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Germán Puga and Kym Anderson

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Contact details:
Wine Economics Research Centre
School of Economics
University of Adelaide
SA 5005 AUSTRALIA
Email: wine-econ@adelaide.edu.au

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# Statistical methods in grape and wine research for quantifying the impact of climate change

Germán Puga[1,2*] and Kym Anderson[2,3]

[1]Centre for Agricultural Economics and Development, University of Western Australia, Perth, WA 6009, Australia

[2]Wine Economics Research Centre, University of Adelaide, Adelaide, SA 5005, Australia

[3]Arndt-Cordon Department of Economics, Australian National University, Canberra, ACT 2601, Australia

*corresponding author: german.puga@uwa.edu.au

## Abstract

Studies analysing the impact that climate change could have on the wine sector are important for determining appropriate adaptation strategies. Statistical methods provide a useful approach for estimating future climate impacts. Yet they are underused despite the availability of data and the low costs of using statistical models when compared to some other approaches. This review aims to explain how some statistical methods can be used to quantify the impact of climate change in grape and wine research. It first focuses on how to estimate appropriate models of the impact of climate or weather on wine-related outputs. It then explains the challenges of using those statistical estimates to predict the impact of climate change. Last, the review compares statistical methods with other approaches and justifies combining different methods as a way of devising more insights for the wine sector.

climate change, climate adaptation, statistical models, viticulture, wine sector

## 1. Introduction

There is an overwhelming consensus on the threats (and in some cases opportunities) that climate change poses to the world's current national wine industries (IPCC, 2023). However, there is often disagreement on how climate change may affect different wine regions.[1] That disagreement is not surprising given how complex it is to make predictions with a high degree of uncertainty. Studies examining the potential impact of climate change are useful for dealing with that uncertainty. The insights from such studies are relevant for developing individual business and industry-wide strategies, much of them involving climate adaptation alternatives.

This topic's relevance has resulted in a wide range of studies assessing the impact of climate change on the wine industry. Many of these studies have used experiments (e.g., Sadras et al. (2017)) or process-based crop models (e.g., Yang et al. (2022)), while others have used statistical methods (e.g., Ashenfelter (2008)). Still, there is considerable potential for more and better data-driven insights on future climate risks using statistical models. Cutting-edge models have been widely used to project climate impacts on annual crops (Ortiz-Bobea, 2021), but less in grape and wine research. Datasets on wine-related outputs are common in the wine industry, both at the regional and firm levels. Where these data are available, statistical models can lead to powerful insights that can be produced at little cost because they can be quickly estimated using readily available software.

This review aims to explain how to use statistical methods to quantify the impact of climate change in grape and wine research. It does not focus on the results and insights from studies using these methods, but rather on how to apply the methods themselves.[2] In doing so, the review adapts advanced methodologies to the context of wine applications and advises on how to deal with common challenges and limitations of these methods. Many of these issues are specific to grape and wine research. To the best of our knowledge, this is the first review focusing on how to best apply statistical methods to quantify the potential impact of climate change on the wine industry. Given that other approaches such as machine learning methods and process-based crop models can lead to very powerful often complementary insights, the review also compares these other approaches with statistical methods.

The remainder of this review is organised as follows. The next section provides examples of studies that have used statistical models to quantify the impact of climate weather, and/or climate change. The following five sections relate to the first step when predicting the impact of climate change, that is, using statistical models to quantify the impact of climate or weather on an output. Then, another section focuses on the challenges of the second step, which consists of using the estimates from the statistical models to quantify the impact of climate change projections. A

[1] For example, van Leeuwen et al. (2013) argue the degree in which climate change will decrease viticultural suitability in the major wine regions is not as high as that predicted by Hannah et al. (2013).

[2] For less methodologically focused reviews see Ashenfelter and Storchmann (2016), van Leeuwen et al. (2024), and Santos et al. (2020a).

subsequent section explains why (and how) statistical methods should be combined with other approaches for obtaining more powerful insights. The last section concludes by summarizing key insights. Noteworthy, the review is written in a way that a reader with a basic understanding of ordinary least squares (OLS) linear regression will understand. It explains the differences between statistical methods and estimation strategies, and how to choose appropriate functional forms.

## 2. Examples of statistical models

Researchers have used statistical methods to quantify climate impacts on various outputs such as grape and wine production, grape yields and prices, and wine prices and quality. Other applications of statistical models include analyses of the impact of climate change on the compression of the harvest period and the evolution of grape or wine characteristics such as sugar or alcohol level. Table 1 provides examples of studies that have used statistical models for the abovementioned applications.

Table 1 does not provide an exhaustive list of the studies that have relied on statistical models in grape and wine research. The studies listed in this table are not necessarily the most relevant either. This table simply lists 22 studies to provide a wide variety of examples in terms of applications and data structures — which are described below. Some of these studies have been conducted by economists; others by grape or wine scientists. A few of them represent powerful examples of multidisciplinary research. Figure 1 maps the number of studies from Table 1 performed in each country.

**Table 1. Examples of studies using statistical models to estimate the impact of climate, weather, and/or climate change on the wine industry.**

| Study | Method | Summary |
|---|---|---|
| Alston et al. (2011) | Statistical analysis with panel data | Determines the impact of weather on grape sugar content in California. They show that the increasing sugar levels in grapes (and alcohol in wine) are mostly an unintended consequence of wineries responding to market demand and little by climate change. |
| Ashenfelter (2008) | Statistical analysis | Explains how the future price of (aged) Bordeaux wines can be explained by seasonal weather characteristics. It builds on a series of famous studies that challenged the ability of wine experts to predict wine quality. |
| Ashenfelter and Storchmann (2010a) | Statistical analysis with panel data | Uses a dataset of wine prices in the Mosel Valley (Germany) to determine the impact of climate change on growers' revenues. They show that higher temperatures lead to substantial increases in revenues. |

| | | |
|---|---|---|
| Ashenfelter and Storchmann (2010b) | Statistical analysis | Uses a variety of datasets and data structures to determine the impact of (mainly) solar radiation on vineyard prices. They predict increases in the value of vineyards in the Mosel Valley due to increases in wine quality driven by climate change. |
| Bock et al. (2013) | Statistical analysis with time series data | Uses an extremely long dataset (1805-2010) to look at the impact of temperatures on yield and must sugar content in Franconia, Germany. They show that a small but economically/agronomically significant proportion of the observed increases in yields and must sugar content can be attributed to increases in temperature. |
| Cameron et al. (2021) | Statistical analysis with panel data | Uses a dataset for Victoria's regions to look at the impact of weather on changes in grape maturity. Building on the model developed by Cameron et al. (2019), they show that the advancement of grape maturity is mostly explained by the advancement of veraison. |
| Chevet et al. (2011) | Statistical analysis | Uses extremely long datasets on phenological stages, prices, and yields in Bordeaux (1800-2009). They show that the impact of temperature on yields have become weaker, but that on prices has become stronger. |
| Corsi and Ashenfelter (2019) | Statistical analysis | Uses datasets on expert ratings and weather for Italian wines. They uncover the influence of weather on expert ratings, and how this influence differs to that in other regions like Bordeaux. |
| Cross et al. (2017) | Statistical analysis with cross-sectional data | Estimates the impact of terroir attributes on vineyard prices in California. Building on the model developed by Cross et al. (2011), they compare the relative influence on vineyard prices of appellations of origin versus biophysical characteristics including climate. |
| Haeger and Storchmann (2006) | Statistical analysis with cross-sectional data | Uses a dataset of Pinot Noir wines in the US to analyse their price determinants. They show that the optimal climate is similar to that of Burgundy. |
| Jarvis et al. (2019) | Statistical analysis with panel data | Uses a dataset from vineyards across Australia to model the impact of weather on the advancement of grape maturity. They shed light on the issue of compression of the harvest period. |
| Jones et al. (2005) | Statistical analysis with panel data | Determines the impact of growing season temperature on vintage quality of various wine regions around the globe. After controlling for technology, they show how the impact of this variable differs across wine regions. |
| Mondoux (2022) | Statistical analysis with panel data | Estimates the impact of hail in Switzerland's vineyards on the country's wine retail market. He shows that while hail can lead to higher wine prices, those price increases are very small compared to the decrease in the quantity of wine sold. |
| Niklas (2018) | Statistical analysis with panel data | Quantifies the impact of weather on wine production in Germany. She shows that warmer years lead to higher production. |

| | | |
|---|---|---|
| Oczkowski (2016) | Statistical analysis with cross-sectional data | Determines the effect of weather on wine quality and prices in Australia. He shows that the ideal growing season temperatures for high-quality production of most mainstream varieties fall within the ranges suggested by Jones et al. (2012). |
| Puga et al. (2020) | Statistical analysis with panel data | Estimates the impact of the European grapevine moth on grape production in Mendoza, Argentina, also uncovering the impact of weather variables. They show that the average impact of hail is five times higher than that of frost, leading to a decrease in yields of about one-fifth. |
| Puga et al. (2022a) | Statistical analysis with cross-sectional data | Quantifies the impact of growing season temperature on grape prices in Australia. Building on Webb et al. (2008), they show that the estimate of the negative influence of higher temperature on grape prices is about three times lower than when not controlling for the characteristics of production systems of the regions. |
| Puga et al. (2023) | Statistical analysis with panel data | Quantifies the impact of climate change on grape yields in Australia. They suggest that climate change may lead to higher yields in most cooler regions but lower yields in the major hotter regions. |
| Quiroga and Iglesias (2009) | Statistical analysis with time series data | Analyses the impact of weather on grape production in Cordoba, Spain. They show how weather influences grape yields compared to other crops and derive policy implications. |
| Santos et al. (2011) | Statistical analysis with time series data | Quantifies the impact of weather on grape yields in Duoro Valley, Portugal. They project that climate change may lead to higher yields in that region. |
| Santos et al. (2020b) | Statistical analysis with time series data | Predict wine production in Duoro and Port, Portugal. They provide a case study on how wine production can be forecasted using weather data. |
| Smith and Alston (2024) | Statistical analysis with panel data | Assesses at the impact of weather on wine prices and ratings in California. They found that high temperatures, especially if post-veraison, have a particularly high negative impact on grape quality. |

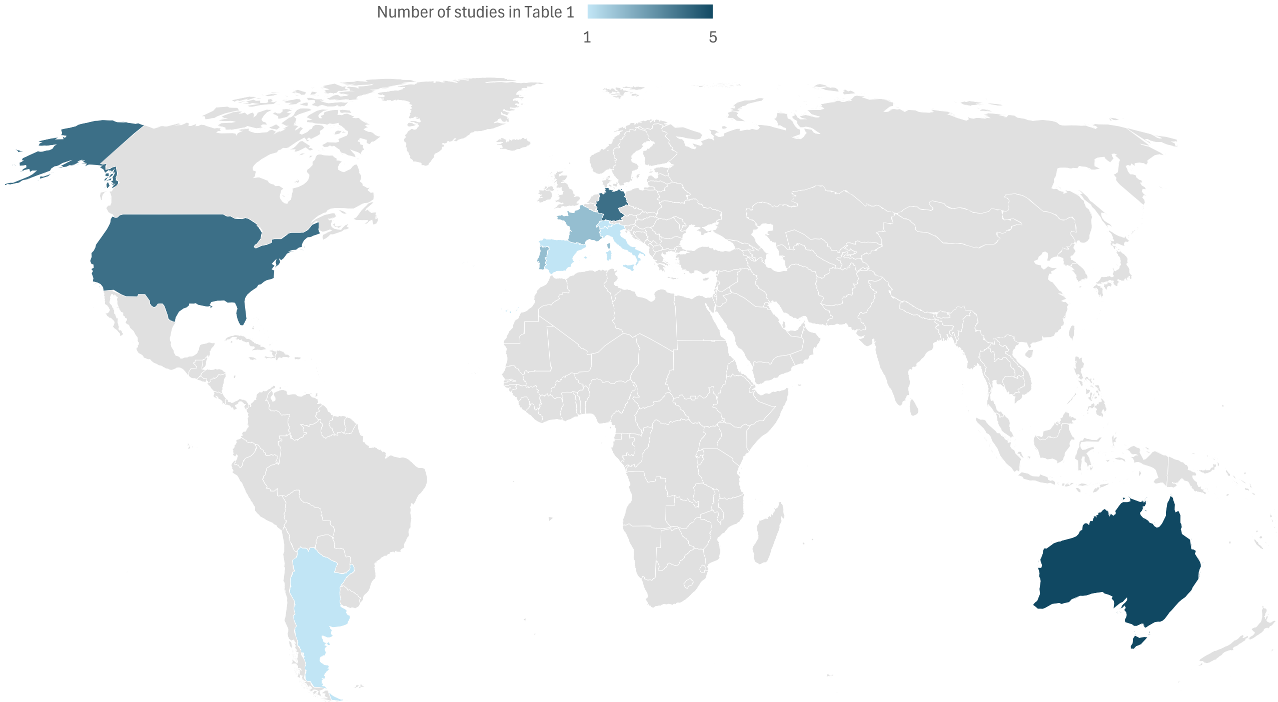


**Figure 1. Numbers of studies from Table 1 performed in each country.**

Notes: This map does not necessarily reflect the state of research on statistical models used to estimate the impact of climate, weather, and/or climate change on the wine industry; it simply shows the locations of the studies mentioned in Table 1. It does not include the study by Jones et al. (2005), which uses data for various countries.

## 3. Three types of statistical methods

Grape and wine research has relied on three main types of statistical methods: cross-sectional, time series, and panel data approaches. These three types of methods differ in the data they use. Table 1 provides examples of studies using each of these data types. The differences in the types of data can be easily explained with the following examples of datasets concerning wine regions. In a cross-sectional dataset, there is information available for different regions in a year or period (e.g., the average over two decades). In a time-series dataset, there is information for one region over several years. A panel dataset is a combination of both; there are data for different regions across various years.

The grape and wine research literature includes many applications of time series data, sometimes covering very long periods. Examples of such studies are Ramos et al. (2008) and Camps and Ramos (2012) in Spain, Santos et al. (2011, 2013, 2020b) in Portugal, Teslić et al. (2016) in Italy, Bock et al. (2013) and Koch and Oehl (2018) in Germany, and Lobell et al. (2007) in the United States. While these studies have provided very powerful insights, this review focuses on cross-sectional and (mainly) panel data models. There is a wealth of often underutilized regional and firm-level data that could be used for cross-sectional and panel data analyses that could provide valuable knowledge to the wine industry.[3]

## 4. Cross-sectional and panel data models

For simplicity, this section focuses on statistical models of the impact of climate or weather on grape yields (tonnes per hectare).[4] A cross-sectional model of the impact of climate on yields could take the form:

$$Yield_r = \alpha + \boldsymbol{Climate}_r \boldsymbol{\beta} + \epsilon_r, \tag{1}$$

where $Yield_r$ is the average yield of region $r$ across a period of time (years).[5] The independent variables of interest ($\boldsymbol{Climate}_r$) are a set of region-specific climate variables calculated either as climate normals or as the average weather across the time period. The coefficients of interest are denoted by $\boldsymbol{\beta}$, $\alpha$ is the intercept, and $\epsilon_r$ the error term.

A similar model to (1), but estimated with panel data, could be:

$$Yield_{rt} = \alpha + \boldsymbol{Weather}_{rt} \boldsymbol{\beta} + \varphi_r + \tau_t + \epsilon_{rt}, \tag{2}$$

where $Yield_{rt}$ is the yield of region $r$ in year $t$.[6] The weather variables for each region are year-specific ($\boldsymbol{Weather}_{rt}$), unlike the climate variables for each region in model (1). The region fixed effects ($\varphi_r$) capture all time invariant characteristics of region $r$, whether they are observable or not. There are also time fixed effects ($\tau_t$) that aim to capture time shocks common to all regions.[7]

The key difference between models (1) and (2), apart from model (1) capturing the impact of climate on yields while model (2) estimates the effect of weather on yields, is that model (2) has

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[3] Other reviews focus on the use of cross-sectional and panel data methods for climate change impact assessments. For example, Mendelsohn and Massetti (2017) review a widely used cross-sectional method (i.e., the Ricardian approach) and Blanc and Schlenker (2017) review the panel data method, both in the context of agriculture. Yet, the way these approaches should be used depends on the nature of the crop/industry. This review provides guidelines and insights that are specific for grape and wine research, which often differ to those for annual crops.

[4] Wooldridge et al. (2021) provide a more detailed introduction of cross-sectional and panel data methods.

[5] It would also be possible to estimate a cross-sectional model for just one year. However, it is better to aggregate across years (a time period). Using data for a short period of time such as one year would imply issues of omitted variable bias due to year-specific variables that influence yield and are not controlled for in the model. Instead, using average data for a relatively long period of time helps neutralise those year-specific omitted variables.

[6] It is more common to specify the dependent variable as its natural logarithm. In this example, such specification would imply that each weather variable has the same proportional impact on yield in each region. Further, specifying the dependent variable in natural logarithm can help deal with extreme values by narrowing the range of the variable, as well as alleviate issues of heteroskedasticity (Wooldridge et al., 2021).

[7] Fixed effects can be interpreted as dummy variables.

stronger identification properties than model (1), mainly because it includes both region and time fixed effects (Dell at al., 2014).

An advantage of grape and wine data is that there is often information for different grape varieties. In such case, model (2) could then become:

$$Yield_{vrt} = \alpha + \boldsymbol{Weather}_{rt}\boldsymbol{\beta} + \varphi_{vr} + \tau_t + \epsilon_{vrt}. \tag{3}$$

The main difference between models (2) and (3) is that in the latter the dependent variable ($Yield_{vrt}$) is the yield of variety $v$ in region $r$ and year $t$, as opposed to just the yield of region $r$ in year $t$. Therefore, model (3) has more degrees of freedom than model (2).[8] The weather variables are still region-specific as there is usually no data for the specific locations within a region where each variety is planted. The variety-by-region fixed effects ($\varphi_{vr}$) capture all time-invariant observable and unobservable characteristics of each variety-by-region combination, which is more specific than having just region fixed effects ($\varphi_r$) as in model (2).

When estimating a model such as (2) or (3), it may be tempting to interact the time fixed effects ($\tau_t$) with dummies for groups of regions. In that way, it would be possible to capture for time shocks that affect different groups of regions each year, hence making these shocks more specific. The issue with doing that is that weather data is in practice always subject to a certain degree of measurement error. Having time fixed effects for different groups of regions can lead to those fixed effects absorbing a great proportion of the variance in the weather variables, meaning that great part of the remaining variation in the data is mostly noise (Fisher et al., 2012).

Another way of controlling for other variables that affect yield in models (2) or (3) would be to simply add them to the models. This is important because despite their strong identification properties, panel data models can be subject to omitted variable bias when relevant variables other than weather are not incorporated in the models. While it is possible to add these variables, this should only be done if these variables are exogenous, something that is false in many wine applications. That is the main reason why statisticians often prefer to simply rely on time fixed effects to capture those time-varying omitted variables.

Ultimately, the interest is on the $\beta$ coefficients of the impact of weather variables on yield. These coefficients represent the average effect of their respective weather variables on grape yield. In practice, these effects may vary across varieties (van Leeuwen et al., 2023; Plantevin et al., 2022). It is possible to get variety-specific effects of the impact of weather on yields if interacting those varieties with the weather variables. However, that might not work due to the small sample size of

[8] A cross-sectional model like (1) could also be estimated at the variety-by-region level.

the datasets that are available in viticulture. That said, it could be feasible in other applications, notably when modelling wine prices or quality as those datasets can be considerably larger than those for grape yields.

## 5. Estimation strategies

A cross-sectional model like (1) could be easily estimated using the OLS estimator.[9] Instead, using OLS to estimate a panel data model such as (2) or (3) would lead to biased estimates. When using panel data, the climate statistics literature has favoured another estimator: the fixed effects estimator. How this estimator works can be explained following the example of model (2).

If (2) is true, then it is also true that:

$$\overline{Yield}_r = \alpha + \overline{\boldsymbol{Weather}}_r \boldsymbol{\beta} + \varphi_r + \bar{\epsilon}_r. \tag{4}$$

In this model, $\overline{Yield}_r$ is the average yield in region $r$ over the period, and $\overline{\boldsymbol{Weather}}_r$ represents a set of region-specific weather variables averaged over that same period. Note that estimating (4) would in practice be the same as estimating (1).

Subtracting (4) from (2) gives:

$$\left(Yield_{rt} - \overline{Yield}_r\right) = \left(\boldsymbol{Weather}_{rt} - \overline{\boldsymbol{Weather}}_r\right)\boldsymbol{\beta} + \tau_t + (\epsilon_{rt} - \bar{\epsilon}_r). \tag{5}$$

The fixed effects estimator is the equivalent of estimating (5) using the OLS estimator. Importantly, estimating model (5) implies that the $\boldsymbol{\beta}$ coefficients represent the impact of weather shocks. These are deviations from the average weather in a region that are random and exogenous (Auffhammer, 2018). That constitutes a major difference between model (4) and (5); model (4) captures the impact of climate over the period covered in the dataset, rather than weather.

There are many other estimators commonly used with panel data, but the climate statistics literature has favoured the use of the fixed effects estimator over others such as the random effects estimator (Blanc & Schlenker, 2017). However, applications with other estimators may be appropriate in some cases such as when dealing with dynamic models.

A dynamic model includes a lag of the dependent variable as an explanatory variable. In viticulture, the weather in one year influences yields not only in that year but also in subsequent years (Giulpart et al., 2014; Molitor and Keller, 2017). Those dynamics may justify a dynamic model of

[9] Other estimators such as weighted least squares (WLS) could also be used, and in some cases, they might be more appropriate.

the impact of weather on yields, as such a model would allow for a simple way of estimating long-run impacts of (short-term) weather shocks.[10] However, the potential influence of alternate bearing in grape production makes the interpretation of such a model ambiguous (see Puga et al. (2023) for a discussion).

Beyond the yield example, there are many applications where the choice of a dynamic model is easier to justify, for example when looking at grape or wine prices using panel data. In such cases, using the OLS or the fixed effects estimator could lead to biased estimates. For dynamic models of that type, it would be more appropriate to use alternative estimators such as that developed by Arellano and Bond (1991) following the correction method developed by Windmeijer (2005).

A final consideration when defining the estimation strategy, whether it concerns a panel data or a cross-sectional model, relates to spatial autocorrelation and the treatment of the standard errors. When using variety-by-region combinations the climate/weather data are usually available for each region (as opposed to variety by region), so it is a good practice to cluster standard errors at the regional level. Doing so may help but not be sufficient for dealing with the issue of spatial autocorrelation, which in turn could lead to overconfident estimates. Ortiz-Bobea (2021) explains how to avoid issues of spatial autocorrelation in climate impact studies.

## 6. Representing climate or weather

The examples discussed above have not touched on the specification of the climate or weather variables. Representing climate/weather is a complex task because there is a wide range of variables influencing an output. In practice, it is impossible to account for all (or even many) variables in a statistical model. Instead, researchers must choose just a few key indexes to represent climate/weather. These indexes usually include temperature and precipitation variables (Ashenfelter and Storchmann, 2016), but many others can be employed (Puga et al., 2022b). Examples of other relevant variables are solar radiation, insolation, evaporation, vapour pressure deficit, evapotranspiration, and wind (Jones et al., 2012).

Grape and wine researchers tend to copy functional forms. Put differently, they sometimes use the same climate/weather variables as in previous studies conducted in other places. For example, Ashenfelter's famous 'Bordeaux equation' (see Ashenfelter (2008) for a discussion) has been very influential on models of the impact of weather on grape prices/quality, often in regions with a climate different from that of Bordeaux. This should not be promoted because the relevance of climate

[10] A dynamic model might be justified by the dynamics of growers' behaviour (Chavas et al., 2019), although to a lesser extent in the case of winegrowing.

variables and the way they impact an output commonly differ across countries. However, there are a few points that all researchers should consider in their modelling choices.

One important consideration is to get different impacts for different climates. That means, for example, that an increase in precipitation does not have the same impact in drier or wetter regions. Figure 2 shows an example of a relationship of this type, estimated by Puga et al. (2023) for Australia. Such a functional form can be achieved with a quadratic specification.

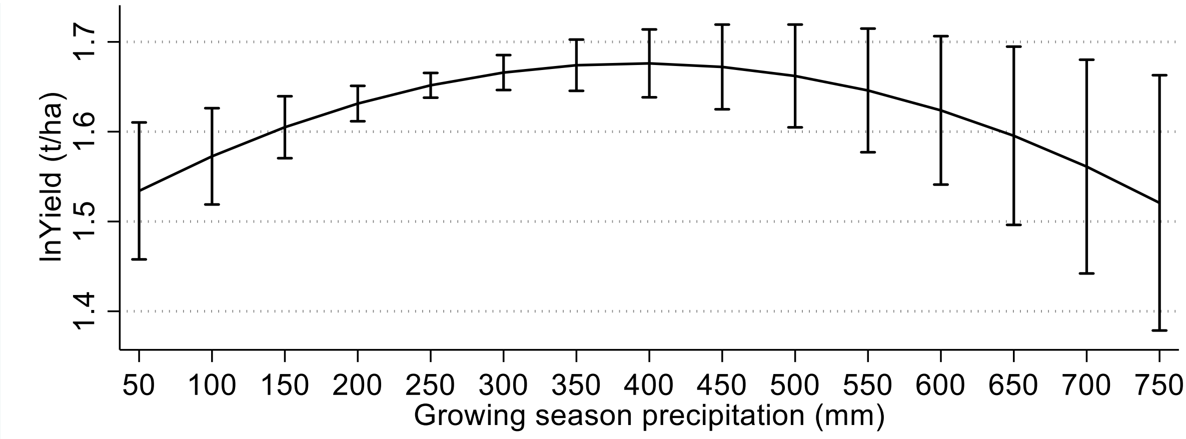


**Figure 2. Predicted natural logarithm of grape yield as a function of growing season precipitation in Australia.**

Notes: Estimated by Puga et al. (2023). The plot shows the predictive margins with 95% confidence intervals.

Another way of getting different impacts by climate is by working with temperature bins or continuous temperature functions. Schlenker and Roberts (2009) popularised this approach. In wine research, similar models could help to statistically differentiate between growing and killing degree days, as well as different impacts by climate across temperature accumulation ranges. More recently, researchers have also investigated how the impact of temperature changes throughout different phases of the growing season using a similar approach (e.g., Ortiz-Bobea et al. (2019)). That said, most of the studies that have used the approach initiated by Schlenker and Roberts (2009) use extremely large yield datasets for annual crops, usually in the United States. The potential of these methods in grape and wine research is more limited because datasets are smaller.

Also important is to model interactions between variables when this makes sense from a scientific perspective. For example, growing season temperature could sometimes be interacted with growing season precipitation. In other cases, properly modelling interactions can be more challenging. In some regions, warmer years may lead to higher frost damage due to the impact that warmer temperatures can have in advancing phenological stages earlier in the growing season (Sgubin et al, 2018). Such interactions are complex, hence difficult to model.

Besides choosing the variables, a researcher needs to decide whether to specify them in levels (e.g., growing season precipitation) or in logs (e.g., natural logarithm of growing season precipitation). Using levels leads to a straightforward interpretation in which a unit increase in the climate/weather variable can be associated with a certain percentage change in the output of interest (e.g., yield). Using logs can sometimes lead to misinterpretation issues, which is why specifying climate/weather variables in levels is the standard practice in the climate statistics literature (Camargo and Hsiang, 2015; Hsiang, 2016).

## 7. Data representativeness and quality

There is often little discussion on the representativeness and quality of the data even though the representativeness of the data can have a substantial impact on the quality of the analysis itself. A critical consideration relates to the representativeness of the climate/weather data. The goal is to have climate/weather data that represents the part of a region where the vineyards are planted.

Spatial data for a wine region is usually superior to data based on a particular location within that region. However, that spatial data may not properly represent the areas in which the vineyards are planted. A useful strategy to increase the representativeness of the climate/weather data is to compute an area-weighted average for each climate/weather variable within a region, in which the weight of each grid is proportional to the area share of the region's vineyards that belongs to that grid (Ortiz-Bobea (2021) provides an overview on how to do this).

The climate/weather data can be improved not only based on its spatial dimension but also its temporal one. Most studies define the growing season as a given by a specific set of dates. This is the case of most of the examples listed in Table 1 (e.g., Puga et al. (2022a, 2023), Smith and Alston (2024)). When possible, the length of the growing season for each region could be adjusted to ensure it is from that region's budburst to harvest.

Importantly, in addition to the representativeness of the climate/weather data, the usefulness of the statistical model will be largely affected by the quality of the grape or wine data. Independently of whether the dependent variable is yield or any other, these data can also be subject to measurement error. The representativeness and quality of grape or wine data can be affected by inconsistent (or inappropriate) metrics or measurement techniques, as well as other issues such as outliers, missing values, and duplicates.

Panel data models can deal with unbalanced datasets, but it is important to contemplate whether those data gaps may affect the insights from the models. Ideally, the dataset should have a high degree of temporal and spatial variability for then making more accurate predictions of future climate change impacts.

It is also important to consider the representativeness and quality of the data to determine the most appropriate type of model. For example, Puga et al. (2022) quantify the impact of growing season temperature on grape prices in Australia using a dataset that could have been used for estimating a panel data model. However, that grape price data does not account for some price adjustments that are done after reporting the prices based on the 'quality' of the wine. Since a panel data model would have estimated the impact of weather shocks on grape prices due to changes in 'quality', the authors use a combination of other models based on pooled cross-sectional data.

## 8. Predicting future climate impacts

The first step, using statistical models to estimate the impact of climate variables, is often very challenging. The second step also is complex, as it requires employing the estimates from the first step to quantify the potential impact of climate change projections.

Much of the literature on statistical models for assessing climate change risks has focused on the issue of accounting for long-run adaptation. That relates to the history of this literature. Cross-sectional models became popular in the mid-1990s after being introduced by Mendelsohn et al. (1994).[11] Then, following Deschênes and Greenstone (2007), the panel data approach became the most used statistical method for climate change risk assessments. While panel data models have better identification properties than cross-sectional models, they estimate the impact of weather shocks rather than climate. Consequently, the panel data approach has been criticised for not accounting for long-run adaptation because it relies on short-run estimates of weather shocks to assess the implications of long-run changes in climates. Hence, the panel data approach is often criticised for leading to an underestimation of climate change impacts.[12]

Nevertheless, in the case of grape and wine research, this limitation is less relevant for three reasons. The first reason is that grape growing is a capital-intensive activity with very long investment horizons (Ashenfelter and Storchmann, 2016). Because they are costly, adaptation processes are slower. Ineffective or limited adaptation leads to smaller differences between short-run responses to weather shocks and long-run responses to changes in climate (Kolstad and Moore, 2020). Therefore, not accounting for long-run adaptation in perennial crops such as grapevines is less relevant than for annual crops.

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[11] These cross-sectional models rely on a Ricardian theoretical framework. Mendelsohn and Massetti (2017) provide a review of this approach. In wine-related applications, it is more common to use cross-sectional models that are unrelated to this theory (e.g., Puga et al. (2022a)).

[12] That said, hybrid approaches have emerged in recent years. These approaches take advantage of the cross-sectional dimension of panel data to account for long-run adaptation. Examples of studies using these hybrid approaches are Butler and Huybers (2012), Moore and Lobell (2014, 2015), and Burke and Emerick (2016).

The second reason why not accounting for long-run adaptation is less important in wine-related applications is that cross-sectional variation may not be an ideal source of information on long-run adaptation. In annual crops, outputs like yield tend to be maximised, meaning that a region with a certain climate type may be more likely to adopt technologies from another region with a different climate type if its climate shifts towards the one of that other region. This is not necessarily the case in the wine industry, where regions have long been associated with certain wine styles. Therefore, wine regions are more likely to adapt in a way that would allow them to maintain those wine styles rather than adopting those of regions that now have similar climates to the ones they expect in the future but different wine styles. That, in turn, means that using cross-sectional variation to account for long-run adaptation could sometimes lead to inaccurate projections of future climate impacts.

The third reason why not accounting for long-run adaptation is less relevant in grape and wine research relates to the relative importance of doing so. Even a model that does well at capturing long-run adaptation only accounts for technologies that are already available. As climate changes, so do technologies. Therefore, only accounting for already-available technologies may still overestimate future climate impacts, although if already-available technologies are not available (or are less available) in the future, climate impacts may be underestimated. An example of this last case is water becoming scarcer and/or more expensive in irrigated regions (Puga et al., 2023).

Not capturing both already-available and not-yet-available adaptation possibilities is not the only issue of the second step. Many other sources of uncertainty are difficult to capture when using the estimates from the first step to quantify the impact of climate change projections, independently of whether that first step has relied on panel data or cross-sectional models. There is always a degree of statistical uncertainty concerning those estimates from the first step. It is appropriate to discuss the implications of that type of uncertainty when relying on average effects for making predictions.

As well, climate scientists recognise a high degree of uncertainty in climate change projections (IPCC, 2023). A few strategies can be employed to (try to) deal with this type of uncertainty. One such strategy consists of using recent well-grounded climate projections. This is because there are large ongoing efforts in climate modelling leading to constant improvements of climate projections. Climate change projections differ based on the characteristics of the climate models used and the assumed representative concentration pathways. Therefore, it is useful to use different emission scenarios and climate models to quantify the bandwidth of uncertainty of future climate impacts. Also important is to discuss the different degrees of certainty that climate scientists have on the different climate variables. For example, precipitation projections often carry a lower degree of certainty than on those for temperatures.

Even when leaving statistical and climate uncertainty aside, and without worrying about the issue of capturing long-run adaptation, there is another important aspect that should always be considered. It is those characteristics of future weather events that are difficult to capture, because those events are not well represented in the data. A way of avoiding this issue consists of making sure not to extrapolate beyond the observed values in the data. For example, if growing season temperature varies between 15°C and 22°C in the data used in a statistical model, then using the estimates of that model would lead to unreliable estimates of the impact of climate change for growing season temperatures well over 22°C. To avoid this issue of extrapolation beyond the observed values in the data, Puga et al. (2023) use climate change projections for 2050 rather than longer timeframes.

Still, even if not extrapolating beyond the observed values in the data, some events are difficult to capture. Put differently, the insights of statistical models are very limited when it comes to unprecedented climatic conditions. This is because these conditions are not observed in the data, meaning that it is not possible to get reliable estimates that reflect such changes.

One example of a phenomenon that is complex to capture is carbon fertilisation (Kahn et al., 2022). Another is the intensification of climatic events. For example, a second year of drought will likely be more detrimental for grape yields than the first one, even if both droughts are of the same magnitude. This is particularly important in viticulture due to the perennial characteristics of grapevines. Yet, there is often insufficient data to estimate models aimed at capturing climatic intensification. Carbon fertilization and climatic intensification are just some examples of unprecedented climatic conditions that are difficult to capture with statistical models.

In spite of the abovementioned limitations of the use of statistical models to quantify the impact of climate change, these models can provide very useful information. This is evident from many of the examples listed in Table 1 (e.g., Alston et al. (2011), Ashenfelter and Storchmann (2010a,b), Cameron et al. (2021), Oczkowski (2016)). Statistical methods can provide useful insights to plan adaptation strategies despite their limitations to account for long-term adaptation. This is because by knowing the impacts of climate or weather on an output, and with information on the projected climate, it is possible to infer in which way the wine industry may need to adapt to climate change. As well, in recent years, new statistical methods have become increasingly useful at providing insights on adaptation strategies.

## 9. Combining approaches

Two other widely used methods for climate risk assessments in grape and wine research are experiments and process-based crop models. Experiments can reconstruct future climate conditions, but they are expensive, and their results are sometimes difficult to extrapolate to other settings. On the other hand, process-based crop models are based on calibrated biophysical models, meaning that they can be applied to a wide range of settings.[13] Like experiments, they can also help assess the impacts of climatic conditions that have not yet been observed.

Since statistical methods rely on the already-observed data, they often have disadvantages compared to experiments and process-based crop models when it comes to quantifying future impacts of climate extremes or patterns that have not yet been observed, as well as phenomena like carbon fertilization (Antle and Stöckle, 2017). However, statistical methods have a fundamental advantage because of relying on observed data: they account for growers' behaviour and actual responses to changes in climate/weather (Blanc and Reilly, 2017).

Also, more recent machine learning approaches based on observed data have a promising potential for climate risk assessments (e.g., Maimaitiyiming et al. (2019)). Machine learning models often perform well at predicting outcomes. An example of a very useful machine learning model is random forests, which ranks the relevance of each independent variable based on metrics like Gini impurity or mean decrease in accuracy (Plantevin et al., 2024). Since the goal is to predict climate impacts, a method with high predicting power may be preferred. After all, making accurate predictions is usually more relevant than uncovering causal relationships between climate/weather and wine-related outputs, which is a key strength of many statistical models. However, much of the variation in wine-related outputs such as yield depends on characteristics other than climate/weather. Therefore, machine learning approaches that allow for causal inference can be especially useful — as it is the case with some of the statistical methods described in this review.

A proper analysis of future climate impacts should go beyond the use of statistical methods. When possible, it should be complemented with results from studies using other methods such as experiments, process-based crop models, and/or machine learning models. Importantly, an analysis of this type should also rely on expert opinion.

Research in the assessment of climate impacts has recently focused quite heavily on data-driven approaches, sometimes underestimating expert opinions (Auffhammer, 2018). That is itself contradictory given that the choice of a statistical model is based on expert opinions; the same applies to experiments and process-based crop models. The results of a data-driven analysis could be very different based on modelling choices. Therefore, research in grape and wine research could give more importance to expert opinion approaches. There are ways of quantifying expert opinion that have not yet been used for climate change risk assessments in grape and wine research. For example, the

[13] Yang et al. (2022) explain how these process-based crop models work and provide examples of wine-related applications.

classical method could lead to quantitative estimates of future climate impacts based on a survey of experts (see Colson and Cooke (2018) for a review of this method).

## 10. Concluding remarks

Predicting climate change impacts is an exercise with a high degree of uncertainty for which no approach can give a definite answer. Nevertheless, statistical methods can provide beneficial insights. Since there are many challenges associated with these methods, they should be used for the insights that they can provide rather than those they cannot. Even just estimating the impact of climate or weather (leaving aside climate change projections) can lead to powerful insights to inform adaptation strategies. The potential applications of these methods in grape and wine research are enormous given the availability of data at both regional and firm levels, and their implementation costs when compared to other methods like experiments. While this review illustrates statistical methods with examples concerning grape yields, they can also be used to estimate future climate impacts on grape or wine prices, quality or composition, as well as many other variables such as the compression of the harvest period. As a way of mitigating uncertainty, researchers should try estimating a battery of robustness checks and sensitivity analyses to validate their findings. Further, when possible, the results of statistical methods should be used in combination with those of other methods.

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