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ORIGINAL RESEARCH ARTICLE

The impact of climate change on grape yields: Evidence from Australia

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ABSTRACT

Precipitation patterns are projected to change in different directions across wine regions in Australia, but temperatures are projected to increase in all wine regions, making them less prone to frosts but more prone to heatwaves and more arid. This research aims to estimate how climate change could affect grape yields in Australia. This is, to our knowledge, the first study using a panel data framework to estimate the potential impact of climate change on grape yields. This framework involves a two-step approach in which the first step consists of estimating the impact of weather on grape yields using a fixed effects panel data model, and the second step involves estimating the potential impact of climate change projections using the estimates from the first step. We also estimate a novel hybrid model that interacts weather with climate, potentially accounting for long-run adaptation. The results suggest that climate change by 2050 may lead to higher yields in most regions but lower yields in some of the country's largest regions. Put differently, an increase in yields may be expected in the coolest regions, while a decrease may be expected in the hottest regions. Consequently, the average yield in Australia may change very little.

KEYWORDS: climate change, climate impact, grape yields, panel data framework, wine production

INTRODUCTION

The Australian wine sector is an important industry with 146,244 ha of vineyards, 2360 wineries, and 6250 winegrowers (Wine Australia, 2020). The potential impact of climate change has motivated the Australian wine sector to fund the development of a Climate Atlas that provides information on how climate will change in the various Australian wine regions (Remenyi *et al*., 2020). This Climate Atlas projects that precipitation patterns will change in different directions across wine regions, but temperatures will increase in all regions by an average of 1.2 °C by 2050 and 2.8 °C by 2090 compared to 1997 – 2017. This means these regions will be less prone to frosts but more prone to heatwaves and more arid.

Previous research has shown that climate change may lead to lower prices in Australia as a consequence of changes in grape composition due to changes in temperature (Puga *et al*., 2022a). Meanwhile, the potential impact of climate change on grape yields in Australia is less known. Some studies have estimated the impact of climate change on grape yields in specific regions. For example, Sadras *et al.* (2017) conducted an experiment on the impact of warmer temperatures on yields of Syrah in the Barossa Valley. However, to our knowledge, no study quantifies the potential impact of climate change on grape yields in most regions of Australia.

This study aims to estimate how climate change could affect grape yields in Australia. Specifically, we focus on the implications of forecast changes in three climate variables from the Climate Atlas (Remenyi *et al*., 2020): growing season average temperature (GST), growing season precipitation (GSP), and frost-risk days (FRD). The hypothesis is that climate change (due to changes in GST, GSP, and FRD) will impact yields in different ways across regions in Australia.

To test this hypothesis, we follow a two-step approach in which the first step consists of estimating the impact of weather on grape yields using panel data methods, and the second step involves estimating the potential impact of climate change projections using the estimates from the first step. We show that in a ceteris paribus scenario, the average yield in Australia may change very little, but that many cool regions may have higher yields, and the hottest regions may have lower yields.

Besides providing insights that are relevant to the Australian wine industry, this study is a contribution to the literature on the impact of weather or climate change in grape and wine research. The bulk of this literature focuses on grape or wine quality or prices, with some studies looking at revenues and land values (see Ashenfelter and Storchmann (2016) for a review). A less extensive body of research focuses on the impact of weather or climate change on grape production.

Research on climate impacts on grape yields has relied mainly on either agronomic analyses or other types of statistical analyses (Moriondo *et al.*, 2015). Agronomic analyses are based on biophysical models that are often calibrated with experimental or observed data. One of the main advantages of these models is that they can incorporate environmental factors that are rarely observed in actual-growing conditions or that are hard to model with other types of statistical analyses (Antle and Stöckle, 2017). As such, besides being able to identify the impact of climate variables on yields separately, agronomic models can sometimes account for extreme climatic events and the effect of carbon dioxide (CO_2) fertilisation. Yang *et al.* (2022) provide a summary of agronomic models and cases in which such models have been used in viticultural research and conduct a well-grounded analysis of the impact of water stress on grape yields using a calibrated agronomic model.

By contrast, other types of statistical analyses have the advantage of relying on data from actual farming conditions, therefore, capturing farmers' behaviour and actual responses to climatic events, which are often different to those in controlled settings (Blanc and Reilly, 2017). Most studies of this type that look at the impact of weather or climate change on grape yields or wine production have focused on time series statistical methods. Examples include Lobell *et al*. (2007) in the United States, Ramos *et al.* (2008) and Camps and Ramos (2012) in Spain, Santos *et al.* (2011); Santos *et al.* (2013); Santos *et al.* (2020) in Portugal, Bock *et al.* (2013) and Koch and Oehl (2018) in Germany, and Teslić *et al.* (2016) in Italy. These studies analyse time series that often cover very long periods.

Panel data methods offer stronger identification properties than time series analyses, hence can uncover causal relationships (Dell *et al.*, 2014). While the panel data approach is one of the most commonly used methods for estimating the impact of weather or climate change in agriculture, this approach has been applied very little in viticultural research. This study is an addition to the scarce literature that uses panel data methods to estimate the impact of weather on grape production (e.g., Quiroga and Iglesias, 2009) or wine

TABLE 1. Variables description and summary statistics.

Variable	Description	Mean	SD	Min	Max
Yield	Average yield (t/ha) of cultivar v in region *r* and season *s*.	7.3	6.1	0.0	50.0
GST	Growing season average temperature (°C) in region *r* and season *s*.	18.9	1.7	14.7	23.7
GSP	Total growing season precipitation (mm) in region *r* and season *s*.	278	152	38	888
FRD	Number of frost risk days in region *r* and growing season *s*. A frost risk day is a day in which the minimum temperature falls below 2 °C (Remenyi *et al.*, 2020).	1.8	2.6	0.0	16.0

Notes: The growing season goes from October to April. SD stands for standard deviation.

production (e.g., Niklas, 2017) and the first one (to our knowledge) to use a panel data approach to quantify the potential impact of climate change on grape yields.

We provide a detailed justification of a model for estimating the impact of weather on grape yields and discuss the limitations of this model and the use of this model's estimates in quantifying the potential impact of climate change on grape yields. Further, besides estimating a more-standard model of the impact of weather on yields, we estimate a hybrid model in an attempt to account for long-run adaptation.

Since panel datasets of grape yields are available for many regions and countries, the framework that we use in this study could be applied in other settings. The insights obtained using this framework can complement those obtained using other methods, such as experiments or agronomic models, as well as machine learning models focused on predicting grape yields (e.g., Maimaitiyiming *et al.*, 2019).

MATERIALS AND METHODS

1. Data

The data that we used for estimation are based on four input datasets. The first input dataset provides the area and total crush, and hence the average yield, by cultivar and region, for most Australian wine regions outside of South Australia (Anderson and Aryal, 2015). The time period is 2001 to 2015, although there are no available data on area by cultivar for all the Australian wine regions after 2008, except for 2010, 2012, and 2015. The second input dataset provides the average yield, by cultivar and region, for most regions within South Australia (Anderson and Puga, 2021). This state accounts for more than half of the country's wine production, and the data for it are available from 2001 to 2021.

The third input dataset consists of daily weather information for the Australian wine regions. We extracted these data from SILO (Jeffrey *et al*., 2001), which provides gridded weather data at a 5-kilometre resolution for all of Australia, based on interpolated information from weather stations. We used a shapefile of the Australian wine regions to get, for each region, the spatial average of the daily values of three weather variables: maximum temperature, minimum temperature, and rainfall. With this daily weather information, we then calculated GST, GSP, and FRD.

The fourth input dataset provides climate change forecasts for the Australian wine regions. Remenyi *et al*. (2020) provide well-grounded climate forecasts for 2041 – 2060 and 2081 – 2100. Those climate forecasts are based on Climate Futures Australasian Projections 2019 and assume an RPC8.5 emissions scenario, which is a business-as-usual scenario with limited mitigation. The forecasts provide the three weather variables we constructed (i.e., GST, GSP, and FRD) for the same wine regions we used for calculating our weather variables.

The output dataset we constructed for estimation consists of annual data on yield by cultivar and weather for each of the main wine regions in Australia. This dataset contains information on 52 regions and 61 cultivars (including 'other' cultivars categories), although on average, just 33 cultivars are represented in each region. This is an unbalanced panel dataset; it contains 1736 cultivar-by-region combinations for which there is information on 7.8 years on average, hence totalling 13,600 observations. Table 1 describes each of the variables that we used for estimation and provides their summary statistics. For each region, this dataset also contains the projected values for each of the three weather variables based on Remenyi *et al*. (2020). Since there is not a perfect concordance between the regions of the three input datasets, we had to combine some regions and avoid using others. Still, the regions included in our output dataset cover the vast majority of the Australian grape area.

The area concerning both the weather data and climate change projections corresponds to geographical indications (GIs). Some regions are irrigated, and some are not, but we do not have full information on irrigation of the vineyards (especially for some regions where there is a mix of both irrigated and non-irrigated vineyards). We also do not have access to the specific areas in which the vineyards are located. The average area planted to vines in each GI is 2.4 %, being as low as 0.01 % and as high as 24 % (see Figure 1). As such, in regions where the vineyards are concentrated in some areas, the weather data may not exactly match the actual weather in the vineyards, but it is still a reasonable approximation. The same applies to climate change projections. This is a common case in studies quantifying the impact of weather and climate change on agriculture (Blanc and Schlenker, 2017).

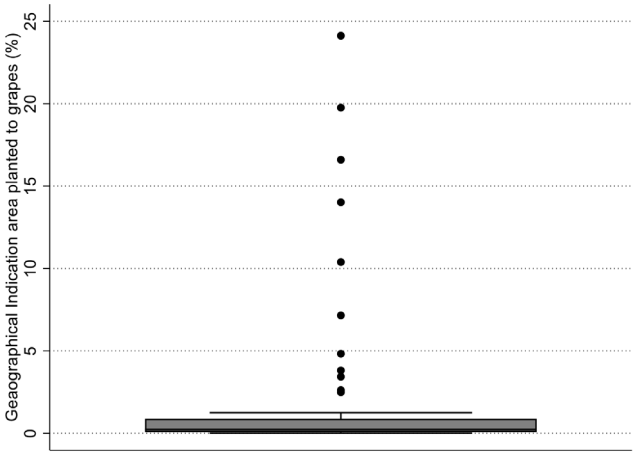


FIGURE 1. Boxplot showing the area in each wine region planted to grapes.

Notes: Based on data from Anderson and Puga (2022), for 49 of the 52 geographical indications (GIs) for which we are predicting the impact of climate change.

2. Methods

The framework we used in this study involves a two-step approach in which the first step consists of estimating the impact of weather on grape yields, and the second step involves estimating the potential impact of climate change projections using the estimates from the first step.

This is arguably the most used framework for estimating the potential impact of climate change in agriculture, and it has been described in detail in the climate change statistics literature (see Kolstad and Moore (2020) for a general review or Blanc and Schlenker (2017) for a review focused on agriculture).

The baseline model for estimating the effect of weather on grape yields is:

$$(1)\ lnYield_{vrs} = \beta_0 + \beta_1 GST_{rs} + \beta_2 GST_{rs}^2 + \beta_3 GSP_{rs} + \beta_4 GSP_{rs}^2 + \beta_5 FRD_{rs} + \mu_{vr} + \tau_s + \varepsilon_{vrs}$$

The dependent variable is the natural logarithm of the yield of cultivar ν in region *r* and season *s*. μ_{vr} are cultivar-by-region fixed effects and τ_s are season fixed effects. The β_s are parameters to be estimated and ε_{vrs} is an error term. The variables of interest in this model are the weather variables GST and its square value, GSP and its square value, and FRD.

While the main reason we chose these weather variables is that they are the key variables in the Climate Atlas (Remenyi *et al*., 2020), the choice of these variables is justified from a viticultural perspective. GST is one of the most commonly used bioclimatic indices in broad-scale studies (Liles and Verdon-Kidd, 2020). The other thermal bioclimatic index, FRD, captures the impact of extreme cold weather. GSP is also a commonly used bioclimatic index and is highly correlated with other relevant precipitation variables (Puga *et al*., 2022b). Using only the variables that depend on the growing season's weather allows us to avoid potential multicollinearity and overcontrol issues.

The square values of GST and GSP are also justified from a viticultural perspective. Temperature has a positive effect on grape growth and development, but when temperatures are too high (e.g., heatwaves), they can lead to lower yields (Cola *et al*., 2020). Higher precipitation can lead to higher yields, especially in non-irrigated regions where soil moisture depends on rainfall. However, excessive precipitation can lead to lower yields, mainly due to the incidence of grape pathogens such as *Botrytis cinerea* (Kelly *et al*., 2022).

The cultivar-by-region fixed effects (μ_{vr}) control for all time-invariant observable and unobservable characteristics, and the season fixed effects (τ_s) account for seasonal shocks that affect all cultivar-by-region combinations. These fixed effects give the model strong identification properties (Deschênes and Greenstone, 2007). An alternative option would be to interact the season fixed effects with dummy variables for different groups of regions in an attempt to control for more group-specific time-varying shocks than with just the season fixed effects. The issue with this option is that group-specific fixed effects can absorb a great amount of the weather variance, amplifying the measurement error in the weather data (Fisher *et al.*, 2012). Since the weather of each wine region may not be an exact match of the weather in which the vineyards are planted, we chose not to add group-specific season fixed effects.

Another choice was to use the logarithm of yield instead of yield. Some advantages of using the natural logarithm of the dependent variable include mitigating issues of heteroskedasticity and dealing with outlying or extreme values by narrowing the range of the variable (Wooldridge *et al.*, 2021). Perhaps more importantly, this specification implies that the weather variables have the same *proportional* impact on yields across region-by-variety combinations. This is more sensible than assuming that the weather variables have the same impact on yields across variety-by-region combinations, which would be the case if the dependent variable would be yield instead of its natural logarithm.

We used the estimates of model (1) to quantify the potential impact of the climate change forecasts of Remenyi *et al*. (2020) on grape yields. This estimation assumes a ceteris paribus scenario and relies on the assumption that the impacts of short-run events (weather) are the same as those of long-run events (changes in climates). In practice, the impacts of weather may be different to the impacts of changes in climate as there is medium- and long-run adaptation (Hsiang, 2016). There can also be differences due to climatic intensification and general equilibrium effects, among other issues (Dell *et al*., 2014).

In an attempt to account for adaptation effects, we estimated a separate hybrid model:

$$(2)\ lnYield_{vrs} = \beta_0 + \beta_1 GST_{rs} + \beta_2 GST_{rs}^2 + \beta_3 GSP_{rs} + \beta_4 GSP_{rs}^2 + \beta_5 FRD_{rs} + \gamma_1 GST_{rs} * \overline{GST}_r + \gamma_2 FRD_{rs} * \overline{FRD}_r + \mu_{vr} + \tau_s + \varepsilon_{vrs}$$

For each region , the variables $\overline{\text{GST}}_r$ and $\overline{\text{FRD}}_r$ are the average values between the 2001 and 2021 seasons of the GST and FRD variables, respectively. This model allows weather to be a function of the average weather of each region (i.e., cross-sectional variation). Therefore, the γ_s coefficients can sometimes be interpreted as evidence of adaptation (Kolstad and Moore, 2020).

We also estimated another version of model (2) in which we interacted GSP in a given region and season with the average value of GSP between the 2001 and 2021 seasons in that same region. The estimate of this interaction is not statistically significant, but this result may not be reliable because such a model does not account for differences in irrigation across regions. Since we do not have good data on irrigation, we chose not to add an interaction between GSP and its average value in model (2).

Unlike model (1), model (2) has a very low predictive power. This is a consequence of the inclusion of the interaction terms between weather and average weather, which leads to issues of multicollinearity. Therefore, model (1) is our preferred model for estimating the impact of weather (and then climate change) on grape yields. We only used model (2) to get insights on potential adaptation strategies based on the climate of the regions.

We estimated models (1) and (2) using the fixed effects estimator with robust standard errors. This is arguably the most used estimator in the literature. Using other panel data approaches, such as the random effects estimator, may lead to biased estimates since the group fixed effects (i.e., cultivar-by-region fixed effects in this case) may be correlated with

TABLE 2. Estimation results of the impact of weather on (the natural logarithm of) grape yields in Australia.

Variable	Model (1)	Model (2)
GST	0.3826***	0.2997**
	(0.149)	(0.143)
GST2	- 0.0093**	- 0.0574***
	(0.0041)	(0.0212)
GSP	- 0.0010***	- 0.0008***
	(0.0003)	(0.0003)
GSP2	- 1.21e-06***	- 1.12e-06***
	(3.55e-07)	(3.56e-07)
FRD	- 0.0098	- 0.0313**
	(0.0078)	(0.0156)
GST*$\overline{GST}$		0.0986**
		(0.0406)
FRD*$\overline{FRD}$		0.0049**
		(0.0025)
Constant	- 2.2516	- 18.9596***
	(1.40)	(7.30)
Season fixed effects	Yes	Yes
Group fixed effects	Yes	Yes
Number of observations	13,600	13,600
Number of groups	1,736	1,736
Goodness of fit	Pseudo-R^2 = 0.0312	Pseudo-R^2 = 0.0450
Rho	0.5769	0.9374

Notes: GST is the growing season average temperature (°C). GSP is the total growing season precipitation (mm). FRD is the number of frost risk days (i.e., days in which the minimum temperature is lower than 2 °C). The growing season goes from October to April. Significance levels are * = 10 % level, ** = 5 % level, *** = 1 % level. The standard errors are in brackets. Each group is a cultivar-by-region combination. Rho is the fraction of variance due to group fixed effects and shows the proportion of variation explained by the group fixed effects.

the independent variables (Blanc and Schlenker, 2017). Since the weather variables are at the regional level rather than at the cultivar-by-region level, as a robustness check, we also estimated models (1) and (2) using the fixed effects estimator with robust standard errors clustered at the regional level.

Incorporating cultivar-by-region fixed effects and estimating the models using the fixed effects estimator implies time-demeaning the data for all the variables (Wooldridge *et al.*, 2021). In this case, time-demeaning involves subtracting the mean for each variety-by-region combination. As a result, the weather variables are transformed into deviations from their average, hence weather shocks (Blanc and Schlenker, 2017). Instead, the average weather (or climate) is accounted for in the variety-by-regions fixed effects, which are not computed when using the fixed effects estimator.

RESULTS

The second column of Table 2 shows the results of model (1), which is our preferred model. The coefficients of the weather variables are statistically significant at the 5 % or 1 % level, except for the coefficient of FRD, which is statistically significant only at the 21 % level. The signs of the coefficients suggest that both GST and GSP have inverted U-shape effects on yields and that FRD has a negative impact on yields. The inverted U-shape effect of GST may be explained by its positive influence on plant and berry growth but the negative effect of heat stress, while the inverted U-shape effect of GSP may be explained by both the positive impact of higher soil moisture and the negative impact of diseases that are enhanced by high precipitation (for a review see Jones *et al.*, 2011).

These effects are illustrated in Figure 2. This figure shows the predicted natural logarithm of yield for different levels of the three weather variables while keeping all other variables fixed at their main values. Yields are expected to increase with increases in GST, but the effect of higher GST becomes negative after 20.6 °C. Similarly, higher GSP is expected to lead to higher yields, but that effect becomes negative after 392 mm. The effect of FRD is negative, with an extra FRD leading to a decrease of 3.1 % in yields on average.

The mechanisms behind these yield responses to weather should be interpreted with caution. These three weather

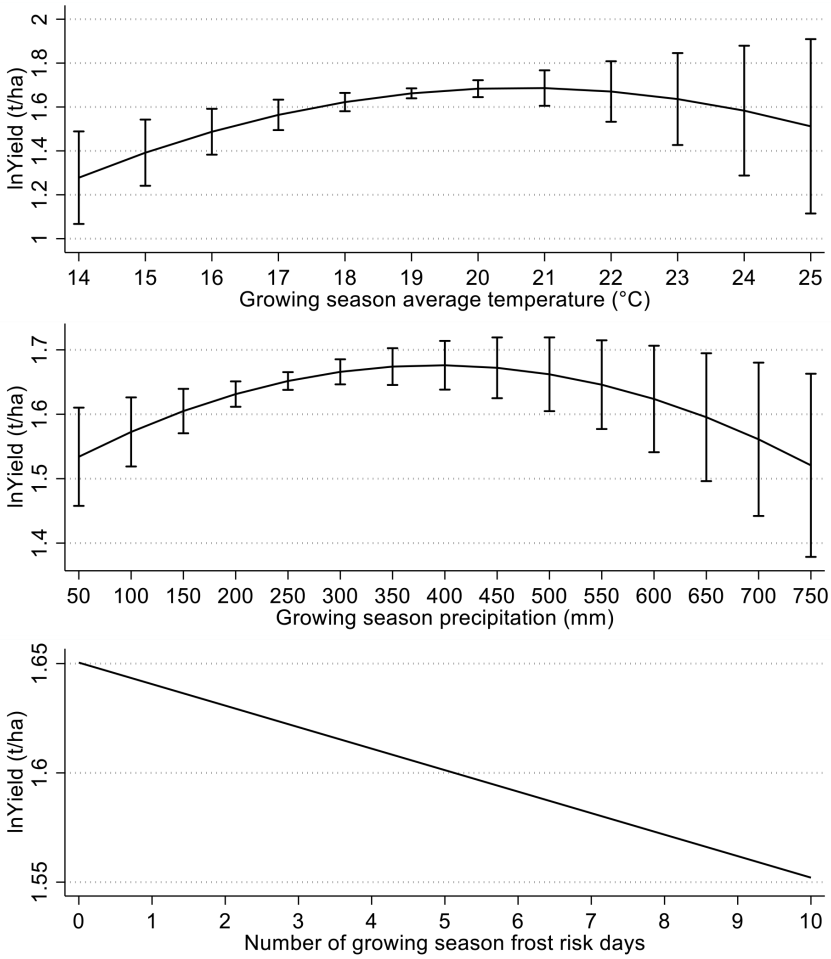


FIGURE 2. Predicted natural logarithm of grape yield as a function of weather.

Notes: Based on the estimates from model (1). The top two plots show the predictive margins with 95 % confidence intervals. The bottom plot does not show the confidence intervals due to the singularity of the covariance matrix when the delta method is applied because of a high number of zeros in the data. Therefore, the confidence intervals for this plot cannot be retrieved. The 95 % confidence intervals correspond to the predictions; these are not the confidence intervals of the marginal effects.

variables (GST, GSP, and FRD) are correlated with other weather variables. For example, higher GST also correlates with heat stress. Therefore, the yield response to GST may be explained more by the impact of heatwaves than simply the increase in GST (see Venios *et al.* (2020) for a review on the impact of average and extreme temperatures on grape production).

Also important is the fact that Figure 2 shows the average yield responses to weather shocks. Some differences across varieties and regions may be expected, being influenced by the characteristics of the production systems. For example, the yield response to changes in GSP may likely be different in irrigated vs non-irrigated vineyards.

Table 3 reports the 1997 – 2017 climate and climate change projections for most of the main Australian wine regions, as well as the expected impact of climate change projections on grape yields in those regions. In a ceteris paribus scenario, the changes in climate (specifically, GST, GSP, and FRD) between 1997 – 2017 and 2041 – 2060 are expected to increase yields by 3.7 % on average across wine regions. Yields are expected to increase in 41 of these 52 regions and decrease in the other 11. Those 11 regions, however, include the main large hot irrigated regions of Australia (Riverland, Riverina, and Swan Hill–Murray Darling), which account for about 41 % of the Australian vineyard area and often up to two-thirds of the country's grape production. As such, assuming that the area by region does not change, the area-weighted average of the expected impact of climate change on yields by 2050 is 0.6 % higher. Figure 3 shows how climate change by 2050 is projected to increase yields in most of the cooler and sometimes smaller regions and decrease yields in the largest and hottest regions.

Compared to the 1997 – 2017 climate, the projections for 2081 – 2100 are expected to increase yields in fewer regions than the 2041 – 2060 projections (32 of 52 instead of 41) and decrease yields in more (20 instead of 11). As with the projected impacts by 2050, yields may increase in the coolest regions and decrease in the hottest regions. By the end of the century, yields are expected to increase by an unweighted average of 2.9 % across regions. However, assuming that the area by region remains constant, the area-weighted average yield is expected to decrease by 3.8 %.

The results shown in Table 3 and Figure 3 are consistent with our hypothesis independently of whether we use the climate

change projections for 2041 – 2060 or 2081 – 2100. That is, climate change (due to changes in GST, GSP, and FRD) will impact yields in different ways across regions in Australia.

The second column of Table 2 shows the results of model (2), which we used in an attempt to account for non-linear effects that could, in some cases, be interpreted as adaptation to climate. The interaction between GST and its 21-year average is positive and statistically significant at the 5 % level. This means that the higher temperatures may have a less negative impact in warmer regions than in cooler regions. Part of this result might be explained by adaptation and, more specifically, by choice of production systems that lead to higher yields with higher temperatures in warmer regions.

The interaction between FRD and its 21-year average is positive and statistically significant at the 5 % level. This means that an extra frost risk day is expected to have a higher negative impact in warmer regions where frosts are less common than in cooler regions. This result might be explained, in part, by the adaptation techniques of growers in the regions that are more prone to frosts. Note that by adding the interaction between FRD and its 21-year average, the estimate for FRD remains negative as in model (1) but is now significant at the 5 % level.

As a robustness check, we estimated model (1) using the fixed effects estimator with robust standard errors, as reported in Table 2, but with the standard errors clustered at the regional level. The coefficients are the same as in the first column of Table 2, but the standard errors are different and often larger (results are omitted to save space). The GST and GST^2 coefficients are no longer statistically significant, but a Wald test suggests that they are jointly significant at the 8 % level. Therefore, we argue that the results of our preferred model are robust to this alternative estimation. We also estimated model (2) and with the standard errors clustered at the regional level and concluded that this model is also robust to this estimation method.

DISCUSSION

An important consideration when estimating the potential impact of climate change is not to extrapolate beyond the observed values of the estimation sample. The black dots in Figure 4 represent observed values of GST and GSP in each region and season. The orange squares show the forecasted climate by 2041 – 2060 and the blue triangles represent the forecasted climate by 2081 – 2100. Some of the climate projections for the end of the century (the blue triangles) are beyond the observed values in the data (the black dots), something that does not seem to be a problem with the mid-century climate projections (the orange squares). This, in turn, means that the climate change impact projections in the last column of Table 3 should be interpreted with more care due to possible issues of extrapolation beyond the observed values.

Therefore, we focus on the climate change impact estimates for 2041 – 2060. These estimates show that the average yield in Australia may change very little. However, consistent with our hypothesis, substantial differences across regions are projected.

The hottest regions may become the most negatively affected. While higher temperatures may lead to lower quality in most regions, the three largest hot-irrigated regions may have temperatures that are too high to produce grapes of decent quality (Puga *et al.*, 2022a). Consequently, up to two-thirds of the present grape production (due to the large production volumes of the Riverland, Riverina, and Swan Hill–Murray Darling) may be in regions in which both grape quality and yields may be negatively affected.

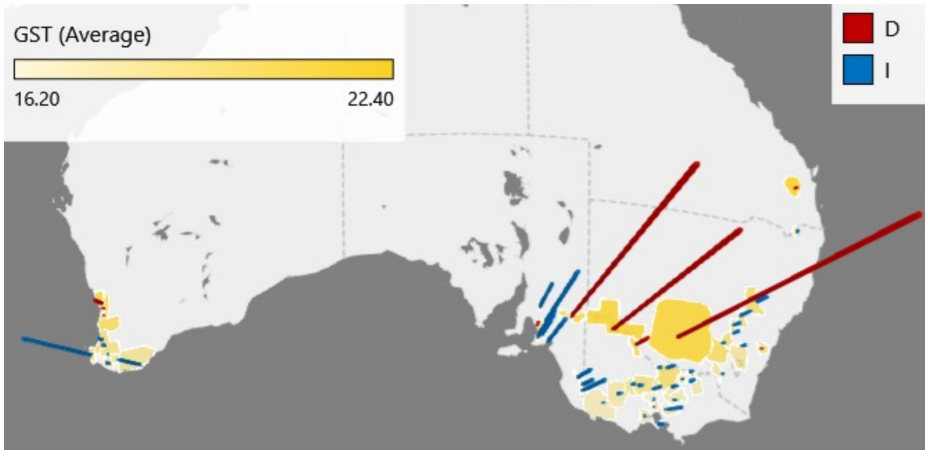


FIGURE 3. Geographical indications, area planted to vineyards, 1997 – 2017 GSTs, and projected changes in yields by 2041 – 2060.

Notes: The areas in yellow represent the geographical indications. GST stands for growing season average temperature (°C). The growing season goes from October to April. Each vertical bar is in a location within each geographical indication. The height of each bar is proportional to the area planted to vineyards in that region, based on data from Anderson and Puga (2022). The colour of each bar shows whether grape yields are projected to decrease (D) or increase (I) by 2041 – 2060 compared to 1997 – 2017, based on the estimates of model (1) and the climate change projections of Remenyi *et al.* (2020).

TABLE 3. Area (as % of Australia's total vineyard area), 1997 - 2017 climate and climate change projections, and expected impact of climate change projections on grape yields for the Australian wine regions based on the estimates from model (1).

Part 1/2

Region	Area (%)	1997 – 2017 climate			2041 – 2060 climate				2081 – 2100 climate			
		GST	GSP	FRD	GST	GSP	FRD	Impact (%)	GST	GSP	FRD	Impact (%)
Adelaide Hills	2.24	17.9	263	0.5	19	296	0.2	5.8	20.4	278	0	8.2
Adelaide Plains	0.44	20.6	182	0	21.6	170	0	–1.5	23.1	156	0	–6.7
Alpine Valleys	0.19	16.9	549	8.7	18.4	532	4.8	13.6	20.4	510	1.9	23.3
Barossa Valley	6.72	19	220	0.9	20.3	225	0.2	3.4	21.8	209	0	1.7
Beechworth	0.08	17.8	433	6.1	19.4	413	3.2	9.5	21.3	403	1.1	13.0
Bendigo	0.46	18.7	250	2.6	20.1	234	0.8	4.5	21.7	234	0.2	4.4
Blackwood Valley	0.23	18.6	194	0.6	20.1	175	0.2	3.1	21.8	152	0	1.0
Canberra District	0.32	17.6	401	8	19	443	4.1	10.1	20.9	437	1.5	15.8
Clare Valley	3.17	19.1	229	2.5	20.4	239	0.7	4.4	22	230	0.1	3.0
Coonawarra	3.57	17.3	267	3.4	18.7	233	1.6	7.8	20.3	211	0.7	11.5
Cowra	0.48	20.6	349	2.9	22	400	1	0.4	24.1	381	0.2	–7.8
Eden Valley	1.36	18.4	221	1.5	19.5	255	0.4	6.0	21	239	0.1	6.9
Geelong	0.21	17.2	289	0.3	18.3	285	0.1	6.2	19.6	274	0	10.4
Geographe	0.25	19.4	188	0.4	21.1	183	0.1	1.3	22.8	162	0	–3.7
Glenrowan	0.13	19.5	295	2.5	21.1	296	1.2	2.4	23	281	0.3	–2.1
Goulburn Valley	0.76	19.6	259	1.8	21	242	0.6	1.5	22.6	237	0.1	–1.6
Grampians	0.39	17.1	255	3.3	18.6	247	1	10.3	20.1	237	0.3	14.7
Granite Belt	0.18	18.7	573	1.6	20.1	617	0.8	1.9	22	635	0.2	0.0
Great Southern	1.42	18	260	0	19.5	188	0	2.4	20.9	163	0	2.2
Gundagai	0.25	19.8	358	4.3	21.3	383	2	2.7	23.3	374	0.6	–2.1
Heathcote	0.87	18.5	280	2.7	19.8	259	0.8	5.0	21.5	256	0.2	5.5
Henty	0.12	16.6	293	2	17.8	266	0.9	8.3	19.3	245	0.2	14.8
Hilltops	0.43	19.5	347	6.7	21	382	2.6	5.5	23.1	368	0.8	1.7
Hunter Valley	1.74	20.2	534	0.7	21.4	584	0.3	–1.9	23.2	589	0.1	–7.2
Langhorne Creek	3.99	19.2	171	0	20.1	174	0	1.8	21.3	168	0	1.4
Macedon Ranges	0.11	16.2	353	5.4	17.5	350	2.1	13.2	19.2	334	0.6	23.2
Manjimup	0.04	18.1	243	0	19.6	200	0	3.3	21.2	168	0	2.4
Margaret River	3.63	18.9	206	0	20.3	198	0	2.4	22.1	164	0	–1.2
McLaren Vale	4.52	18.6	236	0	19.8	230	0	3.0	21.3	215	0	2.7
Mornington Peninsula	0.58	17.4	358	0	18.6	324	0	5.6	20.2	313	0	9.4
Mudgee	0.81	19.5	448	2.4	20.9	477	0.9	2.2	22.8	486	0.2	–1.6
Murray Darling	11.70	21.9	165	0.1	23.2	151	0	–5.1	24.9	149	0	–14.9
Swan Hill	1.39	20.8	183	0.5	22.3	173	0	–2.5	24	169	0	–10.1
Orange	0.83	18.1	427	8	19.5	475	3.3	9.1	21.6	462	1.1	12.2
Padthaway	2.44	17.8	202	4.8	19.3	205	1	10.2	20.8	190	0.2	12.1
Peel	0.03	20.2	183	0.7	21.7	175	0.1	–0.7	23.5	157	0	–7.7
Pemberton	0.25	18.2	287	0	19.7	243	0	3.4	21.3	202	0	2.1
Perricoota	0.28	19.9	212	1.5	21.3	200	0.4	0.7	23	198	0.1	–3.8
Perth Hills	0.09	21.1	190	0.1	22.6	193	0	–3.0	24.3	178	0	–11.9
Pyrenees	0.37	18	241	2.6	19.4	239	0.8	7.0	20.9	237	0.2	9.0
Riverina	14.04	21.8	228	0.7	23.3	233	0.1	–4.4	25.3	223	0	–16.7
Riverland	14.17	21.1	148	0.3	22.4	140	0	–2.8	23.9	134	0	–9.7

Region	Area (%)	1997 – 2017 climate			2041 – 2060 climate				2081 – 2100 climate			
		GST	GSP	FRD	GST	GSP	FRD	Impact (%)	GST	GSP	FRD	Impact (%)
Rutherglen	0.30	19.7	323	3.2	21.2	306	2	1.4	23.1	300	0.6	–2.6
South Burnett	0.16	22.4	541	0.1	23.9	585	0	–8.3	25.7	602	0	–20.8
Southern Highlands	0.09	18	572	1.3	19	735	0.7	–5.6	20.7	702	0.2	–0.1
Strathbogie Ranges	0.47	17.6	356	3.6	19	343	1.8	8.0	20.8	335	0.5	12.1
Sunbury	0.05	17.6	317	0.7	18.6	314	0.4	5.1	20	297	0.1	8.8
Swan District	0.54	21.8	157	0	23.4	148	0	–6.1	25.2	135	0	–17.5
Tumbarumba	0.16	17.5	455	9.2	18.9	463	5.9	9.9	20.8	464	2.3	17.1
Upper Goulburn	0.29	16.9	422	4	18.2	412	2.6	9.3	20	396	0.9	17.1
Wrattonbully	1.87	17.5	229	5.2	19	223	1.5	10.6	20.6	202	0.4	13.6
Yarra Valley	1.60	16.3	539	1.9	17.5	503	1.1	10.8	19.1	473	0.3	20.6
Unweighted average		18.8	305	2.3	20.2	307	1.0	3.7	21.9	295	0.3	2.9
Weighted average		19.9	229	1.1	21.3	226	0.4	0.6	22.9	215	0.1	–3.8

Notes: Area is the 2016 vineyard area for 2016 as a percentage of the total vineyard are in Australia. The regions covered in this table represented 91 % of the Australian vineyard area in 2016. GST is the growing season average temperature in °C, GSP is the total growing season precipitation in mm, and FRD is the number of frost risk days (i.e., minimum temperature < 2 °C) in the growing season. The growing season goes from October to April. The impact is the projected percentage change in yield due to changes in climate (i.e., GST, GSP, and FRD) based on the estimates from model (1). The weighted averages use the 2016 vineyard area of each region as the weights.

As such, the findings of this study favour the viewpoint of those who argue that Australia should shift its production towards cooler regions and away from the largest hot irrigated regions. Although the 2081 – 2100 estimates of the impact of climate change are less reliable, they also support this viewpoint.

While this study provides a robust statistical analysis of the potential impact of climate change on grape yields (especially for the projected climate by 2041 – 2060), there are some sources of uncertainty in the results. The main limitations are that we have assumed a ceteris paribus scenario and used the estimates of short-run events (weather shocks) to estimate the impact of long-run events (changes in climate).

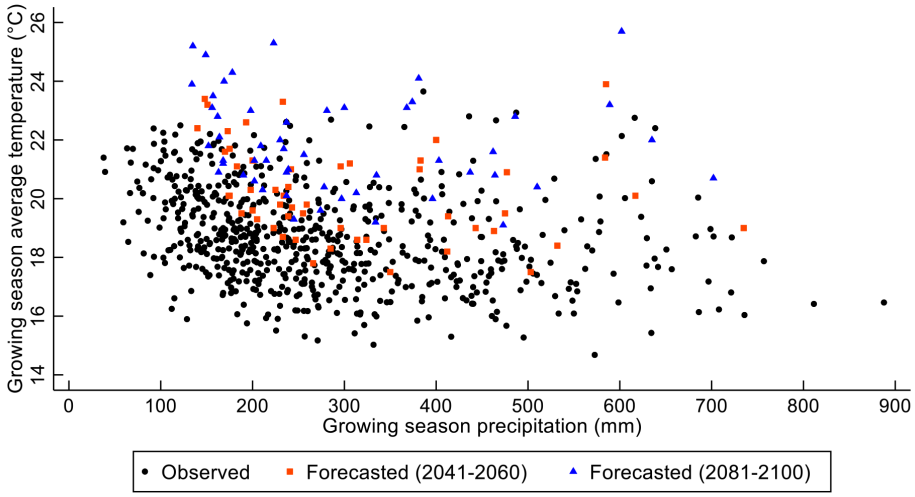
Consequently, the estimates of model (1) do not account for medium- and long-run adaptation. While we acknowledge the statistical limitations of model (2), its statistically significant interactions between seasonal weather and the average weather across seasons suggest different effects of weather based on the climate. These results might be due in part to adaptation. In the future, changes in the characteristics of the production systems and the choice of more-appropriate plant material may help adapt to climate change (van Leeuwen and Destrac-Irvine, 2017; van Leeuwen *et al*., 2019).

We argue, however, that model (2) provides poor evidence of adaptation because profit-maximising decisions do not always imply maximising yields. In the warmer regions of Australia, grape growers tend to use trellis systems and production strategies that are adequate for achieving high yields. However, grape growers in the cooler regions usually use canopy management strategies and production technologies that are better suited for producing high-quality grapes. In fact, 10 % of Australia's grape growers perform crop thinning, a practice that is rare in the warmest regions but common in the cooler regions, with rates of adoption that in some regions are higher than 50 % (Nordestgaard, 2019). When price premiums for quality lead to growers' profit-maximising behaviour that do not necessarily translate into yield-maximising behaviour, there are issues with hybrid models that attempt to capture adaptation. This is because adaptation efforts may not necessarily be targeted at increasing yields but rather at maximising profits.

Nevertheless, while not accounting for adaptation may lead to overestimating the effect of climate change, the estimates of the effect of weather may still provide plausible indications of the potential impact of climate change. This is because grape growing is capital intensive, involving large up-front investment with a very long investment horizon, hence slower, high-cost adaptation processes. Ineffective or limited adaptation and adjustments lead to smaller differences between short-run responses to weather shocks and long-run responses to climate change (Kolstad and Moore, 2020). This means that the estimates of the impact of weather on yields could often be a better indicative of the impact of climate change on grape yields than, for example, on yields of annual crops for which adaptation is easier or faster.

Slower adaptation processes mean that accounting for climatic intensification may often be more relevant when analysing the potential effect of changes in climate. Grapevine yields form over two consecutive seasons, meaning that the weather in one season has an influence on both the current and the following season (Guilpart *et al.*, 2014; Molitor and Keller, 2017). Model (1) does not account for the dynamic impacts of weather on grape yields.

FIGURE 4. GST and GSP for the observed values of weather in the dataset and for the climate projections for the Australian regions for 2041 – 2060 and 2081 – 2100.



Notes: The growing season goes from October to April.

As a result, it provides short-run estimates of the impact of weather (the impact in season *s*) rather than its long-run estimates (the impact in both season *s* and season *s* + 1).

An important example of climatic intensification is drought prevalence: droughts are projected to become more frequent in Australia's wine regions (Remenyi *et al*., 2020), potentially leading to lower average yields, although some studies suggest there are priming effects on the tolerance of vines to recurrent droughts (Zamorano *et al*., 2021). The perennial characteristic of grapevines means that a second consecutive drought year may lead to lower yields than a first drought year.

In a few decades from now, growers may have less short-run adaptation strategies (i.e., irrigation) for dealing with droughts than in the period of observed data (2001 – 2021). Therefore, the Australian wine industry should increase its ongoing efforts to become more resilient to droughts, something that could be achieved by choice of appropriate rootstocks (De Souza *et al*., 2022) or cultivars that are more tolerant to drought (Plantevin *et al*., 2022). Some of these non-traditional cultivars might have good potential in the Australian market (Mezei *et al*., 2021).

CONCLUSION

We have estimated the impact of weather shocks on grape yields in Australia for analysing the potential impact that climate change may have on grape yields. By 2050, climate change may lead to higher yields in most regions of Australia. This may be the case in many cooler regions but not in the hottest regions, including the country's largest regions. These results are consistent with our hypothesis that climate change (due to changes in GST, GSP, and FRD) will impact yields in different ways across regions in Australia. However, these results also mean that by assuming constant grape areas by region, the area-weighted average yield may change very little.

While this study provides a robust statistical analysis of the potential impact of climate change on grape yields, there is still some uncertainty in the results. The main limitations are that our framework assumes a ceteris paribus scenario and that it uses the estimates of short-run events (weather shocks) to estimate the impact of long-run events (changes in climate). In an attempt to account for adaptation, we have estimated a hybrid model, but due to statistical limitations and the characteristics of grape production, this model is not very useful for this purpose. Nevertheless, because adaptation in grape production is limited, not accounting for adaptation may still lead to plausible estimates of the potential impact of climate change.

The panel data approach used in this study could be applied in other settings. Datasets that allow for more statistical power could be used to model the long-run effects of weather, as well as how yield responses to weather vary by variety. There is also potential to explore alternate specifications to the one in model (1). For example, Schlenker and Roberts (2009) developed a method for quantifying the non-linear impacts of temperature on yields after computing different thresholds and marginal effects of growing and killing degree days. That method could potentially be applied to analyse the impact of weather on grape yields. Further, the framework used in this study could also be applied to quantifying the impact of weather or climate change on grape or wine quality, prices, costs, profits, and the compression of the harvest period.

In Australia, further research could look at the impact of other climate variables and the impact of climatic events such as droughts, which are expected to increase in the future and may lead to potentially different effects of climate change from the ones we have estimated. This is because it may become harder and more costly (or even impossible in vineyards with no irrigation) to maintain adequate soil moisture levels to achieve their target yields. More research also is needed to understand the impact that climate change may have on

costs and overall profits. For example, a warmer and drier climate may lower the need for fungicides but hugely raise the cost of irrigating in the hottest regions. Growers and wine businesses could then use that information and that presented in this study to develop profitable strategies that account for the potential impacts of climate change.

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