Adaptation to Frost and Heat Risks in French Viticulture: Are Grape Growers Dumb Farmers?

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Adaptation to Frost and Heat Risks in French Viticulture: Are Grape Growers Dumb Farmers?

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Abstract

Climate change poses a threat to wine-grape production by increasing the risks of spring frost and heat. Understanding grape-growers' ability to adapt to these risks is crucial for determining the potential extent of damage. We combine data from a representative farm survey with a daily gridded weather database and employ a fixed-effect panel model to estimate the effects of frost and high temperatures on grape yield. Leveraging spatial variations in climate and temporal variations in weather, we assess whether the marginal negative effects of frost and heat are mitigated in frost- and heat-prone areas, implicitly testing for the presence of adaptation. Our findings indicate that frost and high temperatures adversely affect grape yields. However, growers in regions more susceptible to frost and heat shocks experience lower yield losses, suggesting adaptation to these risks. The extent of adaptation appears significant: growers with the highest frost (heat) climatology exhibit a reduction in the marginal negative effect of frost (heat) by 87% (89%) compared to those with the lowest climatology. Our study demonstrates the potential for substantial adaptations in French viticulture, challenging the notion of a "dumb farmer scenario" for grape growers in France.

Keywords: Adaptation, climate change, crop yields, wine grapes, agriculture, France.

JEL Codes: Q11, Q12, Q15, Q54

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1 Introduction

Agriculture is one of the sectors most exposed to climate change, and estimating its impact on agricultural production is crucial for determining the appropriate mitigation strategy. The preferred methodology involves regressing crop yields on year-to-year weather variations, conditionally on individual fixed effects, and uses these panel estimates to forecast the effect of climate change. Using this approach, several studies have found that climate change is likely to have deleterious effects on crop yields (e.g., Chen et al., 2016; Gammans et al., 2017; Roberts et al., 2013; Schlenker and Roberts, 2009; Tack et al., 2015; Welch et al., 2010; Zhang et al., 2017).

However, the panel approach has been criticized for its inability to account for the potential long-run adaptation that farmers may employ in response to climate change[1]. If farmers adapt in the long run—meaning if they adjust their practices to mitigate the adverse effects of individual weather shocks whose frequency is increasing with climate change[2]—damages from climate change could be overestimated. Hence, estimates of the impact of climate change on crop yields using the panel approach are reliable only under the assumption of no long-run adaptation, often referred to as the "dumb farmer scenario".

Building on the panel approach, recent studies have leveraged temporal variations in weather and spatial variations in climate to evaluate whether farmers in heat-prone areas experience weaker yield losses due to heat, with the implicit aim of estimating long-term adaptation[3]. If farmers experiencing a climate more prone to heat shocks have lower heat-induced yield losses, it suggests that adaptation to heat risk has occurred. Moreover, this approach allows for the estimation of the

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[1] Some studies suggest that introducing weather variables in quadratic forms allows for capturing long-term adaptation (e.g., McIntosh and Schlenker, 2006). However, the extent to which these estimates successfully capture it remains unclear (Carter et al., 2018).

[2] The terms ”climate” and ”weather” are related, but they represent two different concepts. Hsiang (2016) define weather as a random variable described by a probability distribution called climate.

[3] Other studies exploit temporal variations in climate to assess whether heat-induced yield losses decrease over time, with the same implicit aim (e.g., Lobell et al., 2014; Malikov and Miao, 2019; Roberts and Schlenker, 2011). Furthermore, these two approaches have been used outside of agriculture (e.g., Barreca et al., 2015, 2016; Hsiang and Narita, 2012).

cumulative effectiveness of all adaptation strategies, which are numerous, by quantifying the extent to which adaptation reduces the sensitivity of crop yield to high temperatures.[4]

Focusing on staple crop producers, these studies have yielded mixed results[5], with some studies documenting no adaptation (Gammans et al., 2017; Schlenker and Roberts, 2009) or limited adaptation capacities (Taraz, 2018), while others have provided evidence of strong adaptive adjustments (Butler and Huybers, 2013; Keane and Neal, 2020). Thus, the question of whether and to what extent adaptation occurs in agriculture remains open, and further research is needed.

In this paper, we contribute to the emerging literature that seeks to assess the extent of farmers' adaptation by investigating whether grape growers in France are adapted to the risks of spring frost and high temperatures. To the best of our knowledge, no study has addressed the issue of adaptations in the wine sector, despite its considerable economic and cultural importance worldwide. This is particularly true in France, one of the world's top wine producers and exporters, where wine production accounts for over 15 percent of agricultural production in value and supports nearly 500,000 direct and indirect jobs (CNIV, 2019).

We focus on frost and heat risks because exposure to high temperatures is expected to increase with climate change, while the risk of late frost is anticipated to be higher for the northeast wine-producing regions of France (Sgubin et al., 2018). Both of these risks have the potential to negatively impact the profitability of grape production by reducing grape yields and wine quality (Van Leeuwen et al., 2019). It is thus essential to estimate whether grape growers are adapted to these risks in order to obtain reliable estimates of the impact of climate change on grape-growing profitability.

Unlike staple crops, where agricultural revenues are largely driven by yields, revenues from wine-growing production also depend on grape quality (Van Leeuwen and Darriet, 2016; Van Leeuwen

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[4] This benefit is achieved at the cost of ignoring the mechanisms through which farmers have adapted. Another strand of the literature focuses on this issue by explicitly regressing variables expected to adjust on climate or weather fluctuations (e.g., Amare and Balana, 2023; Aragón et al., 2021; Bareille and Chakir, 2023; Cui, 2020; Cui and Xie, 2022; Seo and Mendelsohn, 2008; Sesmero et al., 2018; Wang et al., 2010).

[5] The literature exploiting temporal variations in climate has also yielded mixed results. For example, Roberts and Schlenker (2011) find that the detrimental effect of extreme heat on staple crop yields has decreased since 1960 in the U.S., while Lobell et al. (2014) show that corn yields are increasingly sensitive to drought.

et al., 2019). Thus, we expect that adaptations in grape production will help mitigate the negative impact of adverse weather shocks not only on yields but also on quality. In this paper, we focus on assessing the extent of adaptations that reduce the adverse effects of spring frost and high temperatures on grape yield, leaving aspects related to quality for future research.

Methodologically, we combine data from a representative farm survey with a daily gridded weather database to estimate the effects of frost and heat on grape yields. Subsequently, we leverage temporal variations in weather and spatial variations in climate to assess whether grape growers in regions prone to spring frost and high temperatures are adapted to these risks. This is achieved by interacting our frost and heat variables with their climatologies. If adaptation to these risks occurs—meaning if grape growers experiencing a climate more prone to frost and heat adjust to mitigate the negative effects of those shocks on grape yield—then frost-induced and heat-induced yield losses should be weaker for grape growers in frost-prone and heat-prone areas. Then, we quantify the degree of adaptation by comparing the sensitivity of yield to frost and heat among growers experiencing different climatologies.

We find two main results. First, our models reveal that the relationship between temperature and grape yield is highly non-linear. Grape yields increase weakly with moderate temperatures until 29°C, but sharply decrease with higher temperatures beyond this optimal range. Specifically, our preferred model indicates that shifting 24 hours of temperatures from 29°C to 39°C reduces grape yield by approximately 3.4%. The frost-induced yield losses are also significant, with each additional negative °C decreasing grape yield by approximately 4.8%. Second, we find that grape growers are strongly adapted to spring frost and heat risks. The negative marginal effect of spring frost (heat) on grape yields is weaker for grape growers in frost-prone (heat-prone) areas. Specifically, the sensitivity of yield to spring frost (heat) for the most exposed grape producer is lower by approximately 87% (89%) compared to the yield sensitivity of the least exposed producer.

We make the following contributions. Firstly, we are the first to estimate the extent of adaptation among grape growers. Previous studies focus on adaptation among staple crop producers, while some others focus on determining the relationship between grape yield and weather without investigating whether grape growers are adapted to it (e.g., Chevet et al., 2011; Lobell et al., 2007; Niklas, 2017). Secondly, our study is the first to consider adaptation to frost risk. Earlier studies have mainly focused on determining the extent of adaptation to heat risk. Thirdly, we provide the first grape-specific estimates of the impact of weather on yields on a large scale in France. Chevet et al. (2011) demonstrate that wine prices and yields depend on weather conditions, but their findings are difficult to generalize as they focus on a single château in Bordeaux. Finally, our study is the first to link grape yield to heat using the degree-day approach. Previous studies focusing on grape yields rely on average temperatures which may fail to fully account for the effect of extreme temperatures (Ashenfelter and Storchmann, 2016).

The rest of the paper is organized as follows. Section 2 presents the data and gives summary statistics. Section 3 describes our empirical method, and Section 4 presents our main results. In Section 5, we run several robustness checks. Finally, we conclude and discuss the limitations of our study and future research in Section 6.

2 Data

We merge a representative farm survey with a daily gridded weather database with fine resolution to create a dataset encompassing grape yields and weather variables for the years 2002-2021.

2.1 Dependent variable

We obtain grape yields for the years 2002-2021 using the French Farm Accountancy Data Network (FADN)[6], a representative farm survey at the national level in France. This database contains annual accounting records from commercial farms exceeding a certain size threshold[7]. These farms are sampled over multiple years, typically around five, resulting in datasets characterized by un-

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[6] While data on grape yields has been available since 1968, we chose to restrict the sample to the years 2002-2021. This decision was made because the FADN began reporting the municipality where each farm has its headquarters in 2002. Prior to 2002, the smallest available location scale was the department, which did not allow for a precise linkage of farm-level grape yields with weather conditions.

[7] The farm size has to be large enough to constitute the primary source of income for the farmer and generate sufficient revenue to sustain the livelihood of the farmer's family.

balanced panels. We restrict the sample to farms specialized in viticulture[8], resulting in 12,978 observations.

Grape yields are calculated as farm-level grape production divided by the hectares of vineyards under production. **Table 1** reports descriptive statistics for grape yields:

Table 1: Descriptive Statistics: Grape Yields

	Mean	Std.Dev.	Min	Max
Yield (100kg/Ha)	76.16	32.88	0.00	244.72

Few observations (less than five) of grape yields are recorded as 0, which is unusually low. We exclude these observations from the sample, but our results remain unchanged even when included. Additionally, we retain grape yields from irrigated vineyards[9]. However, considering that irrigation may not be a sustainable adaptation strategy (Van Leeuwen et al., 2019), we conduct a robustness check of our results by only considering grape yields from dry-farmed vines in Section 5.

Figure 1 reports the evolution of the mean grape yield over time:

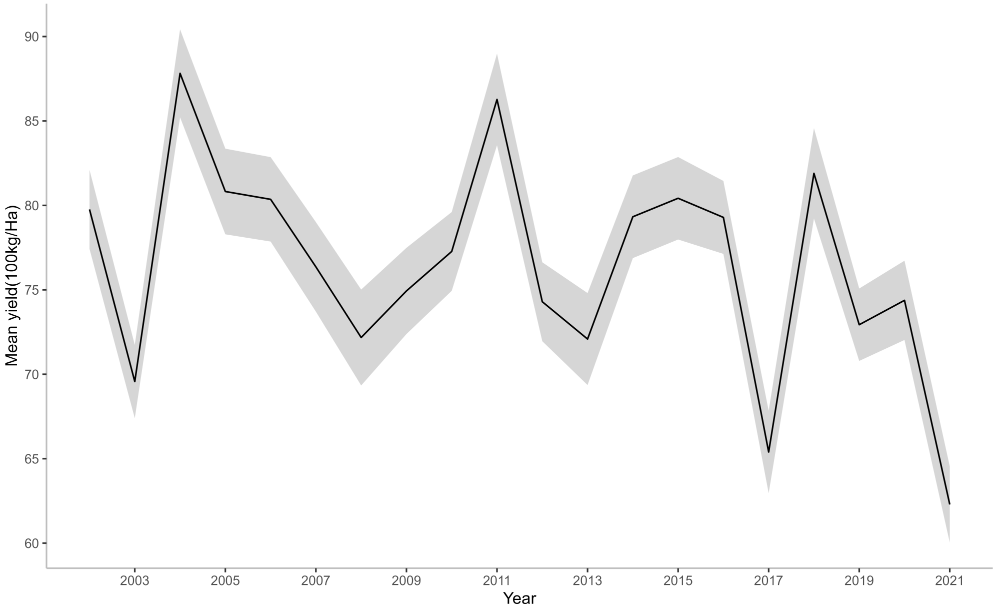

Figure 1: Mean Grape Yield Over Time

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[8] It implies that viticulture constitutes the primary source of their potential agricultural revenues.

[9] Vines are primarily dry-farmed in France, although a minority of grape growers use irrigation, particularly in the Mediterranean basin.

Figure 1 suggests that spring frost and heat are detrimental to grape yields. The mean grape yield was at its lowest in the years 2017 and 2021, coinciding with significant spring frost episodes, and relatively low in 2003, coinciding with a significant heat wave. Our econometric model will help determine if this correlation can be interpreted as a causal effect. If so, climate change has the potential to negatively affect grape yield by increasing the risks of spring frost and heat. However, the extent of the potential damages will depend on whether grape growers adapt.

2.2 Weather variables

We use weather information from the SAFRAN database, which provides daily weather data on 8 km × 8 km grid squares for France, to construct several weather indicators, including heat and frost indicators, at the grid cell level. Then, we associate each farm with the grid cell containing the centroid of the municipality where its headquarters are located, along with the corresponding weather indicators.

We first calculate weather variables on a daily basis before aggregating them over the growing season. We define the growing season as the period from April 1st to September 30th, as budbreak generally occurs from late March to mid-April, and harvest often takes place in mid-September in France. Given that we use grape yield data for the years 2002-2021, this process is repeated for 20 growing seasons spanning from 2002 to 2021.

2.2.1 Capturing the effects of extreme heat

Previous studies use average temperature over the growing season to estimate the effect of heat on grape yields (e.g., Chevet et al., 2011; Niklas, 2017). By averaging temperatures over a specific period, these studies may not fully account for the effects of extreme heat[10]. Early studies estimating the impacts of climate change on staple crop outcomes have faced similar criticism (e.g., Deschênes and Greenstone, 2007).

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[10] See Ortiz-Bobea (2021) and Schlenker and Roberts (2009) for a further discussion about the drawbacks of relying on average temperatures.

In response, later work specified temperature variables using the agronomic definition of degree days. Schlenker et al. (2006) and Schlenker and Roberts (2009) demonstrate that models using such variables are better at predicting the effects of climate change compared to those relying on average temperatures.

We build on the degree day approach and construct an indicator of extreme heat, denoted as Killing Degree-Days (*KDD*), frequently used in this literature. Its construction involves calculating first the Degree-Days (*DD*), which quantify the accumulation of heat above a specified temperature threshold on a daily basis.

We follow Schlenker and Roberts (2009) and use a sinusoidal interpolation of temperature exposure within each day to calculate Degree-Days with threshold b at grid cell g for day d of growing-season t:

$$DD_{gdt;b} = \begin{cases} 0 & \text{if } T_{\max} \leq b \\ T_{\text{avg}} - b & \text{if } b \geq T_{\min} \\ \frac{(T_{\text{avg}}-b)S+(T_{\max}-T_{\min})sin(S)/2}{\pi} & \text{if } T_{\max} > b \text{ and } T_{\min} < b \end{cases} \tag{1}$$

where $T_{\min}$ ($T_{\max}$) is the minimum (maximum) temperature observed at grid cell g in day d of growing season t, $T_{\text{avg}} = \frac{T_{\max}+T_{\min}}{2}$ and $S = cos^{-1}(\frac{2b-T_{\max}-T_{\min}}{T_{\max}-T_{\min}})$. $DD_{gdt;b}$ represents the accumulation of heat above b°C experienced on day d of growing season t at grid cell g[11].

Then, we compute Killing Degree-Days (*KDD*), which is the total accumulation of heat above a given temperature threshold b during the growing season t. Thus, it is simply the sum of daily degree-days associated with that threshold over the growing season:

$$KDD_{gt;b} = \sum_{d=1}^{183} DD_{gdt;b} \tag{2}$$

For a sufficiently high temperature threshold b, we expect *KDD* to capture adverse weather

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[11] There are 183 days between April 1st and September 30th. Thus, $DD_{g,1,2002;b}$ represents the heat accumulation above b°C experienced at grid cell g on April 1st, 2002. In the same way, $DD_{g,183,2021;b}$ is the heat accumulation above b°C observed at grid cell g on September 30th, 2021.

conditions for grape yields, such as water and heat stress. Schlenker and Roberts (2009) found that the temperature threshold above which heat accumulation becomes detrimental is 29°C for corn yields. Thus, subsequent studies focusing on the effect of heat on corn yields have typically chosen a value of *b* around 29°C for *KDD* (e.g., Baltagi et al., 2023; Butler and Huybers, 2013; Keane and Neal, 2020).

However, since the temperature threshold is crop-specific[12] and our study is the first to estimate the effect of heat on grape yields using the degree days approach, we employ a data-driven approach frequently used in the literature to determine the optimal value of *b* (see Section 3 for further details).

We also construct Growing Degree-Days (*GDD*), an indicator commonly used alongside *KDD* to avoid confounding the effect of extreme heat with those of moderate heat. *GDD* is calculated as follows:

$$GDD_{gt;b} = \sum_{d=1}^{183} DD_{gdt;10} - \sum_{d=1}^{183} DD_{gdt;b} \tag{3}$$

Thus, it denotes the total accumulation of heat between 10°C and *b*°C during the growing season[13]. We expect *GDD* to be positively related to grape yields, as vine growth requires sustained moderate warmth exposure (Spellman, 1999).

2.2.2 Capturing the effects of frost

Most of the studies focusing on estimating the effects of weather on staple crop yields have neglected the role of frost. A notable exception is Tack et al. (2015), who find that freezing temperatures are one of the largest drivers of yield losses. To capture frost, we sum the absolute values of negative temperatures experienced during the growing season. Daily *FROST* at grid cell *g* for day *d* of growing season *t* is given by:

$$FROST_{gdt} = |min(0; T_{\min})| \tag{4}$$

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[12] For instance, Schlenker and Roberts (2009) found that the temperature threshold for soybean is 30°C, while it is 32°C for cotton.

[13] When the temperature is below 10 °C, most of the grapevine physiological processes decline (Venios et al., 2020).

We then sum daily $FROST$ values over the growing season to obtain the accumulation of negative temperatures during that period:

$$FROST_{gt} = \sum_{d=1}^{183} FROST_{gdt} \tag{5}$$

We expect $FROST$ to be negatively related to grape yields because spring frost is known to cause significant damage to young leaves and emerging flower clusters (Spellman, 1999).

Table 2 reports descriptive statistics for these three weather variables, with *GDD* and *KDD* calculated using a temperature threshold of 29°C:

Table 2: Descriptive Statistics: Weather Indicators

Variable	Mean	Std.Dev.	Minimum	Maximum
FROST	0.52	1.77	0.00	23.60
GDD	1573.22	246.07	819.33	2156.97
KDD	35.82	31.47	0.00	243.10

2.2.3 Exploiting spatial variations in climate

To estimate the extent of adaptation to frost and heat risks, our empirical approach relies on determining whether frost-induced and heat-induced yield losses are lower for grape growers in frost- and heat-prone areas. Therefore, we need variables that capture the frequency of freezing and extreme heat for each area.

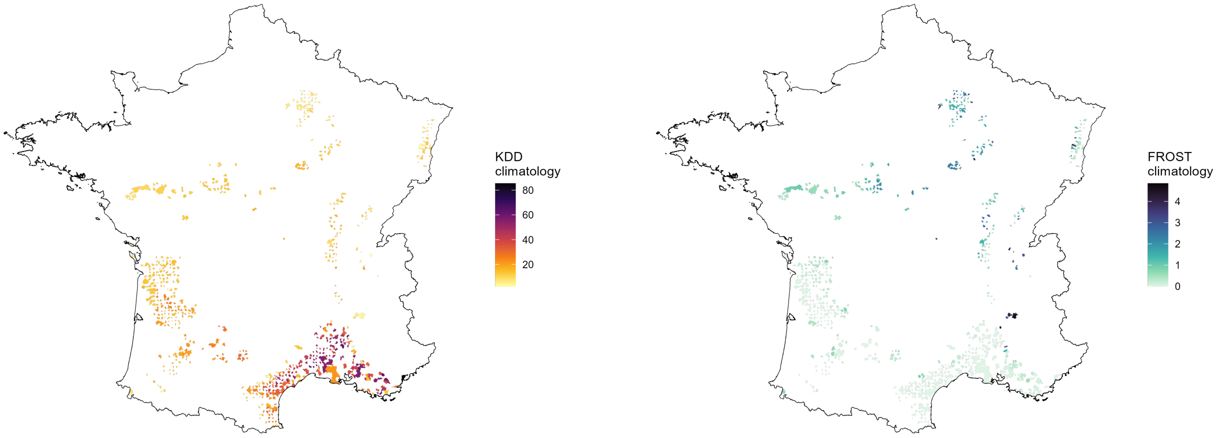
We draw on previous studies that leverage spatial variations in climate to assess the extent of adaptation (e.g., Butler and Huybers, 2013; Hsiang and Narita, 2012) to obtain such indicators. We calculate $FROST$ and KDD climatologies for each grid cell g as the long-run averages of their weather counterparts:

$$\overline{KDD}_{g;b} = \frac{\sum_{t=2002}^{2021} KDD_{gt;b}}{20} \tag{6}$$

$$\overline{FROST}_{g} = \frac{\sum_{t=2002}^{2021} FROST_{gt}}{20} \tag{7}$$

where $\overline{KDD}_{g;b}$ and $\overline{FROST}_g$ are respectively the climatologies of KDD and $FROST$ at grid cell g. It is standard in the literature to consider the climatology of an indicator as a proxy for its probability of occurrence (e.g., Hsiang and Narita, 2012). Thus, a unit whose $FROST$ (KDD) climatology is high is more $FROST$-prone (KDD-prone) compared to a unit whose $FROST$ (KDD) climatology is low.

Figure 2 illustrates the spatial variations of KDD and $FROST$ climatologies across France.



(a) KDD climatologies

(b) FROST climatologies

Figure 2: Spatial Variations of Climatologies

As expected, grape growers in the southern wine-producing regions, such as Languedoc, Provence, and the Rhône Valley, frequently face heat shocks, while grape growers in the northern ones, such as Alsace, Burgundy, Champagne, and the Loire Valley, regularly experience episodes of frost. In Section 3, we explain in greater detail how we exploit this spatial heterogeneity in climate to estimate the extent of adaptation to frost and heat risks.

3 Methodology

Our empirical objective is to assess whether grape growers adapt to frost and heat risks and, if so, to simultaneously estimate the cumulative efficiency of all adaptation strategies. We address both of these questions by drawing upon the literature that leverages spatial variations in climate to evaluate the extent of farmer adaptation.

This methodology involves proceeding in two steps. Firstly, we estimate the effects of frost and heat on grape yields using the standard panel approach. Secondly, we exploit the spatial heterogeneity in frost and heat climatologies to assess whether and to what extent the marginal negative effect of frost and heat on grape yields is weaker for grape growers located in frost- and heat-prone areas.

3.1 Linking frost and heat to grape yield

We built on the standard panel approach to model the effect of frost and heat on grape yields. Using this methodology, and based on the agronomic concept of degree-days, previous studies have shown that the relationship between staple crop yields and temperature is highly non-linear (e.g., Schlenker and Roberts, 2009; Tack et al., 2015). In general, it has been found that freezing temperatures are damaging to crop yield, while exposure to moderate temperatures is beneficial to crop growth until reaching a crop-specific threshold, above which heat accumulation begins to be detrimental. To determine the optimal value of this temperature threshold, we model grape yield as a piecewise linear function of heat accumulation:

$$y_{igt} = f_i + \beta_1 FROST_{gt} + \beta_2 GDD_{gt;l_1} + \beta_3 KDD_{gt;l_1} + \beta_{41} t + \beta_{42} t^2 + \varepsilon_{igt} \tag{8}$$

where y_{igt} is log yield for farm i, associated with weather grid cell g, at the end of growing season t. $FROST_{gt}$ is our freezing temperatures indicator, which is the sum of negative temperatures experienced during the growing season t at grid cell g. $GDD_{gt;l_1}$ stands for Growing Degree-Days, which is the accumulation of heat between 10°C and l_1°C during the growing season t at grid cell g.

$KDD_{gt;l_1}$ is Killing Degree-Days, which is the accumulation of heat above l_1°C during the growing season t at grid cell g. l_1 is the optimal temperature threshold beyond which heat accumulation is expected to become damaging to grape yield. In the estimation, we allow the data to determine l_1 by looping over all possible thresholds between 11°C and 40°C and selecting the model with the highest R-squared[14].

The model includes farm fixed effects f_i to account for all unobserved farm-specific, time invariant determinants of grape yield, such as soil quality and farmer management ability. By conditioning on farm fixed effects, weather parameters are identified using variations in farm-specific deviations of weather about unit averages. Given that our dependent variable is in log, these are semi-elasticities. β_1 is the percentage change in grape yields caused by an additional negative degree. Similarly, β_2 represents the percentage change of grape yields resulting from an additional growing degree-day. Lastly, β_3 denotes the percentage change of grape yields observed after an additional killing degree-day. We expect $\beta_1 < 0$ and $\beta_3 < 0$ since $FROST$ captures spring frost and KDD captures water and heat stress, both known to impact grape yield negatively. Conversely, we expect $\beta_2 > 0$ since exposure to moderate temperatures is crucial for vine development[15].

The equation also includes a linear and quadratic time trend at the national level $\beta_{41}t + \beta_{42}t^2$ to control for the effect of technical progress. This specification has been widely used in the literature focusing on the effects of weather on agriculture (e.g., Gammans et al., 2017; Schlenker and Roberts, 2009; Tack et al., 2015). Another strand of this literature uses year-fixed effects to remove the unobserved factors common to all units in a given year (e.g., Annan and Schlenker, 2015; Chen et al., 2016; Keane and Neal, 2020; Taraz, 2018). We do not use year-fixed effects because extreme weather events are correlated across units. In this case, adding time effects would leave too little meteorological variation to obtain a precise identification of the effects of extreme events on yields

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[14] The same methodology has been used by Burke and Emerick (2016) and Schlenker and Roberts (2009) to determine the optimal temperature threshold for staple crop yields. The only difference is that both of these studies only include *GDD* and *KDD*.

[15] By incorporating three different variables to model the effects of temperatures on grape yields, we address the criticism often directed towards studies that solely rely on average temperature, which tends to diminish the impact of extreme temperatures. Moreover, **Equation (8)** enables the effects of moderate and high temperatures to be asymmetric on yields, whereas studies using average temperature with a squared term assume the effect of temperature to be symmetric around the threshold.

(Ortiz-Bobea, 2021).

Finally, it is conventional in the literature assessing the effect of weather on agricultural outcomes to assume that the error terms ε_{igt} are spatially correlated across units, with the correlation likely to be positive (e.g., Auffhammer et al., 2013; Bareille and Chakir, 2023; Gammans et al., 2017). In this case, adopting simple heteroscedasticity robust standard errors is not sufficient and leads to incorrect inference, resulting in estimated standard errors that are narrower than they truly are (Ortiz-Bobea, 2021). To address this issue, standard errors are clustered at the department level, which is a common solution adopted in the literature (e.g., Annan and Schlenker, 2015; Taraz, 2018; Wang et al., 2021).

3.2 Estimating the extent of adaptation

Weather parameters in **Equation (8)** are identified using presumably random year-to-year weather variations, thus possessing strong identification properties. Consequently, numerous studies have employed panel estimates similar to those in **Equation (8)** to forecast the impacts of climate change on agricultural outcomes (e.g., Deschênes and Greenstone, 2007; Gammans et al., 2017; Schlenker and Lobell, 2010; Schlenker and Roberts, 2009; Welch et al., 2010).

However, **Equation (8)** does not account for the effects of long-term adaptations, which necessitate a longer time period than a year to be implemented. Therefore, estimates of the effects of climate change based on **Equation (8)** may be misleading if farmers adapt in the long run, underscoring the critical need to assess the extent of long-term adaptation.

More recent studies rely on an augmented version of **Equation (8)** and leverage spatial variation in climate to assess whether heat-induced yield losses are weaker for farmers located in heat-prone areas, with the implicit purpose of testing for the presence of long-run adaptation (e.g., Butler and Huybers, 2013; Keane and Neal, 2020).

This strategy is based on the premise that if farmers adapt to heat shocks—meaning that those experiencing a climate more prone to heat adjust their practices to reduce the sensitivity of crop yield to this hazard—then the marginal negative effect of heat should be weaker for farmers located in heat-prone areas. Thus, demonstrating that heat-induced yield losses are lower for farmers located in heat-prone areas compared to those experiencing a climate less prone to heat would suggest the presence of long-run adaptation.

Moreover, by quantifying the difference in crop yield sensitivity to heat between farmers experiencing different heat climatologies, this approach allows for the estimation of the cumulative efficiency of all adaptation strategies. This is crucial for determining whether adaptation will help cope with climate change.

We built on this approach and present the following model, a modified version of **Equation (8)**, to implicitly estimate whether grape growers are adapted to frost and heat risk:

$$
\begin{aligned}
y_{igt} = f_i + \beta_{11} FROST_{gt} + \beta_{12} FROST_{gt} \times ln(\overline{FROST}_g) + \beta_2 GDD_{gt;l_1} + \\
\beta_{31} KDD_{gt;l_1} + \beta_{32} KDD_{gt;l_1} \times ln(\overline{KDD}_{g;l_1}) + \beta_{41} t + \beta_{42} t^2 + \varepsilon_{igt} \quad (9)
\end{aligned}
$$

where $\overline{FROST}_g$ is the climatology of $FROST$ calculated at grid cell g and $\overline{KDD}_{g:l_1}$ is the climatology of KDD calculated at grid cell g.

Equation (9) allows for the comparison of the negative marginal effect of frost and heat across units experiencing different climatologies and is well suited to provide indirect evidence of adaptation. This specification implies that the negative marginal effects of $FROST$ and KDD are a non-linear function of their climatologies :

$$\frac{\partial y_{igt}}{\partial FROST_{gt}} = \beta_{11} + \beta_{12} \ln(\overline{FROST}_g) \quad (10)$$

$$\frac{\partial y_{igt}}{\partial KDD_{gt;l_1}} = \beta_{31} + \beta_{32} \ln(\overline{KDD}_{g:l_1}) \quad (11)$$

As explained in the previous subsection, we expect $\beta_{11} < 0$ and $\beta_{31} < 0$ since spring frost and high temperatures are expected to be detrimental to grape yield. Our coefficients of interest are β_{12} and β_{32}. If $\beta_{12} > 0$ and $\beta_{32} > 0$, the negative marginal effects of $FROST$ and KDD shrink, albeit at a decreasing rate, as their climatologies increase. In simpler terms, this would imply that frost-and heat-induced yield losses are lower for grape growers located in frost- and heat-prone areas compared to those experiencing a climate less prone to frost and heat, when facing similar frost and heat shocks.

This would suggest that grape growers adapt to frost and heat risks. Growers more susceptible to $FROST$ or KDD have greater incentives to adapt than those less prone to these extreme weather shocks. Consequently, grape yields of the former have to be less negatively affected than those of the latter when facing similar weather hazards.

Moreover, β_{11} and β_{31} represent the reduction in grape yield sensitivity to frost and heat, respectively, measured in percentage points, following a 1% increase in frost and heat climatologies. Consistent with previous studies, we assume that this reduced yield sensitivity is entirely attributable to adaptation[16]. Thus, β_{11} and β_{31} serve as our measure of the cumulative effectiveness of all adaptation strategies.

4 Results

4.1 Impacts of frost and heat on grape yields

We begin by estimating **Equation (8)** over the chosen thresholds. The threshold with the best fit for our full sample is 29°C[17]. Tabular results of the preferred model are reported in column (1) of **Table 3**. As anticipated, both frost and heat have detrimental effects on grape yields. More specifically, an additional negative °C during the growing season is associated with a 3.1% yield reduction, while shifting 24 hours of temperatures from 29°C to 39°C decreases grape yield by approximately 2.3%[18]. Additionally, we find that grape yields increase weakly with exposure to

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[16] As highlighted by Keane and Neal (2020), this methodology captures both active adaptation by growers, such as the adoption of heat-tolerant grape varieties or frost protection instruments, and natural adaptation. Accounting for both types of adaptation is crucial for obtaining an unbiased estimate of the impact of climate change.

[17] In Section 5, we conduct a robustness check by considering alternative temperature thresholds.

[18] However, upon comparing the KDD coefficients from previous studies (e.g., Burke and Emerick, 2016; Keane and Neal, 2020; Schlenker and Roberts, 2009), we observe that the sensitivity of grapevines to heat appears to be lower than that of corn. This observation aligns with expectations, considering that grapevines are generally considered relatively drought-tolerant species. Nonetheless, our findings demonstrate that high temperatures still have a negative impact on grape yields.

moderate temperatures, as one additional growing degree-day is associated with a yield increase of approximately 0.04%[19].

Our results highlight that climate change has the potential to negatively affect grape yields, as climate change is expected to increase the risks of spring frost and heat. However, the magnitude of potential damages will ultimately depend on whether growers adapt to these risks. To gain insight into the existence of adaptation to frost and heat risks, we divide our full sample into two sub-samples and re-estimate **Equation (8)** for each. The first sub-sample comprises grape growers experiencing cooler climates, while the second comprises growers experiencing hotter climates[20]. If grape growers can adapt to frost and heat risks, we expect frost-induced (heat-induced) yield losses to be lower in the cooler (hotter) sample.

Table 3: FE-OLS estimates of the impacts of temperature on grape yields

	(1) Full sample	(2) Cool	(3) Hot
FROST	-0.031***	-0.027***	-0.05**
	(0.004)	(0.004)	(0.02)
GDD	0.0005***	0.00069***	0.00044**
	(0.0001)	(0.00011)	(0.00016)
KDD	-0.0023***	-0.0059***	-0.0017***
	(0.0004)	(0.0010)	(0.0005)
R^2	0.689	0.726	0.610
Observations	12978	6460	6518

The dependent variable is the logarithm of grape yield. All regressions include a linear and quadratic national time trend and farm fixed effects. Standard errors are clustered at the department level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Column (2) of **Table 3** reports the regression results for the cooler sample, while Column (3) reports those of the hotter sample. The negative slope associated with $FROST$ is less steep in the

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[19] Schlenker and Roberts (2009) also observed a similar asymmetry between the effects of growing degree days and killing degree days on staple crop yields.

[20] To classify grape growers into the cold or hot sample, we calculate the climatology of the average temperature over the growing season for each grower. We then compare the average temperature climatology with the median of the distribution of average temperature climatologies. If a grower's average temperature climatology is below (above) the median, they are classified as cold (hot).

cooler sample, while the slope associated with *KDD* is less steep in the hotter sample. Therefore, grape growers experiencing cooler climates have lower frost-induced yield losses, while heat-induced yield losses are lower for growers experiencing hotter climates. These results suggest that adaptation to frost and heat risks has occurred to a considerable extent. Specifically, the negative marginal effect of *FROST* for the cooler sample is approximately 49% lower than that for the hotter sample, while the negative marginal effect of *KDD* for the hotter sample is approximately 72% lower than that for the cooler sample.

These preliminary results suggest that grape growers are strongly adapted to frost and heat risks. However, the methodology employed does not allow for testing the statistical difference of the *FROST* and *KDD* coefficients between both samples. Additionally, it's important to note that our results may be influenced by the way we decide to split our original sample. In subsection 4.2, we aim to address these limitations by employing a more rigorous methodology to estimate the extent of adaptation.

4.2 Adaptation to frost and heat risks

Table 4 presents coefficient estimates for **Equation (9)**. All of our coefficients of interest are statistically significant, indicating that both *FROST* and *KDD* affect grape yields and that yield sensitivity to *FROST* and *KDD* depends on *FROST* and *KDD* climatologies. According to **Equation (9)**, the average marginal effect of *FROST* is -0.0482, implying that an additional negative °C reduces yields by 4.82%, while the average marginal effect of *KDD* is -0.0034, implying that an additional killing degree-day decreases yields by 0.34%[21]. We observe that the average marginal effects of *FROST* and *KDD* obtained by estimating **Equation (9)** are higher compared to those reported by **Equation (8)**, thereby highlighting the substantial bias of the standard fixed-effects model that ignores adaptation[22].

However, even if **Equation (9)** shows that the average marginal effects of *FROST* and *KDD*

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[21] We calculate the average effects of *FROST* and *KDD* by employing **Equation (10)** and **Equation (11)**, using the estimated coefficients from **Table 4** while fixing *FROST* and *KDD* climatologies to their respective means.

[22] Keane and Neal (2020) found a similar result and provides mathematical evidence for the bias of the standard fixed-effects model when adaptation occurred.

Table 4: FE-OLS estimates of the impacts of temperature on grape yields: with adaptation

	(1)
FROST	-0.061***
	(0.011)
FROST$\times ln(\overline{FROST})$	0.030***
	(0.008)
GDD	0.00058***
	(0.00009)
KDD	-0.010***
	(0.003)
KDD$\times ln(\overline{KDD})$	0.0020**
	(0.0007)
R^2	0.691
Observations	12978

The dependent variable is the logarithm of grape yield. All regressions include a linear and quadratic national time trend and farm fixed effects. Standard errors are clustered at the department level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

are higher than those highlighted in **Equation (8)**, it also induces that the marginal negative effect of $FROST$ (*KDD*) is lower for grape growers experiencing higher $FROST$ (*KDD*) climatologies. Specifically, a 1% increase in $FROST$ (*KDD*) climatology reduces the marginal negative effect of $FROST$ (*KDD*) by approximately 3 (0.2) percentages points. Put simply, frost- and heat-induced yield losses are lower for grape growers in frost- and heat-prone areas.

Our findings are illustrated in **Figure 3**, which displays the spatial distribution of $FROST$ and *KDD* sensitivities across France[23]. **Figure 3** illustrates that the marginal effects of $FROST$ and *KDD* remain negative for all grape growers in France, suggesting that adaptation to frost and heat risks is costly. However, it also highlights substantial variations in $FROST$ and *KDD* sensitivities across the country. Specifically, the negative marginal effect of *KDD* is less detrimental in the Southern wine-producing regions, such as Languedoc, Provence, and the Rhône Valley. In contrast, $FROST$ sensitivities tend to display the opposite pattern. Frost-induced yield losses are lower for

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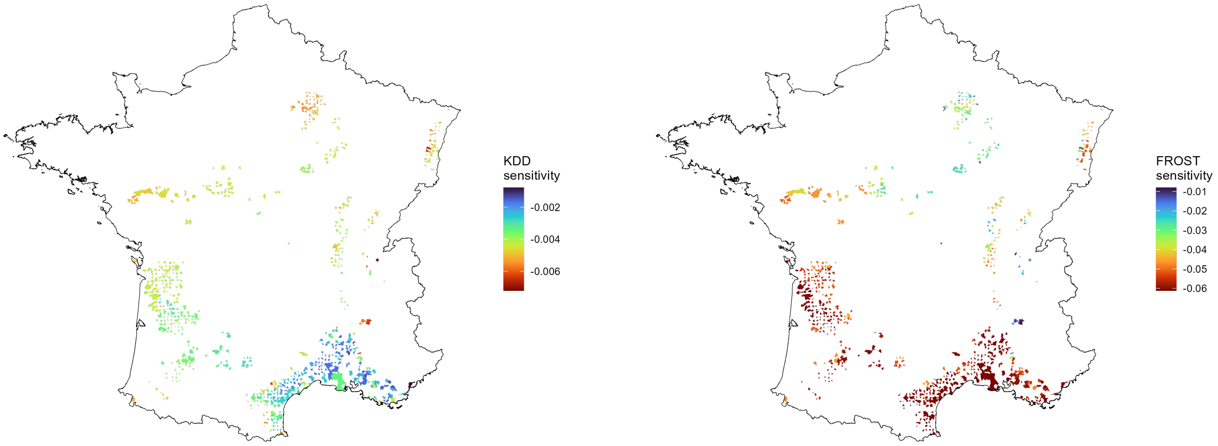
[23] $FROST$ and *KDD* sensitivities are calculated using **Equation (10)** and **Equation (11).**



(a) KDD sensitivities

(b) FROST sensitivities

Figure 3: Spatial Variations of Sensitivities

the Northern wine-producing regions of France, such as Burgundy and Champagne.

Adaptation emerges as the most plausible explanation for this result. Grape growers experiencing climates more prone to frost and heat have higher incentives to adapt to these risks. Consequently, frost- and heat-induced yield losses are lower for growers in frost- and heat-prone areas. Moreover, the extent of adaptation is considerable. For instance, adaptation allows for the $FROST$ (KDD) sensitivity of the grape grower experiencing the highest $FROST$ (KDD) climatology to be lower by approximately 87% (89%) compared to that of the grower experiencing the lowest $FROST$ (KDD) climatology.

Our results demonstrate that grape growers in France are strongly adapted to frost and heat risks. In the next section, we conduct several robustness checks to assess the stability of our findings.

5 Robustness Checks

In a first robustness check, we re-estimate **Equation (8)** and **Equation (9)** after including additional controls to mitigate potential bias from omitted variables. The first set of additional controls comprises additional weather variables: average relative humidity, average atmospheric radiation, and average wind speed experienced during the growing season. The second set includes input variables: labor expressed in Annual Work Units (AWU), and expenditures on fertilizer and pesticides per hectare. Descriptive statistics for these additional variables are provided in **Table A1**, while the regression results are reported in **Table A2**.

The results indicate that the signs and magnitudes of our parameter estimates of interest, as well as the level of statistical significance, are very similar to those found in our main specifications. Additionally, we observe an inverted-U-shaped relationship between relative humidity and grape yields, as well as between atmospheric radiation and grape yields. Although the signs of the coefficients for wind speed suggest a similar relationship, they are not statistically significant. Regarding the input variables, we find that grape yield increases with labor and pesticide expenditures, while fertilizer expenditures seem to have no effect on grape yields.

In a second robustness check, we exclude irrigated vineyards from our sample and re-estimate **Equation (8)** and **Equation (9)**[24]. The aim of this test is to determine whether the effectiveness of adaptation can be altered when irrigation is not taken into account. **Table A3** reports our estimated coefficients.

Once again, the signs and magnitudes of our estimated coefficients of interest remain stable, suggesting that adaptation to heat risk can be achieved through adjustments in practices other than irrigation. However, we observe that the average marginal effect of *KDD* for the dry-farmed vineyards (-0.0037) is slightly higher than that of the full sample (-0.0034). This discrepancy could be attributed to the effectiveness of irrigation in reducing the marginal negative effect of *KDD*, or it could be explained by the fact that almost all excluded irrigated vineyards are located in the Southern wine-producing regions where heat-induced yield losses are lower.

In a third robustness check, we re-estimate **Equation (8)** and **Equation (9)** using alternative temperature thresholds for *GDD* and *KDD*. We test nine alternative thresholds ranging from 25°C

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[24] FADN contains information regarding the proportion of agricultural land that is irrigated. We exclude from our sample all observations for which the proportion of agricultural land that is irrigated is strictly greater than zero. This procedure leads us to remove 2293 observations.

to 35°C. Results are reported in **Table A4**-**Table A7**.

Our findings remain consistent across all temperature thresholds. Regardless of the threshold considered, we consistently observe a decrease in the marginal negative effect of both *FROST* and *KDD* as their respective climatologies increase. This suggests that grape growers have adapted to the risks of frost and heat.

For our final robustness check, we adopt an alternative approach to address spatial dependence in the error terms. We re-estimate **Equation (8)** and **Equation (9)** while employing Conley spatial standard errors. Conley (1999) uses a non-parametric routine to adjust the variance-covariance matrix for spatial correlation of an unknown form. The idea is to use a kernel that weighs the cross-products in the computation of the covariance matrix based on the spatial distance between observations, where the correlation between errors are assumed to decline with distance.

The regression results are presented in **Table A8**. Our coefficient estimates are even more significant compared to those obtained using standard errors clustered at the department level. Once again, we demonstrate that frost- and heat-induced yield losses are attenuated for growers situated in areas prone to frost and heat.

To summarize, our main results remain consistent across various robustness checks. Whether we include additional controls, exclude irrigated vineyards from the sample, explore a wide range of alternative temperature thresholds for our *GDD* and *KDD* variables, or address spatial dependence in the error terms using alternative methodologies, our key findings remain unchanged.

In Section 6, we delve into the implications of our findings and address certain limitations of our study.

6 Conclusion

In this paper, we estimate the extent of adaptation to spring frost and heat risks among grape growers in France. We combine data from a representative farm survey, which includes information on grape yields, with a daily gridded weather database. We then leverage spatial variations in climate to assess whether grape growers in frost- and heat-prone areas are less vulnerable to frost and heat shocks.

We find that frost and extreme heat have detrimental effects on grape yields. Specifically, an additional negative °C during the growing season decreases grape yields by 4.82%, while shifting 24 hours of temperatures from 29°C to 39°C reduces grape yields by 3.4%. These results highlight the potential negative impact of climate change on grape yields through increased risks of spring frost and heat. However, we find strong evidence of adaptation among grape growers. The marginal negative effect of frost and heat on grape yields is weaker for growers located in frost- and heat-prone areas, suggesting that adaptation has occurred. Specifically, the sensitivity of yield to spring frost and heat for the most exposed grape producer is lower by approximately 87% compared to the yield sensitivity of the least exposed producer.

Our results suggest that there is significant potential for adaptation within the French viticulture sector. Growers located in frost- and heat-prone areas have stronger incentives to adjust their practices to mitigate the adverse effects of spring frost and heat on grape yields. Consequently, the marginal detrimental effect of frost and heat on yields is lower for growers located in areas more prone to spring frost and heat shocks.

A limitation of our approach is that it does not allow us to identify which specific adjustments are responsible for the reduced sensitivity of grape yields to frost and heat. However, we can suggest some explanations. We believe that the reduced heat sensitivity of grape yields in heat-prone areas (i.e., Languedoc, Provence, and the Rhône Valley) may be partially attributed to the use of grape varieties known to be more tolerant to water and heat stress, such as Carignan, Cinsault, Grenache, and Syrah varieties. Additionally, growers in these regions likely use rootstocks and training systems (such as bush vines) that are more adapted to heat. Similarly, growers in frost-prone areas may invest more in frost protection measures, such as heaters and frost protection towers.

Another limitation of our study is that, by focusing on spatial variations in climate rather than temporal variation, we do not address the question of the speed of adaptation. This question is particularly important in French viticulture, as it mainly relies on the Product Denomination of Origin (PDO) scheme. PDO imposes a set of practices on grape growers, which is believed to limit their adaptive capacities to climate change (Ashenfelter and Storchmann, 2016). We leave this topic for future research.

Nevertheless, our study demonstrates that significant adaptive capacities are achievable if grape growers have the freedom to adapt. Therefore, our results suggest that revising the appellation rules may be effective or even necessary to enable winegrowers to adapt and cope with climate change. Moreover, if barriers to adaptation are not too restrictive, estimations of the impact of climate change on grape yields using the standard panel approach would be misleading, underscoring the critical need to model long-term adaptation.

The last limitation of our study is that we focus on adaptation strategies that mitigate the adverse effects of frost and heat on grape yields. However, since wine-growing profitability depends not only on yields but also on quality, a promising area for future research would be to assess the extent of adaptation that allows for a reduction in the detrimental effects of weather on grape quality. The methodology used in this paper appears particularly suitable for addressing this question.

References

Amare, M., and Balana, B. (2023). Climate change, income sources, crop mix, and input use decisions: Evidence from nigeria. *Ecological Economics*, *211*, 107892.

Annan, F., and Schlenker, W. (2015). Federal crop insurance and the disincentive to adapt to extreme heat. *American Economic Review*, *105*(5), 262–266.

Aragón, F. M., Oteiza, F., and Rud, J. P. (2021). Climate change and agriculture: Subsistence farmers' response to extreme heat. *American Economic Journal: Economic Policy*, *13*(1), 1–35.

Ashenfelter, O., and Storchmann, K. (2016). Climate change and wine: A review of the economic implications. *Journal of Wine Economics*, *11*(1), 105–138.

Auffhammer, M., Hsiang, S. M., Schlenker, W., and Sobel, A. (2013). Using weather data and climate model output in economic analyses of climate change. *Review of Environmental Economics and Policy*.

Baltagi, B. H., Bresson, G., Chaturvedi, A., and Lacroix, G. (2023). Robust dynamic space–time panel data models using ε-contamination: an application to crop yields and climate change. *Empirical Economics*, *64*(6), 2475–2509.

Bareille, F., and Chakir, R. (2023). Structural identification of weather impacts on crop yields: Disentangling agronomic from adaptation effects. *American Journal of Agricultural Economics*.

Barreca, A., Clay, K., Deschênes, O., Greenstone, M., and Shapiro, J. S. (2015). Convergence in adaptation to climate change: Evidence from high temperatures and mortality, 1900–2004. *American Economic Review*, *105*(5), 247–251.

Barreca, A., Clay, K., Deschenes, O., Greenstone, M., and Shapiro, J. S. (2016). Adapting to climate change: The remarkable decline in the us temperature-mortality relationship over the twentieth century. *Journal of Political Economy*, *124*(1), 105–159.

Burke, M., and Emerick, K. (2016). Adaptation to climate change: Evidence from us agriculture. *American Economic Journal: Economic Policy*, *8*(3), 106–140.

Butler, E. E., and Huybers, P. (2013). Adaptation of us maize to temperature variations. *Nature Climate Change*, *3*(1), 68–72.

Carter, C., Cui, X., Ghanem, D., and Mérel, P. (2018). Identifying the economic impacts of climate change on agriculture. *Annual Review of Resource Economics*, *10*, 361–380.

Chen, S., Chen, X., and Xu, J. (2016). Impacts of climate change on agriculture: Evidence from china. *Journal of Environmental Economics and Management*, *76*, 105–124.

Chevet, J.-M., Lecocq, S., and Visser, M. (2011). Climate, grapevine phenology, wine production, and prices: Pauillac (1800–2009). *American Economic Review*, *101*(3), 142–146.

CNIV. (2019). *Chiffres clés.* `https://www.intervin.fr/etudes-et-economie-de-la-filiere/chiffres-cles`. (Accessed: 2024-05-12)

Conley, T. G. (1999). GMM estimation with cross sectional dependence. *Journal of econometrics*, *92*(1), 1–45.

Cui, X. (2020). Climate change and adaptation in agriculture: Evidence from us cropping patterns. *Journal of Environmental Economics and Management*, *101*, 102306.

Cui, X., and Xie, W. (2022). Adapting agriculture to climate change through growing season adjustments: Evidence from corn in china. *American Journal of Agricultural Economics*, *104*(1), 249–272.

Deschênes, O., and Greenstone, M. (2007). The economic impacts of climate change: evidence from agricultural output and random fluctuations in weather. *American economic review*, *97*(1), 354–385.

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.

Hsiang, S. M. (2016). Climate econometrics. *Annual Review of Resource Economics*, *8*, 43–75.

Hsiang, S. M., and Narita, D. (2012). Adaptation to cyclone risk: Evidence from the global cross-section. *Climate Change Economics*, *3*(02), 1250011.

Keane, M., and Neal, T. (2020). Climate change and us agriculture: Accounting for multidimensional slope heterogeneity in panel data. *Quantitative Economics*, *11*(4), 1391–1429.

Lobell, D. B., Cahill, K. N., and Field, C. B. (2007). Historical effects of temperature and precipitation on california crop yields. *Climatic change*, *81*(2), 187–203.

Lobell, D. B., Roberts, M. J., Schlenker, W., Braun, N., Little, B. B., Rejesus, R. M., and Hammer, G. L. (2014). Greater sensitivity to drought accompanies maize yield increase in the us midwest. *Science*, *344*(6183), 516–519.

Malikov, E., and Miao, R. (2019). Climate change effects on us agriculture: Distributional heterogeneity, technological adaptability, and spatial spillovers. *Journal of Environmental Economics and Managements*, *98*, 1.

McIntosh, C. T., and Schlenker, W. (2006). Identifying non-linearities in fixed effects models. *UC-San Diego Working Paper*.

Niklas, B. (2017). Impact of annual weather fluctuations on wine production in germany. *Journal of wine economics*, *12*(4), 436–445.

Ortiz-Bobea, A. (2021). The empirical analysis of climate change impacts and adaptation in agriculture. In *Handbook of agricultural economics* (Vol. 5, pp. 3981–4073). Elsevier.

Roberts, M. J., and Schlenker, W. (2011). The evolution of heat tolerance of corn: Implications for climate change. In *The economics of climate change: adaptations past and present* (pp. 225–251). University of Chicago Press.

Roberts, M. J., Schlenker, W., and Eyer, J. (2013). Agronomic weather measures in econometric models of crop yield with implications for climate change. *American Journal of Agricultural Economics*, *95*(2), 236–243.

Schlenker, W., Hanemann, W. M., and Fisher, A. C. (2006). The impact of global warming on us agriculture: an econometric analysis of optimal growing conditions. *Review of Economics and statistics*, *88*(1), 113–125.

Schlenker, W., and Lobell, D. B. (2010). Robust negative impacts of climate change on african agriculture. *Environmental Research Letters*, *5*(1), 014010.

Schlenker, W., and Roberts. (2009). Nonlinear temperature effects indicate severe damages to us crop yields under climate change. *Proceedings of the National Academy of sciences*, *106*(37), 15594–15598.

Seo, S. N., and Mendelsohn, R. (2008). An analysis of crop choice: Adapting to climate change in south american farms. *Ecological economics*, *67*(1), 109–116.

Sesmero, J., Ricker-Gilbert, J., and Cook, A. (2018). How do african farm households respond to changes in current and past weather patterns? a structural panel data analysis from Malawi. *American Journal of Agricultural Economics*, *100*(1), 115–144.

Sgubin, G., Swingedouw, D., Dayon, G., de Cortázar-Atauri, I. G., Ollat, N., Pagé, C., and Van Leeuwen, C. (2018). The risk of tardive frost damage in french vineyards in a changing climate. *Agricultural and Forest Meteorology*, *250*, 226–242.

Spellman, G. (1999). Wine, weather and climate. *Weather*, *54*(8), 230–239.

Tack, J., Barkley, A., and Nalley, L. L. (2015). Effect of warming temperatures on us wheat yields. *Proceedings of the National Academy of Sciences*, *112*(22), 6931–6936.

Taraz, V. (2018). Can farmers adapt to higher temperatures? evidence from india. *World Development*, *112*, 205–219.

Van Leeuwen, C., and Darriet, P. (2016). The impact of climate change on viticulture and wine quality. *Journal of Wine Economics*, *11*(1), 150–167.

Van Leeuwen, C., Destrac-Irvine, A., Dubernet, M., Duchêne, E., Gowdy, M., Marguerit, E., … Ollat, N. (2019). An update on the impact of climate change in viticulture and potential adaptations. *Agronomy*, *9*(9), 514.

Venios, X., Korkas, E., Nisiotou, A., and Banilas, G. (2020). Grapevine responses to heat stress and global warming. *Plants*, *9*(12), 1754.

Wang, J., Mendelsohn, R., Dinar, A., and Huang, J. (2010). How chinese farmers change crop choice to adapt to climate change. *Climate Change Economics*, *1*(03), 167–185.

Wang, R., Rejesus, R. M., and Aglasan, S. (2021). Warming temperatures, yield risk and crop insurance participation. *European Review of Agricultural Economics*, *48*(5), 1109–1131.

Welch, J. R., Vincent, J. R., Auffhammer, M., Moya, P. F., Dobermann, A., and Dawe, D. (2010). Rice yields in tropical/subtropical asia exhibit large but opposing sensitivities to minimum and maximum temperatures. *Proceedings of the National Academy of Sciences*, *107*(33), 14562–14567.

Zhang, P., Zhang, J., and Chen, M. (2017). Economic impacts of climate change on agriculture: The importance of additional climatic variables other than temperature and precipitation. *Journal of Environmental Economics and Management*, *83*, 8–31.

7 Appendix

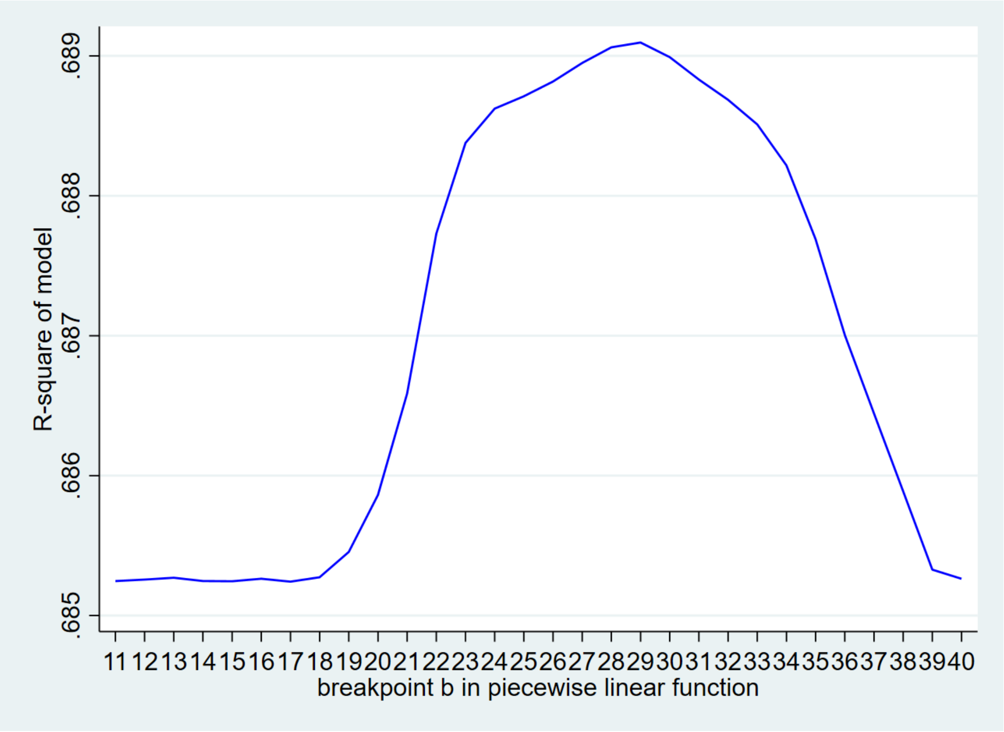

Figure A1: Optimal Temperature Threshold

Table A1: Descriptive Statistics: Additional Controls

Variable	Mean	Std.Dev.	Min	Max
Average Relative Humidity (%)	69.86	5.59	54.89	84.46
Average Atmospheric Radiation (J/cm2)	344253.15	38822.21	232379.60	458490.70
Average Wind Speed (m/s)	2.66	0.73	0.70	6.50
Labor (AWU/Ha)	25.39	26.42	0.91	233.33
Fertilizer Expenditure (euros/Ha)	314.83	693.62	0.00	13911.41
Pesticides Expenditure (euros/Ha)	708.27	691.87	0.00	15386.93

Table A2: Robustness Check: Additional Controls

	(1)	(2)
FROST	-0.030***	-0.056***
	(0.004)	(0.012)
FROST$\times ln(\overline{FROST})$		0.027***
		(0.009)
GDD	0.00035***	0.00047***
	(0.00012)	(0.00013)
KDD	-0.0022***	-0.014***
	(0.0004)	(0.003)
KDD$\times ln(\overline{KDD})$		0.0033***
		(0.0007)
Relative Humidity	0.10***	0.13***
	(0.03)	(0.02)
Relative Humidity^2	-0.0008***	-0.00101***
	(0.0002)	(0.00018)
Atmospheric Radiation	0.00005**	0.00004*
	(0.00002)	(0.00002)
Atmospheric Radiation^2	-4e-11**	-3.3e-11*
	(2e-11)	(1.7e-11)
Wind Speed	0.02	0.04
	(0.05)	(0.05)
Wind Speed^2	-0.002	-0.006
	(0.013)	(0.013)
ln(Labor)	0.11***	0.11***
	(0.02)	(0.02)
ln(Fertilizer)	0.0011	0.0016
	(0.0018)	(0.0018)
ln(Pesticides)	0.035***	0.036***
	(0.008)	(0.008)
R^2	0.694	0.698
Observations	12978	12978

The dependent variable is the logarithm of grape yield. All regressions include a linear and quadratic national time trend and farm fixed effects. Standard errors are clustered at the department level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A3: Robustness Check: Removing Irrigating Vineyards

	(1)	(2)
FROST	-0.031***	-0.064***
	(0.004)	(0.013)
FROST$\times ln(\overline{FROST})$		0.032***
		(0.009)
GDD	0.000535***	0.00063***
	(0.000010)	(0.00008)
KDD	-0.0028***	-0.011***
	(0.0005)	(0.003)
KDD$\times ln(\overline{KDD})$		0.0021**
		(0.0008)
R^2	0.696	0.698
Observations	10685	10685

The dependent variable is the logarithm of grape yield. All regressions include a linear and quadratic quadratic time trend and farm fixed effects. Standard errors are clustered at the department level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A4: Robustness Check: Alternative Temperature Thresholds, 25-30°C, Without Adaptation

	(1) l_1 : 25°C	(2) l_1 : 26°C	(3) l_1 : 27°C	(4) l_1 : 28°C	(5) l_1 : 30°C
FROST	-0.032***	-0.032***	-0.032***	-0.031***	-0.031***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
GDD	0.00050***	0.00052***	0.00051***	0.00050***	0.00047***
	(0.00010)	(0.00011)	(0.00010)	(0.00010)	(0.00009)
KDD	-0.00063***	-0.00086***	-0.0012***	-0.0017***	-0.0032***
	(0.00011)	(0.00015)	(0.0002)	(0.0003)	(0.0005)
R^2	0.689	0.689	0.689	0.689	0.689
Observations	12978	12978	12978	12978	12978

The dependent variable is the logarithm of grape yield. All regressions include a linear and quadratic national time trend and farm fixed effects. Standard errors are clustered at the department level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A5: Robustness Check: Alternative Temperature Thresholds, 31-35°C, Without Adaptation

	(1)	(2)	(3)	(4)	(5)
	l_1 : 31°C	l_1 : 32°C	l_1 : 33°C	l_1 : 34°C	l_1 : 35°C
FROST	-0.030***	-0.030***	-0.030***	-0.030***	-0.030***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
GDD	0.00045***	0.00043***	0.00040***	0.00037***	0.00033***
	(0.00008)	(0.00008)	(0.00007)	(0.00007)	(0.00006)
KDD	-0.0044***	-0.0064***	-0.0095***	-0.0143***	-0.021***
	(0.0007)	(0.0010)	(0.0015)	(0.0023)	(0.0037)
R^2	0.689	0.689	0.689	0.688	0.688
Observations	12978	12978	12978	12978	12978

The dependent variable is the logarithm of grape yield. All regressions include a linear and quadratic national time trend and farm fixed effects. Standard errors are clustered at the department level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A6: Robustness Check: Alternative Temperature Thresholds, 25-30°C, With Adaptation

	(1)	(2)	(3)	(4)	(5)
	l_1 : 25°C	l_1 : 26°C	l_1 : 27°C	l_1 : 28°C	l_1 : 30°C
FROST	-0.07***	-0.07***	-0.07***	-0.06***	-0.059***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.012)
FROST$\times \ln(\overline{FROST})$	0.034***	0.033***	0.033***	0.031***	0.029***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
GDD	0.00058***	0.00057***	0.00058***	0.00058***	0.00056***
	(0.00001)	(0.00009)	(0.00009)	(0.00009)	(0.00008)
KDD	-0.0026**	-0.0037**	-0.0052***	-0.007***	-0.012***
	(0.0012)	(0.0014)	(0.0018)	(0.002)	(0.004)
KDD$\times \ln(\overline{KDD})$	0.0004	0.0006**	0.0009**	0.0014**	0.0027**
	(0.0002)	(0.0003)	(0.0004)	(0.0005)	(0.0011)
R^2	0.690	0.690	0.691	0.691	0.691
Observations	12978	12978	12978	12978	12978

The dependent variable is the logarithm of grape yield. All regressions include a linear and quadratic national time trend and farm fixed effects. Standard errors are clustered at the department level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A7: Robustness Check: Alternative Temperature Thresholds, 31-35°C, With Adaptation

	(1) $l_1 : 31°C$	(2) $l_1 : 32°C$	(3) $l_1 : 33°C$	(4) $l_1 : 34°C$	(5) $l_1 : 35°C$
FROST	-0.058***	-0.057***	-0.057***	-0.058***	-0.060***
	(0.012)	(0.012)	(0.012)	(0.011)	(0.011)
FROST$\times \ln(\overline{FROST})$	0.028***	0.027***	0.027***	0.028***	0.029***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
GDD	0.00053***	0.00050***	0.00045***	0.00040***	0.00035***
	(0.00007)	(0.00007)	(0.00006)	(0.00006)	(0.00006)
KDD	-0.015***	-0.019***	-0.024***	-0.032***	-0.050***
	(0.005)	(0.006)	(0.007)	(0.009)	(0.011)
KDD$\times \ln(\overline{KDD})$	0.0038**	0.0055**	0.009**	0.016**	0.036***
	(0.0016)	(0.0024)	(0.004)	(0.006)	(0.013)
R^2	0.691	0.690	0.690	0.690	0.689
Observations	12978	12978	12978	12978	12978

The dependent variable is the logarithm of grape yield. All regressions include a linear and quadratic national time trend and farm fixed effects. Standard errors are clustered at the department level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A8: Robustness Check: Treating Spatial Dependence Using Conley Standard Errors

	(1)	(2)
FROST	-0.031***	-0.061***
	(0.003)	(0.007)
FROST$\times ln(\overline{FROST})$		0.030***
		(0.005)
GDD	0.00049***	0.00058***
	(0.00004)	(0.00005)
KDD	-0.0023***	-0.0095***
	(0.0002)	(0.0014)
KDD$\times ln(\overline{KDD})$		0.0020***
		(0.0004)
R^2	0.300	0.303
Observations	13238	13238

The dependent variable is the logarithm of grape yield. All regressions include a linear and quadratic national time trend and farm fixed effects. Conley standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$