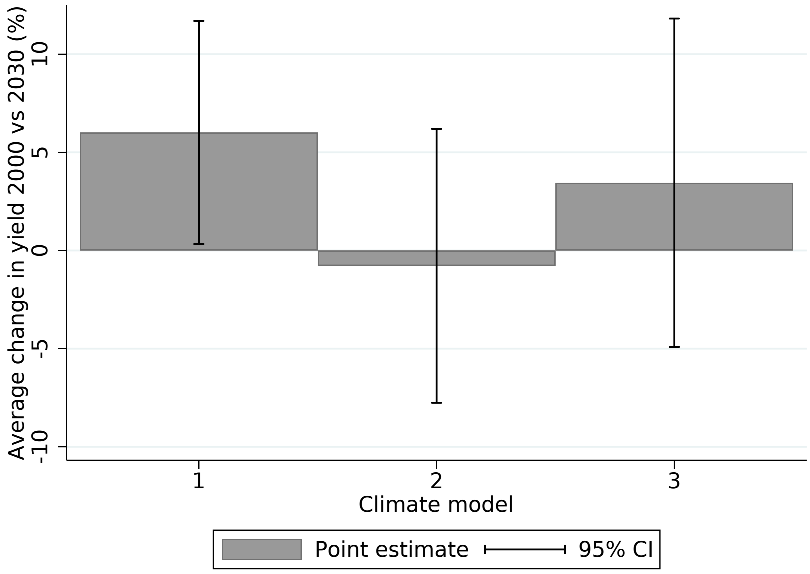
The evidence from the simple test for adaptation implemented before for other crops suggests that in the case of grapevine the effect of KDD is negative in the period 2006-2012, and turns positive afterwards (see Appendix). The difference between the two is statistically significant, and thus we could interpret this as evidence that farmers are adopting measures able to limit the detrimental effects of high temperature.

4.3 Projection of future effects

Corn. Combining our estimates with predictions on future climate, we obtain a projection of the effects of climate change on corn yield in 2030 relative to 2000 under the A1B scenario. The point estimates range from - 0.8 to 6 per cent, depending on the climate model (see Figure 10). The confidence interval are quite wide, even though they do not consider the uncertainty in the climate projections. When using the two climate models that predict less warming (1 and 3), the effect on corn yield is positive; it turns negative in model 2, that predicts 1°higher maximum temperature. This pattern is consistent with the relationship depicted in Figure 7: higher temperature increases corn yield up to approximately 29°, but beyond that further increases are detrimental for the crop. Our results suggest that in the period 2000-2030 the Italian climate is still to the left of the peak, and so agriculture productivity is gaining from more warming. However, the difference in results between models 1-3 and model 2 suggest that if the temperature keeps raising after 2030, the effects on corn production will become negative, even under model 1 and 3. Figure 11 shows some degree of heterogeneity across provinces. In model 1 most Northern provinces around the Po river, where most corn production is concentrated, display positive effects, while they are negatively affected in in model 2.

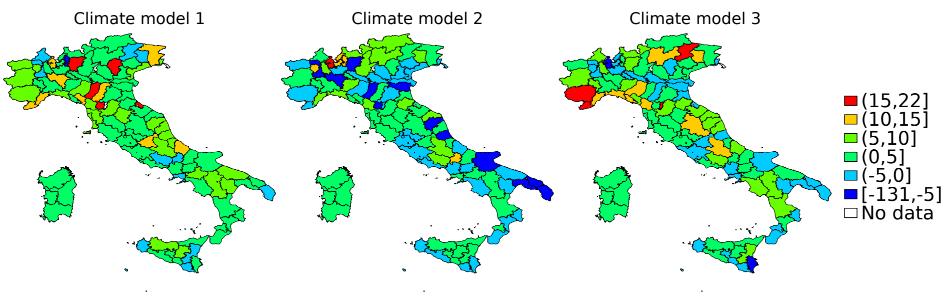
Durum wheat. Under the A1B scenario, the point estimates range between 3 and 5 per cent, depending on the climate model (see Figure 12). Even in this case, the confidence interval are quite wide, even though they do not consider the uncertainty in the climate projections. The effect is larger for climate model 2, that predicts higher

Figure 10: Average effect of climate on corn yield 2030-2000



Note: Models 1, 2 and 3 refer respectively to DMI-HIRHAM5-CHAM5, ETHZ-CLM-HadCM3Q0 and METO-HC-HadRM3Q0-HadCM3Q0.

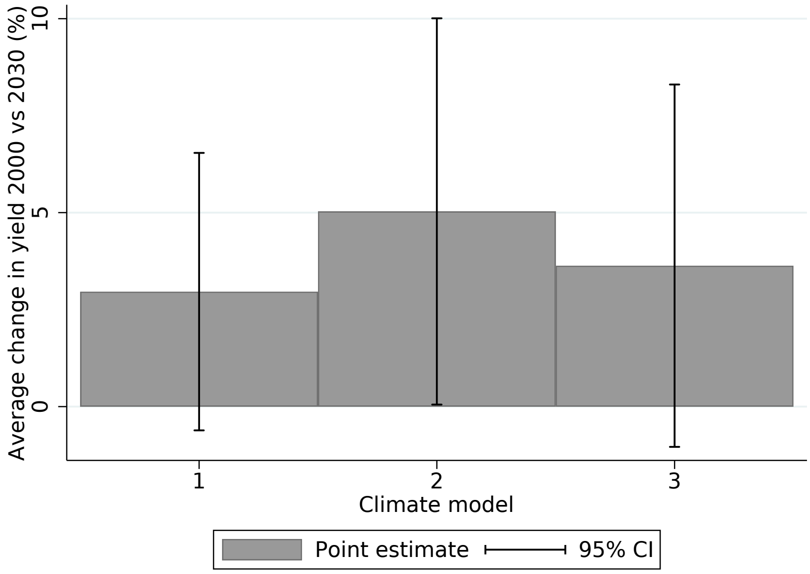
Figure 11: Province-by-province effect of climate on corn yield 2030-2000



Note: Models 1, 2 and 3 refer respectively to DMI-HIRHAM5-CHAM5, ETHZ-CLM-HadCM3Q0 and METO-HC-HadRM3Q0-HadCM3Q0. Effects are in percentage.

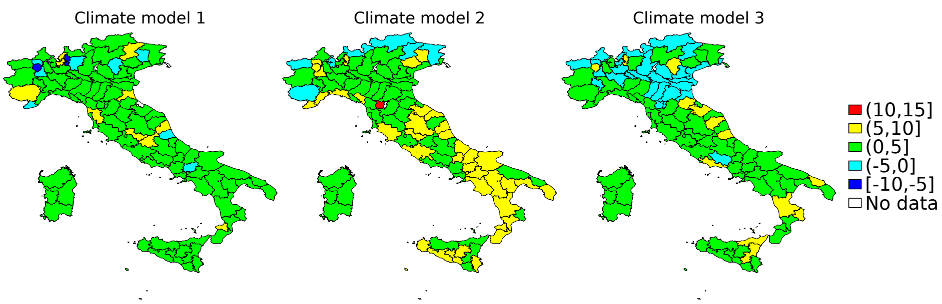
warming. Our results suggest that until 2030 the Italian durum wheat production is not endangered by climate change, and if anything agriculture productivity will be improving. Figure 13 presents the province-by-province projections: the only areas where the effect is negative are located in the North, where durum wheat production is low, while the effect is positive everywhere in the South.

Figure 12: Average effect of climate on durum wheat yield 2030-2000



Note: Models 1, 2 and 3 refer respectively to DMI-HIRHAM5-CHAM5, ETHZ-CLM-HadCM3Q0 and METO-HC-HadRM3Q0-HadCM3Q0.

Figure 13: Province-by-province effect of climate on durum wheat yield 2030-2000

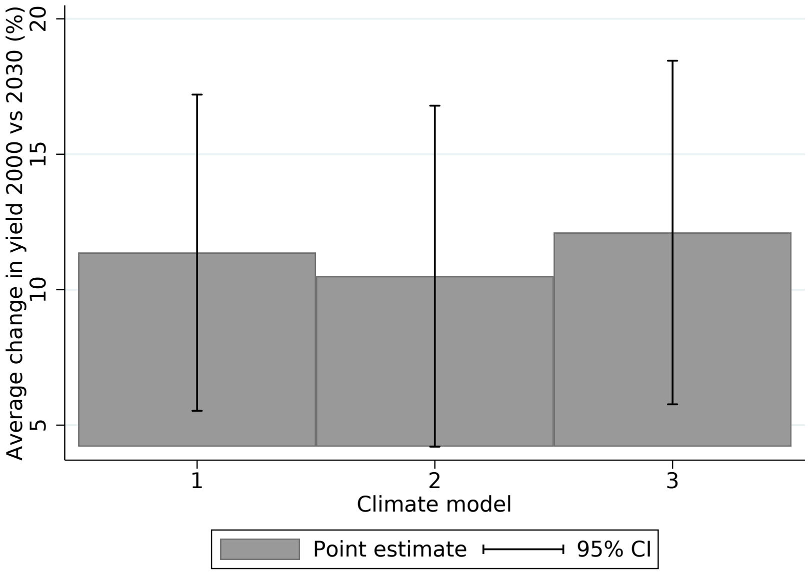


Note: Models 1, 2 and 3 refer respectively to DMI-HIRHAM5-CHAM5, ETHZ-CLM-HadCM3Q0 and METO-HC-HadRM3Q0-HadCM3Q0. Effects are in percentage.

Grapevine. Across the three climate models, the point estimates are remarkably similar and equal to approximately 11 per cent (see Figure 14). The results are similar across climate models because the KDD coefficient is small in absolute value; a small KDD coefficient does not project large differences in global warming into large differences in yields. Furthermore, very few provinces display drops in yields (blue areas in

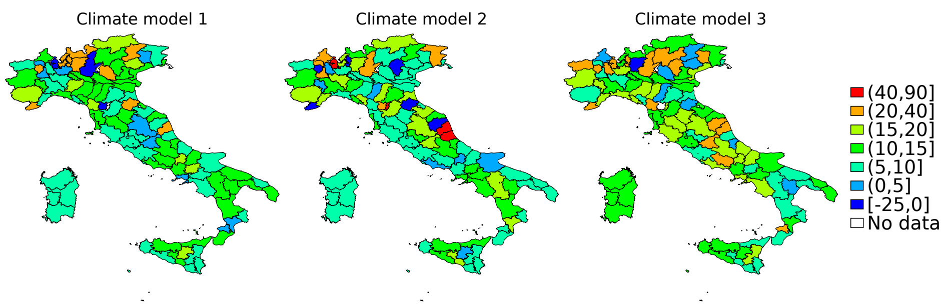
Figure 15) or increases larger than 20 per cent (orange and red areas).

Figure 14: Average effect of climate on grapevine yield 2030-2000



Note: Models 1, 2 and 3 refer respectively to DMI-HIRHAM5-CHAM5, ETHZ-CLM-HadCM3Q0 and METO-HC-HadRM3Q0-HadCM3Q0.

Figure 15: Province-by-province effect of climate on grapevine yield 2030-2000



Note: Models 1, 2 and 3 refer respectively to DMI-HIRHAM5-CHAM5, ETHZ-CLM-HadCM3Q0 and METO-HC-HadRM3Q0-HadCM3Q0. Effects are in percentage.

5 Conclusion

Climate change is likely to have detrimental effect on agriculture output at the global level. Using data over the period 2006-2019, we provide evidence that in Italy corn, durum wheat and, to a lesser extent, grapevine yields are increasing in temperature until approximately 30°, and decreasing thereafter. Under a moderate warming scenario (A1B), our estimates do not translate into a reduction in average yield over the period 2000-2030, likely because climate in these years is still to the left of the optimum peak. Our estimates necessarily imply that under more pessimistic scenarios and/or over longer horizons, the effect of global warming on Italian agriculture will become more negative.

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Appendix A Temperature graph

The graph is produced as follows:

- We fix a minimum temperature and calculate GDD and KDD for a range of maximum temperatures around bound max. In other words, these are the level GDD and KDD for a day with these temperatures.

- We take the difference in GDD and KDD between pairs of days characterized by 1° difference in maximum temperature. Define these differences as ΔGDD and ΔKDD

- We use the estimated coefficients to calculate the projected change in (log) yield induced by having one day with maximum temperature equal to $x°$ relative to one day with maximum temperature equal to $x - 1°$: $percent\Delta\, y = \beta_{GDD} \times GDD + \beta_{KDD} \times KDD$

- We fix the yield at the lowest maximum temperature equal to 100, and apply the $percent\Delta\, y$ cumulatively to all other maximum temperatures

Appendix B Adaptation

Table 5: Effect of weather on log corn yield

	Log corn yield	
GDD 12-29°	0.092***	0.090***
	(0.023)	(0.030)
GDD 12-29°X 2013-2019 (0/1)	-0.005	0.001
	(0.019)	(0.018)
KDD >29°	-0.430	-0.337
	(0.306)	(0.329)
KDD >29°X 2013-2019 (0/1)	0.150	-0.054
	(0.266)	(0.247)
Rain (cm)	0.005*	0.004
	(0.003)	(0.003)
Rain (cm) X 2013-2019 (0/1)	0.000	-0.001
	(0.002)	(0.002)
Rain (cm) X irrigable (0/1)	-0.002	-0.002
	(0.003)	(0.003)
Rain (cm) X irrigable (0/1) X 2013-2019 (0/1)	-0.002	-0.002
	(0.001)	(0.001)
Prov. FE	X	X
Year FE		X
N Obs.	1269	1269
R2	0.25	0.08

Note: Estimation via weighted linear regression; weights equal to the average surface devoted to corn. Conley standard errors (radius 300 km) in parentheses. The sample include 99 Italian provinces over the period 2006-2019. .

Table 6: Effect of weather on log durum wheat yield

	Log durum wheat yield	
GDD 2-28°	-0.016	0.033**
	(0.018)	(0.016)
GDD 2-28°X 2013-2019 (0/1)	0.023***	0.014**
	(0.009)	(0.007)
KDD >28°	-3.685***	-2.444*
	(1.093)	(1.459)
KDD >28°X 2013-2019 (0/1)	3.100	0.045
	(2.263)	(3.286)
Rain (cm)	-0.002	0.001
	(0.002)	(0.002)
Rain (cm) X 2013-2019 (0/1)	0.002	-0.001
	(0.002)	(0.002)
Rain (cm) X irrigable (0/1)	-0.002	-0.003
	(0.004)	(0.004)
Rain (cm) X irrigable (0/1) X 2013-2019 (0/1)	0.000	-0.000
	(0.002)	(0.002)
Prov. FE	X	X
Year FE		X
N Obs.	1187	1187
R2	0.09	0.03

Note: Estimation via weighted linear regression; weights equal to the average surface devoted to durum wheat. Conley standard errors (radius 300 km) in parentheses. The sample include 99 Italian provinces over the period 2006-2019. .

Table 7: Effect of weather on log grapevine yield

	Log grapevine yield	
GDD 2-32°	0.027*	0.078***
	(0.015)	(0.018)
GDD 2-32°X 2013-2019 (0/1)	0.013**	0.005
	(0.006)	(0.004)
KDD >32°	-0.535	-0.239
	(0.518)	(0.509)
KDD >32°X 2013-2019 (0/1)	0.956	1.854***
	(0.617)	(0.626)
Rain (cm)	0.000	-0.001
	(0.002)	(0.002)
Rain (cm) X 2013-2019 (0/1)	0.003*	0.003***
	(0.002)	(0.001)
Rain (cm) X irrigable (0/1)	0.003	0.002
	(0.002)	(0.002)
Rain (cm) X irrigable (0/1) X 2013-2019 (0/1)	-0.003***	-0.002***
	(0.001)	(0.001)
Prov. FE	X	X
Year FE		X
N Obs.	1390	1390
R2	0.09	0.08

Note: Estimation via weighted linear regression; weights equal to the average surface devoted to grapevine. Conley standard errors (radius 300 km) in parentheses. The sample include 99 Italian provinces over the period 2006-2019. .