Essays in Wine Economics

A thesis submitted in partial fulfilment of the requirements for the degree of Doctor of Philosophy

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Declaration

I certify that this work contains no material which has been accepted for the award of any other degree or diploma in my name, in any university or other tertiary institution and, to the best of my knowledge and belief, contains no material previously published or written by another person, except where due reference has been made in the text. In addition, I certify that no part of this work will, in the future, be used in a submission in my name, for any other degree or diploma in any university or other tertiary institution without the prior approval of the University of Adelaide and where applicable, any partner institution responsible for the joint award of this degree.

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I acknowledge the support I have received for my research through the provision of an Australian Government Research Training Program Scholarship. I also acknowledge the support I have received through a Wine Australia Supplementary Scholarship.

Germán Puga

Acknowledgements

Besides acknowledging the support I have received for my research through the provision of an Australian Government Research Training Program Scholarship, I acknowledge the support I have received through a Wine Australia Supplementary Scholarship. I also acknowledge the University of Adelaide for the resources and high-quality student experience provided.

On a personal note, first and foremost, I thank Professor Kym Anderson AC. While officially he has been my co-supervisor, he is by far the person who has given me more guidance. Working with Professor Anderson was my main motivation for coming to Adelaide, and I am very grateful for his support before and during my PhD. He has given me the high-quality advice I was expecting based on his knowledge and experience, but while investing a lot of time and effort into his supervisory role. From what I have seen, having a very senior supervisor who also invests a lot of time in advising is rare, and I am very grateful for that.

I am also grateful to the two other people who have supervised me: Professor Firmin Doko Tchatoka and Professor Wendy Umberger. They too have given me very useful advice that has allowed me to publish a big part of the research I have conducted during my PhD. Professor Umberger was my principal supervisor until late 2021, and I would have liked her to continue in her role if I would have not have been 'asked' by the University to designate another principal supervisor instead. On that note, I appreciate Professor Doko Tchatoka's willingness to become my principal supervisor. In addition to being an outstanding advisor regarding the general direction of my research, he has been especially helpful with the statistical and econometric analyses that I have done.

Besides thanking my supervisors, I thank Professor Gregory Jones, who has provided useful advice and has been very generous with his time. I also acknowledge the support of other co-authors of some of the outputs of this thesis: Dr Richard Smart and Professor Alejandro Gennari. I am also acknowledging other people in the acknowledgements sections of most chapters and appendixes.

As well, I am very appreciative of the support from people who are not mentioned elsewhere in this thesis, but who have given me very useful recommendations, including Dr Benedikt Heid, Dr Virginie Masson, Associate Professor Armando Corsi, and Associate Professor Patrick O'Connor. As well, I thank other academics and PhD students from the

Centre for Global Food and Resources and, more broadly, the School of Economics and Public Policy of the University of Adelaide. Beyond the School, Sandy Hathaway from Wine Australia has helped me understand the existing sources of data related to the Australian wine industry.

Finally, I acknowledge the detailed and prompt feedback provided by the reviewers of this thesis, Professor Nick Vink from Stellenbosch University and Professor Cornelis van Leeuwen from Bordeaux Sciences Agro. Professor Vink is an eminent agricultural economist who is very well-known in various sub-fields, wine economics being one of them. Professor van Leeuwen is one of the most distinguished viticultural scientists in the world. Since this thesis is related to both wine economics and viticulture, it has been fantastic to get feedback from experts in both fields. Both reviewers provided very positive and insightful feedback. While they did not formally request changes, I have modified this thesis following their suggestions. As a result, the quality of some chapters, especially their concluding remarks, have been improved considerably. I am particularly thankful for some ideas for future research outlined by both reviewers.

Dedication

To the Australian taxpayers, and in particular, to those who work in the wine industry.

Abstract

This thesis explores relevant topics in wine economics and viticulture from a multidisciplinary perspective. It is based on six main analytical chapters (i.e., published papers in scientific journals) and two other publications added as appendixes. The first two papers use econometric methods to quantify the potential impact of climate change in Australia. They show that climate change will likely have a negative impact on the country's viticulture, mainly due to the deteriorating effect that higher temperatures could have on grape (and wine) quality. The third paper classifies and describes the world's wine regions based on their climates. It also shows that for maintaining wine styles, winegrowers in many regions may need to source winegrapes from regions with more appropriate (usually cooler) climates or to plant alternative winegrape varieties that do better in their climates. This situation is not different in Australia, as suggested in the first two papers and discussed in the first two appendixes. The fourth paper shows that, far from becoming more diverse, the mix of winegrape varieties is becoming more similar across countries and more concentrated globally. While the main aim of the fifth paper is to analyse how globalisation has changed the impact of some key variables on wine trade flows, it also shows that countries with a more similar mix of winegrape varieties trade more wine (although this is not necessarily a causal relationship). Finally, the last paper estimates the impact of the European grapevine moth on grape production and justifies its eradication program.

Chapter 1

1. Introduction

There are about 4.5 million hectares planted to winegrapes of more than 1,700 varieties (Anderson and Nelgen, 2020a). With these grapes, winegrowers produce about 25 million kl of wine annually, more than two-fifths of which is exported (Anderson and Pinilla, 2021; OIV, 2023). Thanks to the importance of the wine industry and the interest in it, wine economics has emerged as a growing field, not only within agricultural economics but also in related areas (Storchmann, 2012; Castriota, 2020).

This academic subject has been created by a group of economists, statisticians, psychologists, and agronomists (see Orley Ashenfelter's foreword in Castriota (2020)). The growing number of researchers in this field has led to two professional organisations: the European Association of Wine Economists (EuAWE) and the American Association of Wine Economists (AAWE). The AAWE publishes Cambridge University Press *Journal of Wine Economics* and runs annual conferences (15 so far) that gather wine economists from around the world. There is also a wine business professional organisation, the Academy of Wine Business Research (AWBR), which publishes the *International Journal of Wine Business Research*.

This thesis aims at contributing to this growing field by producing research that is relevant to the wine industry. Like the field of wine economics itself, the nature of this thesis is multidisciplinary. As such, this thesis contributes to the agricultural economics discipline, but also (and to a higher degree) to viticulture and the impact that climate change may have on winegrowing, and to a lesser extent to adjacent fields such as wine business.

A major component of this thesis focuses on Australia. This country is the world's fifth largest wine producer and exporter (Wine Australia, 2022). This Australian wine sector, however, is threatened by climate change. Remenyi et al. (2020) project that all the Australian wine regions will become hotter and that most will become dryer. This thesis quantifies part of the impact that climate change may have in the Australian wine industry, and analyses the changes that have taken (and should take) place in the country's mix of winegrape varieties in light of climate change but also other issues such as prohibitive wine tariffs from China.

Another important component of this thesis targets the world as a whole. Much of this component also relates to the issue of climate change and the mix of winegrape varieties. It seeks to classify and describe the climates of the world's wine regions and to derive implications in a context of climate change, as well as to better understand recent changes that have taken place in the world's mix of winegrape varieties. Another part of this world-focused component investigates how this mix of winegrape varieties relates to wine trade, while also analysing the impact that globalisation has had on some key variables affecting international wine trade flows.

Last, a minor component of this thesis consists of a case study focused on Argentina – although with broader implications. This study quantifies the impact of arguably the most important pest on grape production (i.e., the European grapevine moth), and justifies its eradication program in Argentina. While it is not the aim of this study, it also relates to the impact of weather in viticulture as it includes some key weather variables in its econometric model.

Table 1.1 shows the structure of this thesis. Besides this introductory chapter and a concluding chapter (**8**), there are six main analytical chapters (**2** to **7**). There are also two appendixes (**1** and **2**) because they too provide information that is relevant and helpful to the wine industry.

The last column of Table 1.1 indicates the current publication status of each paper. The six main analytical chapters (**2** to **7**) are published in Q1 journals. Of the two appendixes that are not intended as main analytical chapters but that are still part of this thesis, **Appendix 1** is published as a conference proceeding and **Appendix 2** is published in an industry journal.

Table 1.1: Title and status of the chapters of this thesis.

Chapter	Title	Status
1	Introduction	Intended only as part of this thesis
2	The impact of climate change on grape yields: Evidence from Australia	Published in *OENO One*
3	Impact of growing season temperature on grape prices in Australia	Published in the *Australian Journal of Grape and Wine Research*
4	A climatic classification of the world's wine regions	Published in *OENO One*
5	Concentrations and similarities across countries in the mix of winegrape cultivars	Published in the *American Journal of Enology and Viticulture*
6	Explaining bilateral patterns of global wine trade, 1962-2019	Published in the *Journal of Wine Economics*
7	The impact of the European grapevine moth on grape production: Implications for eradication programs	Published in the *Journal of Wine Economics*
8	Concluding remarks	Intended only as part of this thesis
Appendix 1	Climate change and the evolving mix of grape varieties in Australia's wine regions	Not intended as a main analytical chapter, but published in the *IVES Conference Series*
Appendix 2	Two decades of grape variety trends in Australia's wine regions	Not intended as a main analytical chapter, but published in the (non-peer reviewed) *Wine and Viticulture Journal*
Appendix 3	References	Intended only as part of this thesis

Other outputs of this thesis have been 12 conference presentations and one poster. These presentations and this poster, and the chapters they relate to, are specified in Table 1.2.

Table 1.2: Presentations at international conferences that arose from the work conducted in this thesis.

<table>
<tr><th>Title</th><th>Conference</th><th>Presentation type</th><th>Related thesis chapters</th><th>Award or scholarship</th></tr>
<tr><td>Statistical methods to quantify the impact of climate change</td><td>Climate Adaptation Conference, 2023</td><td>In-person presentation (Adelaide)</td><td>2, 3, and beyond</td><td></td></tr>
<tr><td>Climate econometrics and wine</td><td rowspan="2">American Association of Wine Economists (AAWE) 15th Annual Conference, 2023</td><td rowspan="2">In-person presentation (Stellenbosch, South Africa)</td><td>2, 3, and beyond</td><td rowspan="2"></td></tr>
<tr><td>Grape variety trends in Australia’s wine regions[1]</td><td>Appendix 2</td></tr>
<tr><td>The use of statistical methods to quantify the impact of climate change in grape and wine research</td><td>Crush 2023 – the grape and wine science symposium, 2023</td><td>In-person presentation (Adelaide)</td><td>2, 3, and beyond</td><td>Registration (sponsored by Wine Australia)</td></tr>
<tr><td>The impact of climate change on the Australian wine industry</td><td>Australasian Agricultural and Resource Economics Society (AARES) 67th Annual Conference, 2023</td><td>In-person presentation (Christchurch, New Zealand)</td><td>2 and 3</td><td>Travel award from AARES to present at the conference</td></tr>
<tr><td>The impact of temperature on grape prices: Evidence from Australia</td><td rowspan="2">American Association of Wine Economists (AAWE) 14th Annual Conference, 2022</td><td rowspan="2">In-person presentations (Tbilisi, Georgia)</td><td>3</td><td rowspan="2">University of Adelaide’s Graduate Research School scholarship
AAWE scholarship to present at the conference</td></tr>
<tr><td>Explaining bilateral patterns of global wine trade, 1962-2019</td><td>6</td></tr>
</table>

Table 1.2 (cont.): Presentations at international conferences that arose from the work conducted in this thesis.

Title	Conference	Presentation type	Related thesis chapters	Award or scholarship
Climate change and the evolving mix of grape varieties in Australia's wine regions	14th International Terroir Congress and 2nd ClimWine Symposium, 2022	In-person presentation (Bordeaux, France)	**Appendix 1**	University of Adelaide's School of Economics and Public Policy grant to present at the conference
The impact of climate change on the Australian wine industry	19th Australian Wine Industry Technical Conference (AWITC), 2022	In-person presentation (Adelaide, Australia)	**2**, **3**, and **Appendix 1**	Registration (sponsored by Wine Australia)
The impact of climate change on the Australian wine industry		Poster presentation (Adelaide)	**2** and **3**	
The impact of climate change on grape yields in Australia	AARES 66th Annual Conference, 2023	Online presentation	**2**	Registration (sponsored by the University of Adelaide's Centre for Global Food and Resources)
The impact of climate change on grape yields in Australia	Crush 2021 – the grape and wine science symposium, 2021	In-person presentation (Adelaide)	**2**	Registration (sponsored by Wine Australia)
Towards a climatic classification of the world's wine regions	AARES 65th Annual Conference, 2023	Online presentation	**4**	Registration (sponsored by the University of Adelaide's Centre for Global Food and Resources) Special Mention for first-time presenter at the conference

Notes: [1]The first author in this conference presentation is Kym Anderson. In all other presentations, the first author is German Puga. All papers and the poster were presented by German Puga.

The content of all the already-published chapters and appendixes of this thesis is the same as in the outlets in which they have been published. There may be some differences due to minor changes after their acceptance (in the proofing stage) and in some of their acknowledgement sections, as well as some minor improvements in the manuscripts themselves. There are also some differences in the supplementary material of some chapters, as these supplementary materials have in some cases been modified to best fit the format of this thesis. For example, in cases where the original supplementary material corresponded to an Excel file.

Chapters **2** to **7** and Appendixes **1** and **2** have differing lengths and structures, based on the requirements of the publisher of each outlet. The writing style also varies across chapters and appendixes, reflecting the contribution of different co-authors as well as the effort to make them more appropriate for each outlet. These differences often extend to the vocabulary used. For example, in those chapters published in science journals, we talk about 'statistical methods' rather than 'econometric methods'. Another example is the use of the word 'cultivar', which is the preferred term in some journals for what we otherwise refer to as a winegrape 'variety'.

Chapters **2** and **3** consist of econometric analyses of the impact of climate change on viticulture in Australia. In **Chapter 2** (Puga et al., 2023), we estimate a panel data model of the impact of weather on grape yields and then use those estimates to quantify the potential impact of climate change projections. The results imply that, under a set of assumptions that include a no-change scenario, climate change by 2050 is likely to lead to higher yields in most regions (including the coolest) but to a decrease in the country's largest (and hottest) regions. Consequently, the area-weighted average yield in Australia may change very little.

Besides impacting yields, climate change could impact the quality of Australian grapes and hence their prices. **Chapter 3** (Puga et al., 2022a) focuses on the impact of growing season temperature on grape prices in Australia. Due to data limitations, we rely on a cross-sectional model rather than a panel data model like the one in **Chapter 2**. This model controls for characteristics of the production systems of the regions and leads to very similar results to the ones of a LASSO model that we estimate as a robustness check. These results suggest that assuming (among other things) a no-change scenario, forecasted changes in growing season temperature by 2050 may lead to lower grape prices (12% on average across regions).

However, changes in the production systems, as growers gradually adapt to climate changes, may help mitigate decreases in quality and prices.

Since **Chapter 3** signals that a decrease in grape quality may likely result from climate change in Australia, that raises the question of how well-suited the country's mix of winegrape varieties is in light of recent climate change projections. **Appendix 1** (Puga et al., 2022b) is appended to this thesis as it provides insights into this research question. In particular, it shows that while there is a wide range of climates across wine regions in Australia, most regions are warm or hot, and dry. Over this century, there have been some adjustments towards climates that may be more appropriate for producing higher-quality wines of the most planted varieties in Australia. However, these adjustments have been relatively small and lower than in other non-European countries. We conclude that for maintaining wine styles, many Australian winegrowers will need to change their mix of winegrape varieties or plant that mix in vineyards with more-appropriate climates.

Appendix 2 (Anderson and Puga, 2023) provides additional insights into the changes that have taken place in Australia's viticulture during this century. As with **Appendix 1**, this appendix is not intended as a main analytical chapter but is part of this thesis as it provides relevant insights to the Australian wine industry. Importantly, this chapter summarises a database that we created for the Australian wine industry (Anderson and Puga, 2022a). The index of tables of this database is shown in **Appendix 2**. This article and this database follow up another article (Anderson and Puga, 2022b) and another database (Anderson and Puga, 2021) focused in South Australia as opposed to Australia as a whole. These two other outputs focused on South Australia are not appended to this thesis since they are older and less-comprehensive versions of what is presented in **Appendix 2**.

Chapters **4** to **6** are global studies also related to climate change or the mix of winegrape varieties. In **Chapter 4** (Puga et al., 2022c) we rely on data on 16 climate variables to classify 813 locations representing 99% of the world's winegrape area[1]. We use principal component analysis (PCA) for data reduction and conduct a k-means cluster analysis with the resulting principal components from the PCA. This leads to an easy-to-interpret three-cluster classification, with premium wine regions in each cluster. Further analysis signals that with

[1] While the main source of that data is Anderson and Nelgen (2020a), German Puga contributed to the compilation of the climate data for that database. That contribution is acknowledged in Anderson and Nelgen (2020b).

both climate change and an increasing preference for premium wines, many of the world's winegrowers may need to change their mixes of varieties or source more of their winegrapes from more appropriate climates. This conclusion is similar to that of **Appendix 1** for Australia.

Chapter 5 (Puga and Anderson, 2023) consists of a descriptive analysis of the mix of winegrape varieties in the world, in a similar way as **Appendix 2** does for Australia. This globally-focused chapter uses the data of Anderson and Nelgen (2020a) but gives additional insights to those of previous studies based on that database. More specifically, it shows a great diversity across countries in terms of both similarities and concentrations, while providing robust evidence that the mixes of winegrape varieties are tending to become more similar across countries and more concentrated within countries and globally. These results are backed by partition and hierarchical cluster analyses (as well as more simple analyses) based on the variety similarity index of Anderson (2010) and a novel variety concentration index. These results point to an increasing scope for winegrowers to diversify and differentiate their product by choosing less-planted varieties, but they also suggest that most of them have found it more profitable to move toward mainstream varieties.

Chapter 6 (Puga et al., 2022d) also relates to the mix of winegrape varieties as it analyses the impact of winegrape similarities on bilateral wine trade patterns. The results indicate that countries trade more wine with each other the closer their mix of winegrape varieties, but the gravity models used in this chapter do not allow us to identify a causal relationship. We also use another set of gravity models to analyse how the impact of some variables affecting wine trade has changed in the second wave of globalization. The results suggest that the impact of distance, common language, and common colonizer on wine trade was lower in the 1991–2019 period than in the 1962–1990 period.

In **Chapter 7** (Puga et al., 2020) we estimate a panel data model to quantify the impact of the European grapevine moth on grape production in Mendoza. The results indicate that this pest led to a decrease in grape production of up to 8% in this province, but that decrease could have been worse without an eradication program. Based on these results and the experiences in Argentina and other countries with eradication programs, we argue that programs for the eradication of this insect may be economically justified in Argentina, and perhaps in other countries.

While the aim of this chapter is not related to climate change or the mix of winegrape varieties, the impact of some key weather variables is estimated in its model. Therefore, it provides information on the impact of three weather variables that are also estimated for Australia in **Chapter 2**, as well as the impact of hail on grape production (which is estimated to decrease yields by about 18.4% per year).

Finally, **Chapter 8** provides conclusions and recommendations. This chapter provides additional comments on the direction of research undertaken and research efforts not included in this thesis, as well as further recommendations and ideas for future research.

Despite the relationships between Chapters **2** to **7** and Appendixes **1** and **2**, all these chapters and appendixes stand alone, so they can be read separately. Therefore, the reader of this thesis could choose the order in which to read its chapters. **Appendix 3** provides a list of all references used in this thesis.

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Chapter 2

Statement of authorship

Title of paper	The impact of climate change on grape yields: Evidence from Australia
Publication status	Published
Publication details	Puga, G., Anderson, K., & Doko Tchatoka, F. (2023). The impact of climate change on grape yields: Evidence from Australia. *OENO One*, forthcoming. https://doi.org/10.20870/oeno-one.2023.57.2.7280

Principal author

Name of principal author (candidate)	German Puga		
Contribution to the paper	Led the study conception and design, reviewed the literature, cleaned the data and prepared the datasets for analysis, performed econometric analyses, and interpreted the results. Wrote drafts/versions of the paper. Presented the paper at seminars and conferences to get feedback. Led the review/publication process.		
Overall percentage	80%		
Certification	This paper reports on original research I conducted during the period of my Higher Degree by Research candidature and is not subject to any obligations or contractual agreements with a third party that would constrain its inclusion in this thesis. I am the primary author of this paper.		
Signature		Date	11/07/2023

Co-author contributions

By signing the Statement of authorship, each author certifies that:

I. the candidate's stated contribution to the publication is accurate (as detailed above);
II. permission is granted for the candidate in include the publication in the thesis; and
III. the sum of all co-author contributions is equal to 100% less the candidate's stated contribution.

Name of co-author	Kym Anderson		
Contribution to the paper	Contributed to the study conception and design, and to the interpretation and discussion of the results. Edited drafts/versions of the paper and helped responding reviewers' questions.		
Signature	**Signed form available at the end of this thesis.**	Date	

Name of co-author	Firmin Doko Tchatoka		
Contribution to the paper	Contributed to the study conception and design (especially in terms of the econometric analyses), and to the interpretation and discussion of the results. Edited drafts/versions of the paper and helped responding reviewers' questions.		
Signature	**Signed form available at the end of this thesis.**	Date	

2. 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. The aim of this research is 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

2.1. Introduction

The Australian wine sector is an important industry with 146,244 ha of vineyards, 2,360 wineries, and 6,250 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℃ by 2050 and 2.8℃ 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 grape prices in Australia, as a consequence of changes in the composition of the berries 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) conduct an experiment on the impact of warmer temperatures on yields of Syrah in the Barossa Valley. However, to our knowledge, there is no study quantifying 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. This approach implies comparing future climate projections with the observed weather over a time period, so it does not capture the impact that climate change has already had on yields. 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. Importantly, this study focuses only on the impact of climate change on yields, leaving aside potential impacts on grape and wine quality and prices, production costs, and profits.

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 are able to 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 separately identify the impact of climate variables on yields, agronomic models can sometimes account for extreme climatic events and the effect of carbon dioxide (CO_2) fertilization. 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, 2013, 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 are able to 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 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).

2.2. Materials and methods

2.2.1. 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 the 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-km 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 that 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 1,736 cultivar-by-region combinations for which there is information on 7.8 years on average, hence totalling 13,600 observations. Table 2.1 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.

Table 2.1: 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 (℃) 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℃ (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.

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 2.1). 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 the climate change projections. This is a common case in studies quantifying the impact of weather and climate change on agriculture (Blanc and Schlenker, 2017).

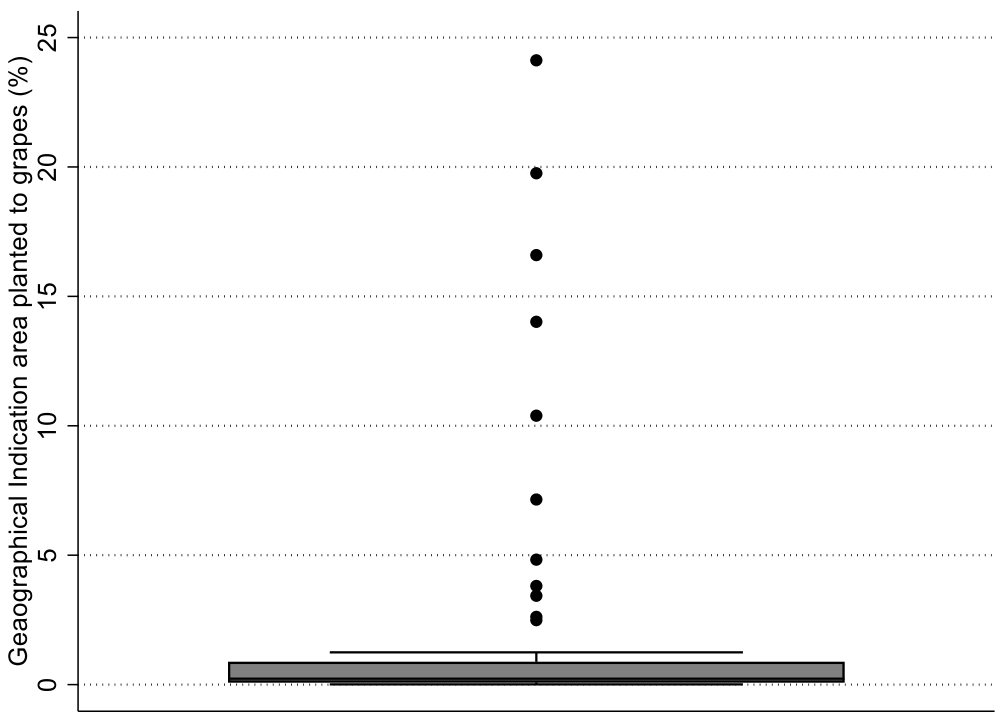

Figure 2.1: Boxplot showing the area in each wine region planted to grapes.
Notes: Based on data from Anderson and Puga (2022), for 49 of the 52 geographical indications (GIs) for which we are predicting the impact of climate change.

2.2.2. Methods

The framework that 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:

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

The dependent variable is the natural logarithm of yield of cultivar v 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 why 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 indexes 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 these 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, hence amplifying the issue of 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 the impacts 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 be differences also 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:

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

For each region r, the variables $\overline{GST}_r$ and $\overline{FRD}_r$ 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 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.

Since the aim of this statistical model is to identify a causal relationship between weather shocks and grape yields, we did not focus on the predicting capability of this model. In other statistical and machine learning approaches it would make sense to train a model with most of the data and then test it using the remaining data. (Some machine learning approaches split the data into three or more sets.) The models used in this study are not ideal for predicting yields, but rather to identify the above-mentioned causal relationships. Therefore, we did not test how well they perform in predicting yields.

2.3. Results

The second column of Table 2.2 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).

Table 2.2: 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)
GST^2	-0.0093**	-0.0574***
	(0.0041)	(0.0212)
GSP	-0.0010***	-0.0008***
	(0.0003)	(0.0003)
GSP^2	-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.

These effects are illustrated in Figure 2.2. 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 392mm. The effect of FRD is negative, with an extra FRD leading to a decrease of 3.1% in yields on average.

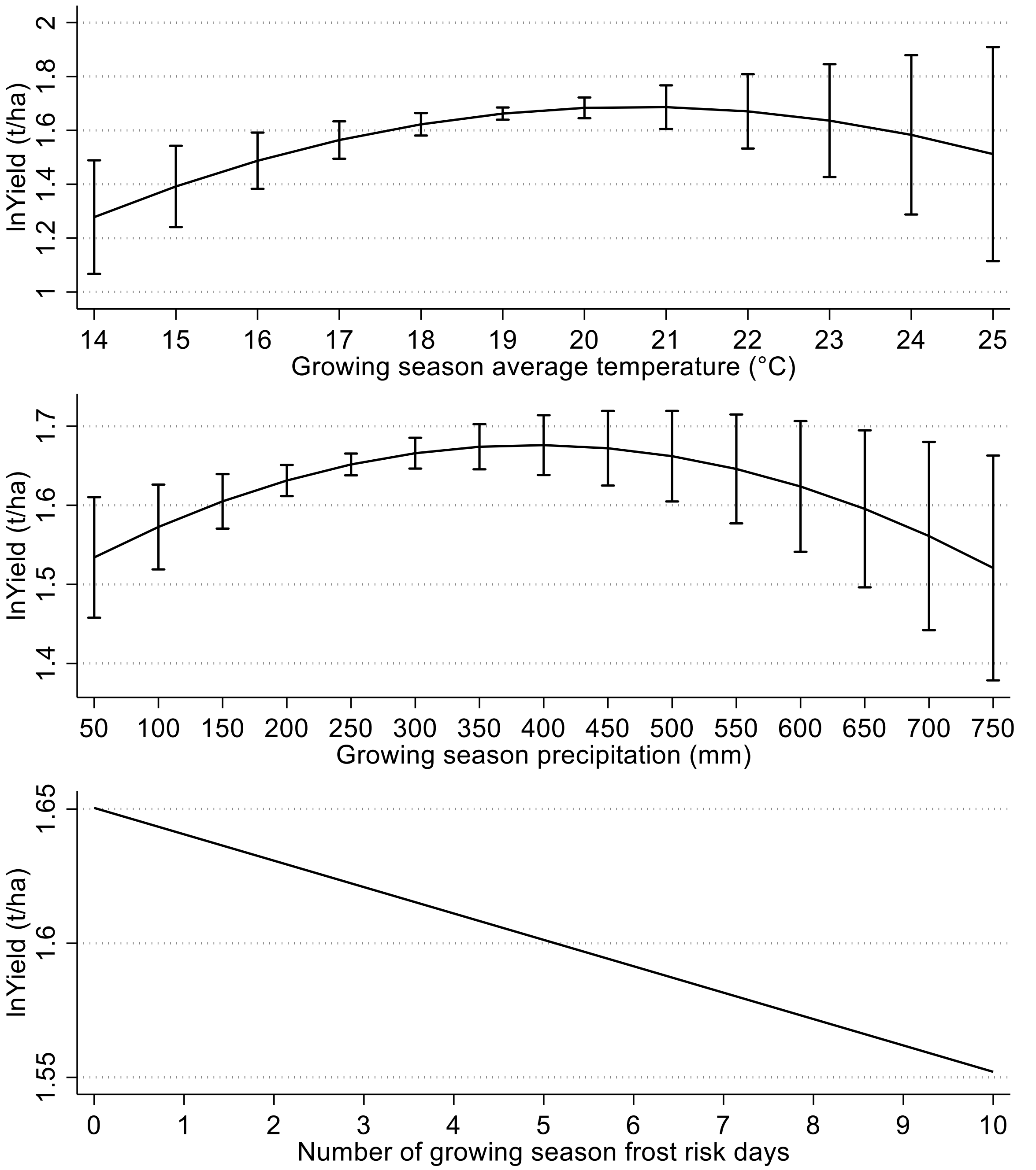

Figure 2.2: Predicted natural logarithm of grape yield as a function of weather.
Notes: Based on the estimates of model (1). The top two plots show the predictive margins with 95% confidence intervals. The bottom plot does not show the confidence intervals due to the singularity of the covariance matrix 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.

The mechanisms behind these yield responses to weather should be interpreted with caution. These three weather 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 2.2 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 2.3 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 2.3 shows how climate change by 2050 is projected to increase yields in most of the cooler and sometimes smaller regions, and to decrease yields in the largest and hottest regions.

Table 2.3: 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 of model (1).

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

Table 2.3 (cont.): 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 of model (1).

Region	Area (%)	1997-2017 climate			2041-2060 climate				2081-2100 climate			
		GST	GSP	FRD	GST	GSP	FRD	Impact (%)	GST	GSP	FRD	Impact (%)
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
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
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

Table 2.3 (cont.): 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 of model (1).

Region	Area (%)	1997-2017 climate			2041-2060 climate				2081-2100 climate			
		GST	GSP	FRD	GST	GSP	FRD	Impact (%)	GST	GSP	FRD	Impact (%)
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 area 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. Impact is the projected percentage change in yield due to climate changes (i.e., GST, GSP, and FRD) based on the estimates of model (1). The weighted averages use the 2016 vineyard area of each region as the weights.

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 the 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 2.3 and Figure 2.3 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.

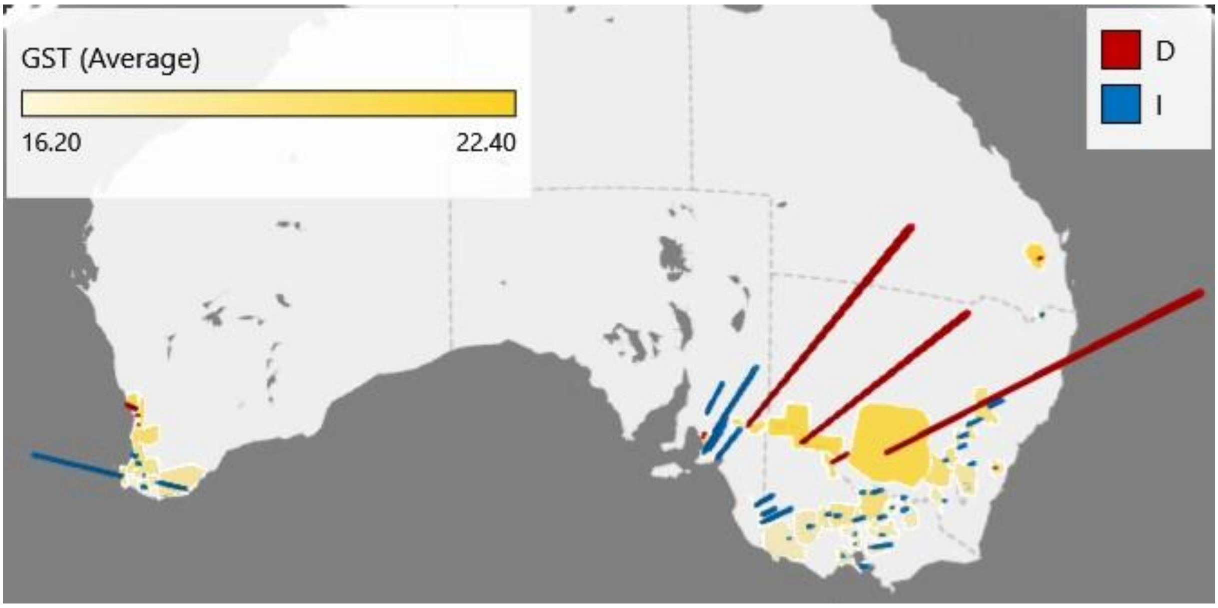

Figure 2.3: Geographical indications, area planted to vineyards, 1997-2017 GSTs, and projected changes in yields by 2041-2060.

Notes: The areas in yellow represent the geographical indications. GST stands for growing season average temperature (℃). 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 grapes 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).

The third column of Table 2.2 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 the 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 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 2.2, but with the standard errors clustered at the regional level. The coefficients are the same as in the second column of Table 2.2, 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) with the standard errors clustered at the regional level and concluded that this model is also robust to this estimation method.

2.4. 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 2.4 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 2.3 should be interpreted with more care due to possible issues of extrapolation beyond the observed values.

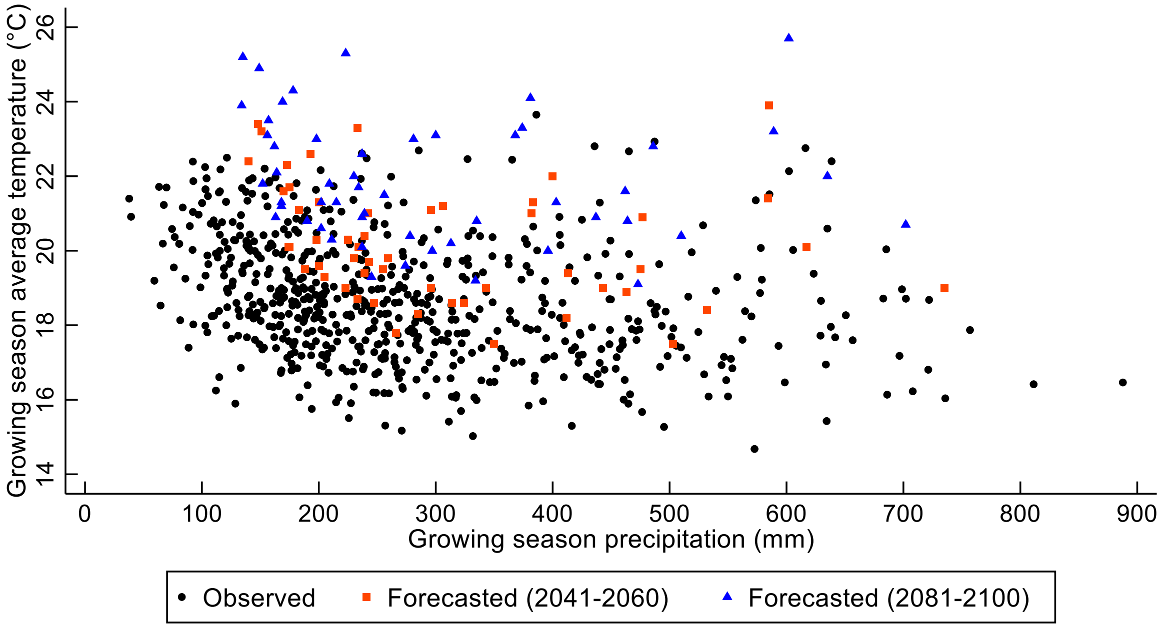

Figure 2.4: GST and GSP for the observed values of weather in the dataset, and for the climate projections for the Australian regions for 2041-2060 and 2081-2100.
Notes: The growing season goes from October to April.

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. 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 that we have 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 adaptation 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-maximizing decisions do not always imply maximizing yields. In the warmer regions of Australia, grape growers tend to use trellis systems and production strategies that are adequate for achieving high yields. But 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-maximizing behaviour that do not necessarily translate into yield-maximizing 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 influences both the current and the following season (Guilpart et al., 2013; Molitor and Keller, 2017). Model (1) does not account for these dynamic impacts of weather on grape yields. As a result, it provides the short-run estimates of the impact of weather (the impact in season s) rather than its long-run estimates (the impact in both seasons s and $s + 1$).

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 fewer 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 the 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).

2.5. 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 of the 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) develop a method for quantifying 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 to 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 raise hugely 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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Chapter 3

Statement of authorship

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Name of principal author (candidate)	German Puga		
Contribution to the paper	Led the study conception and design, reviewed the literature, cleaned the data and prepared the datasets for analysis, performed econometric estimations, and interpreted the results. Wrote drafts/versions of the paper. Presented the paper at seminars and conferences to get feedback. Led the review/publication process.		
Overall percentage	80%		
Certification	This paper reports on original research I conducted during the period of my Higher Degree by Research candidature and is not subject to any obligations or contractual agreements with a third party that would constrain its inclusion in this thesis. I am the primary author of this paper.		
Signature		Date	11/07/2023

Co-author contributions

By signing the Statement of authorship, each author certifies that:

I. the candidate's stated contribution to the publication is accurate (as detailed above);
II. permission is granted for the candidate in include the publication in the thesis; and
III. the sum of all co-author contributions is equal to 100% less the candidate's stated contribution.

Name of co-author	Kym Anderson		
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Signature	**Signed form available at the end of this thesis.**	Date	

3. The impact of growing season temperature on grape prices in Australia

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Abstract

Background and aims: Cross-sectional models are useful for estimating the impact that climate and climate change have on grape prices due to changes in grape quality. The aim of this study is to estimate the impact of growing season temperature (GST) on grape prices in Australia using cross-sectional data.

Methods and results: We use data on average price by cultivar and region for a 10-year period. We estimate a model using (area-) weighted least squares and variables from a principal component analysis to control for 103 characteristics that relate to the production system used in each of 26 regions. Results suggest that a GST increase of 1℃ leads to a decrease of 9% in the average price of grapes. A LASSO model that we use as a robustness check suggests similar results: a GST increase of 1℃ leads to a decrease of 7.3% in the average price of grapes.

Conclusions: Failing to control for characteristics that relate to the production system overestimates the impact of GST on grape prices, suggesting that changes to variables in a production system may help reduce quality losses from climate change.

Significance of the study: This study contributes to the understanding of the issue of omitted variable bias in cross-sectional models, and how to deal with this issue when analysing the impact of climate and climate change in grape and wine research.

Keywords: climate change, climate impact, grape price, grape quality, omitted variable bias

3.1. Introduction

Cross-sectional models allow one to quantify the impact that climate or climate change may have on grape prices due to changes in grape quality. Webb et al. (2008) studied the temperature-quality relationship in grapes in Australia using cross-sectional data. That study failed to control for variables that are correlated with the variable of interest and that may have an influence on the dependent variable, possibly leading to biased estimates of the variable of interest. This is a standard issue with cross-sectional models, as they are very susceptible to omitted variable bias (Dell et al. 2014). Panel data models, by contrast, have better identification properties and are less susceptible to omitted variable bias (Hsiang 2016). However, panel data models estimate the impact of weather shocks rather than climate (Blanc and Schlenker 2017). These estimates do not account for adaptation and may be less useful when estimating the potential impact of climate change (Auffhammer 2018).

The aim of this study is to estimate the impact of growing season temperature (GST) on grape prices in Australia using cross-sectional data. GST is the most widely used thermal-based bioclimatic index in viticulture (Liles and Verdon-Kidd 2020). While extreme temperatures can have a major influence on grape quality (Cola et al. 2019), GST is a useful bioclimatic index that is highly related to grape quality (Jones et al. 2011). The mechanism behind our model can be explained by the impact that GST has on grape quality, and the impact that grape quality has on grape price. This assumption is worth commenting on because quality does not necessarily equates price.

The difference between our analysis and those of other researchers such as Webb et al. (2008) is that our model intends to control for numerous variables related to the production system that may influence price and that may be correlated with GST. We do this by first performing a principal component analysis (PCA) for reducing the dimensionality of the data that relate to 103 characteristics of the production system of each region. Then we use the principal components as control variables. This allows us to deal with omitted variable bias issues while avoiding problems of multicollinearity and overcontrol. As a robustness check, we use a LASSO model. In this analysis, we use data on average price by cultivar and region for a 10-year period, which allows us to minimise the potential for omitted variable bias due to other variables that influence price such as supply-demand imbalances. This is, to our knowledge, the first cross-sectional analysis of the impact of a weather variable on grape prices that controls for numerous characteristics of the production system.

3.2. Materials and methods

3.2.1. Data

We use data for Australia on average price by cultivar and region, average bearing area by cultivar and region, and average yield by cultivar and region, from Anderson and Aryal (2015). These data are mostly available for 2001 to 2012, although we are forced to drop 2009 and 2011 as for those years there are no data on area and regional yield. In many regions, 2009 and 2011 are often remembered as outlying vintages; 2009 due to the 'millennial drought', and 2011 due to excessive rainfall.

For each region, and for the same years, we obtain spatial data on temperature and precipitation from Scientific Information for Land Owners (SILO), based on the area covered by the geographical indication (GI) of each region (Jeffrey et al. 2001). We average the weather for all the 5km x 5km grids that are part of the GI, including those grids that only have part of their surface within the GI. We construct two mean weather variables: growing season average temperature (GST), defined as $GST = \frac{1}{k}\sum_{d=1}^{d=k}((minimum\ temperature + maximum\ temperature)/2)$, where $d = 1$ is the first day of the growing season and $d = k$ is the last day of the growing season; and total growing season precipitation (GSP). While the length of the growing season varies between cultivars and regions in Australia (Pearson et al. 2021), and also between years (Cameron et al. 2021; Jarvis et al. 2019), we define the growing season as the period between October and April.

We also use data on 103 characteristics of the production system of each region, from an Australian Wine Research Institute (AWRI) survey (Nordestgaard 2019). The first column of Table S3.1 lists these 103 variables. While the data on grape prices and weather variables are available for a larger number of regions, our estimation dataset includes 26 regions because those are the regions for which we have information from the AWRI survey. The total number of cultivars is 102. Table 3.1 shows summary statistics for the 26 regions in our dataset. Each cultivar-by-region combination constitutes an observation. Since the regions have 33.1 cultivars on average, the total number of observations is 861.

Table 3.1: Summary statistics for price, GST, GSP, yield, and cultivars for the 26 regions over the time period (2001 to 2012, excluding 2009 and 2011).

Variable	Mean	SD	Minimum	Maximum
Price (AUD/T)	1198	462	410	2453
GST (°C)	18.3	1.7	14.2	21.6
GSP (mm)	323	128	155	569
Yield (t/ha)	7.8	3.8	3.1	20.7
Cultivars (number)	33.1	17.8	1	75

Notes: GST is the growing season average temperature, GSP is the growing season total precipitation, and Yield is the average regional yield across all cultivars. Growing season: October to April. In the statistical models, each of the 861 cultivar-by-region combinations constitutes an observation.

3.2.2. Methods

The aim of our estimation strategy is to identify the impact of GST on grape prices. The baseline model that does not include any control variables other than cultivar is:

$$lnPrice_{vr} = \alpha + \gamma GST_r + \mu_v + \varepsilon_{vr}, \tag{1}$$

where $lnPrice_{vr}$ is the natural logarithm of the average price of cultivar v in region r across the time period. The variable of interest, GST_r, is the mean GST in region r in that same period, and γ is the coefficient of interest. μ_v are cultivar fixed effects that control for price differences between cultivars. α is a constant and ε_{vr} is an error term.

However, model (1) is susceptible to omitted variable bias. Other climate variables and characteristics of the production system that influence price may be correlated with GST. Failing to include these variables can lead to an incorrect estimation of the effect of GST on the price of grapes. Therefore, we estimate:

$$lnPrice_{vr} = \alpha + \gamma GST_r + \beta_1 GSP_r + \beta_2 Yield_r + \mu_v + \varepsilon_{vr}. \quad (2)$$

The control variables GSP_r and $Yield_r$ are the mean GSP and average regional yield across all cultivars, respectively, in region r, for the time period.

While model (2) incorporates two control variables (i.e., GSP_r and $Yield_r$), this model is still susceptible to omitted variable bias. Other characteristics of the production system that affect price are also correlated with GST. Ideally, we would like to incorporate the 103 variables from the AWRI survey that relate to the production system of each region. This is possible if we use principal component analysis (PCA) for data reduction. PCA results in a number of components that is the same as the number of variables, but these components are uncorrelated. The components contain the same information as the variables, but the components are ranked based on the proportion of the variation in the data that they explain. PCA is useful for avoiding redundancy and multicollinearity issues among variables. Usually, the first few components explain a large proportion of the variation in the data. The goal here is to use the principal components as control variables that account for characteristics in the production system of each region. Therefore, we estimate:

$$lnPrice_{vr} = \alpha + \gamma GST_r + \beta_1 GSP_r + \beta_2 Yield_r + \sum_{j=1}^{j=k} \varphi_j PC_{jr} + \mu_v + \varepsilon_{vr}. \quad (3)$$

PC_{jr} is the j^{th} (out of k) principal component of region r, and φ_j is its coefficient.

We use two approaches for choosing the number of principal components. First, we choose all the components with eigenvalues greater than one. Principal components with higher eigenvalues have higher proportions of the variance explained, with one being the mean eigenvalue across all principal components. Second, we look at a scree plot to choose the principal components.

The principal components from this second step are used in a k-means cluster analysis to assess their usefulness. K-means is a partition method that starts with all observations randomly assigned to a predetermined k number of clusters. The mean for each cluster is calculated and each observation is re-assigned to the cluster with the closest mean. This process repeats until no observation changes group. K-means requires specifying a similarity or dissimilarity measure. We use the Euclidean distance, which is arguably the most used measure (Wu 2012). For choosing the number of clusters we use the Calinski and Harabasz (1974) pseudo-F index stopping rule, which Milligan and Cooper (1985) proved to be the best rule for deciding the number of k clusters. The reason for performing this k-means cluster analysis is that if the classification looks reasonable, these first principal components may be suitable for accounting for characteristics of the production system of the regions.

We use weighted least squares (WLS) for estimating models (1), (2), and (3). WLS is a more-appropriate estimation method than ordinary least squares (OLS) because the variables in the regression reflect regional means rather than observations for individual equal-size vineyards. The weight is the average area of cultivar v in region r during the time period. Since GST and the control variables are region-specific, we cluster standard errors by region. As a robustness check, we use OLS with robust standard errors clustered at the regional level for estimating models (1), (2), and (3).

In addition to the abovementioned models, as a robustness check, we estimate the impact of GST on grape prices using LASSO. This method is very useful when there is a large number of variables and one is uncertain as to which of these variables belong to the model. LASSO can be used for prediction, model selection, or inference. In this study, we use LASSO for inference. (See Belloni et al. (2014) for an introduction to the use of LASSO for inference.) That is because our goal is to estimate the impact of GST on (the natural logarithm of) grape prices, together with the standard error, p-value, and related statistics.

There are many types of LASSO estimators. In this study, we use the cross-fit partialing-out estimator, also known as double machine learning. LASSO allows one to include a large number of potential control variables, so large that it could be even greater than the number of observations. The potential control variables that we incorporate in the model are GSP, regional yield, all the cultivars, and all the components from the PCA that have eigenvalues greater than one.

3.3. Results

The results for models (1) and (2) show that the coefficients of GST are negative and statistically significant at the 1% level (see Table 3.2). The interpretation is that a GST increase of 1℃ leads to a decrease in price of 24% based on model (1), or 19.4% based on model (2). (GST impact in percentage = (EXP(GST coefficient)-1)*100.) Since each cultivar-by-region combination constitutes an observation, this price change refers to the average price across the 861 cultivar-by-region observations. The coefficient of GST is of lower magnitude in model (2), after controlling for GSP and regional yields.

Table 3.2: Estimation results for models (1) to (3), where model (3) is the preferred model as it is less susceptible to omitted variable bias.

Variable	Model (1)	Model (2)	Model (3)
GST	-0.2742**	-0.2151**	-0.0946*
	(0.0243)	(0.0321)	(0.0412)
GSP		-0.0006	-0.0006**
		(0.0004)	(0.0002)
Yield		-0.0349**	-0.0054
		(0.0082)	(0.0057)
PC1			-0.0371*
			(0.0149)
PC2			0.0259*
			(0.0107)
PC3			-0.0544**
			(0.0118)
PC4			-0.0065
			(0.0055)
Constant	11.4275**	10.7362**	8.3806**
	(0.4968)	(0.6083)	(0.8101)
R^2	0.8689	0.9117	0.9402

Notes: * = 5% significance level, and ** = 1% significance level. Standard errors are in brackets. GST is the growing season average temperature (°C), GSP is the growing season total precipitation (mm), Yield is the average regional yield (t/ha), and PC stands for principal component. The PCs intend to control for the characteristics of the production system of each region. Therefore, model (3) is the preferred model, as it is less susceptible to omitted variable bias. Models (1) to (3) include cultivar fixed effects (results omitted to save space).

Model (3) incorporates principal components from the PCA of the production systems of the regions. The PCA leads to 22 principal components with eigenvalues higher than one, which explain 98% of the variance in the data on the 103 characteristics of the production system of the 26 regions (see Figure 3.1). We estimate model (3) with the first 22 principal components as control variables. However, a post-estimation analysis of the variance inflator factors (VIFs) of the independent variables shows strong evidence of multicollinearity with this specification (results omitted to save space, but explained in the supplementary material).

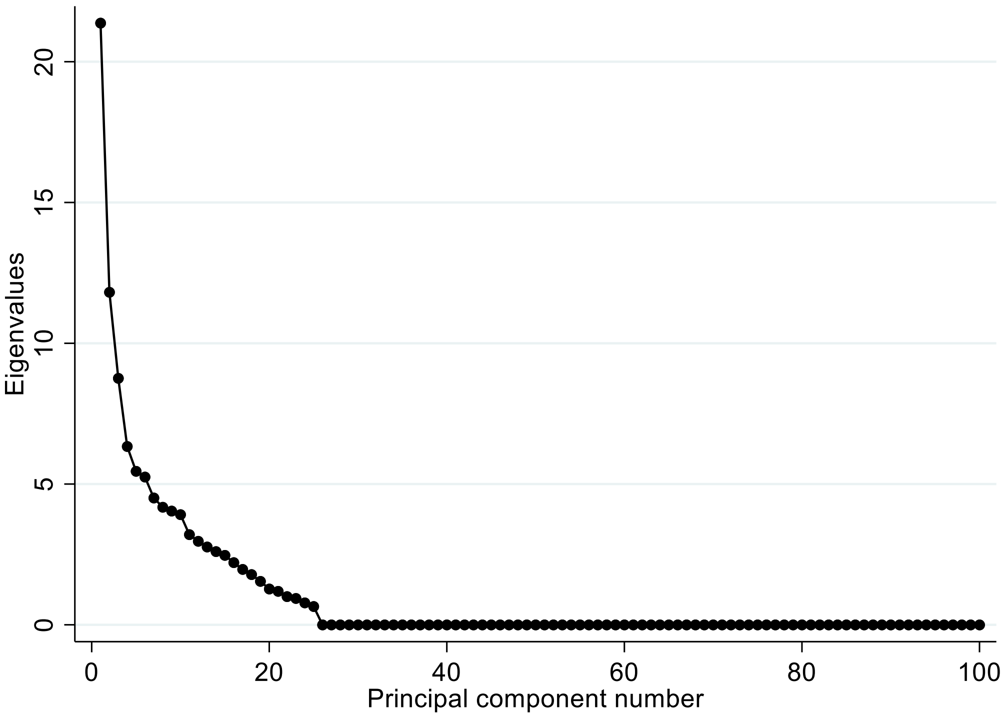

Figure 3.1: Scree plot of eigenvalues after principal component analysis (PCA).

Therefore, we estimate model (3) by using only the first four principal components, which explain 47% of the variance in the data on the 103 characteristics of the production system of the 26 regions. The second column of Table S3.1 shows the percentage of each of the 103 variables that relate to the production system which is explained by the first four principal components. For this specification, the analysis of the VIFs of the independent variables suggests that multicollinearity is not an issue (results omitted to save space, but explained in the supplementary material).

To see how useful these first four principal components may be as a proxy of the production systems of the regions, we use these components for clustering the 26 regions. The Calinski-Harabasz stopping rule suggests that six clusters is the optimal solution from our k-means cluster analysis (see Table 3.3). We believe that this classification groups regions that share similar production systems, and hence that the first four principal components are useful for controlling for regional production system's characteristics that may affect prices. The last seven columns of Table S3.1 show the average value of each of the 103 variables that relate to the production system, for each of the six clusters and for all the regions combined. While the focus of this paper is not on describing the differences between clusters, it is worth noting that the average values for these 103 variables are often very different across clusters.

Table 3.3: Six-cluster classification of the 26 regions based on a k-means cluster analysis of the first four principal components from the principal component analysis (PCA).

Cluster	Regions
1	Beechworth, Geelong, Macedon Ranges, Mornington Peninsula
2	Barossa Valley, Clare Valley, Eden Valley, McLaren Vale, Mudgee, Rutherglen
3	Murray Darling, Riverina, Riverland
4	Coonawarra, Heathcote, Langhorne Creek, Wrattonbully
5	Great Southern, Hilltops, Hunter, Orange
6	Adelaide Hills, Granite Belt, Tasmania, Yarra Valley, Margaret River

The results of model (3) show that GST is statistically significant at the 5% level (see Table 3.2). The interpretation is that a GST increase of 1°C leads to a decrease of 9% in the average price of grapes. When compared to models (1) and (2), the magnitude of the GST coefficient is 66% and 56% lower, respectively. The goodness of fit of model (3) is also higher than that of models (1) and (2), as shown by the higher R^2 of model (3). These results show how cross-sectional estimations of the impact of climate on grape prices can be susceptible to omitted variable bias. Our OLS estimations for these three models, which we use as robustness checks of the WLS estimations, also show that the magnitude of the GST coefficient is substantially lower for model (3) (see Table S3.2).

The LASSO approach, which we use as our robustness check of model (3), incorporates 126 potential control variables (i.e., GSP, regional yield, all the 102 cultivars, and all the 22 components from the PCA that have eigenvalues greater than one). The LASSO model (automatically) selects 45 controls from these 126 potential control variables. GST is statistically significant at the 1% level, and its magnitude is slightly lower than in model (3): its coefficient value is -0.0759 and its standard error is 0.0295. The interpretation of this coefficient is that a GST increase of 1°C leads to a decrease of 7.3% in the price of grapes. These results reinforce our argument on the importance of controlling for variables that relate to the production system.

3.3.1. Impact of changes in GST due to climate change

Model (3) provides a useful estimate of the potential impact that climate change may have on grape prices in a ceteris paribus scenario. Table 3.4 combines the results from the three models with the climate change projections from Remenyi et al. (2020), to quantify the potential impact that changes in GST by 2050 could have on grape prices due to changes in quality. Based on the estimates of model (3), the price of grapes is projected to decrease by between 8.1% and 14.4% across regions, or 11.8% on average. Assuming that the GST coefficient in model (3) is correct, using the estimates of models (1) or (2) would overestimate the impact of changes in GST by 166% or 114%, respectively. These differences suggest that adaptations in the production system may help to mitigate some of the quality losses that may be induced by climate change.

Table 3.4: Projected impact of forecast changes in GSTs (between 1997-2017 and 2041-2060) on grape prices based on the estimates of the three models.

Region	GST (°C)		Projected impact (%)		
	1997-2017	2041-2060	Model (1)	Model (2)	Model (3)
Adelaide Hills	17.9	19	-26.4	-21.3	-9.9
Barossa Valley	19.0	20.3	-31.2	-25.2	-11.7
Beechworth	17.8	19.4	-38.4	-31.0	-14.4
Clare Valley	19.1	20.4	-31.2	-25.2	-11.7
Coonawarra	17.3	18.7	-33.6	-27.1	-12.6
Eden Valley	18.4	19.5	-26.4	-21.3	-9.9
Geelong	17.2	18.3	-26.4	-21.3	-9.9
Granite Belt	18.7	20.1	-33.6	-27.1	-12.6
Great Southern	18.0	19.5	-36.0	-29.0	-13.5
Heathcote	18.5	19.8	-31.2	-25.2	-11.7
Hilltops	19.5	21.0	-36.0	-29.0	-13.5
Hunter	20.2	21.4	-28.8	-23.2	-10.8
Langhorne Creek	19.2	20.1	-21.6	-17.4	-8.1
Macedon Ranges	16.2	17.5	-31.2	-25.2	-11.7
Margaret River	18.9	20.3	-33.6	-27.1	-12.6
McLaren Vale	18.6	19.8	-28.8	-23.2	-10.8
Mornington Peninsula	17.4	18.6	-28.8	-23.2	-10.8
Mudgee	19.5	20.9	-33.6	-27.1	-12.6
Murray Darling	21.9	23.2	-31.2	-25.2	-11.7
Orange	18.1	19.5	-33.6	-27.1	-12.6
Riverina	21.8	23.3	-36.0	-29.0	-13.5
Riverland	21.1	22.4	-31.2	-25.2	-11.7
Rutherglen	19.7	21.2	-36.0	-29.0	-13.5
Tasmania	14.4	15.6	-27.6	-22.3	-10.4
Wrattonbully	17.5	19.0	-36.0	-29.0	-13.5
Yarra Valley	16.3	17.5	-28.8	-23.2	-10.8
Average	18.5	19.9	-31.4	-25.4	-11.8

Notes: GST is the growing season average temperature. Estimated with the three models' results, based on climate change projections from Remenyi et al. (2020).

3.3.2. Differences across cultivars

Model (3) assumes that the impact of GST on grape prices is the same across cultivars. To explore whether the effect of GST varies across some cultivars, we estimate another version of model (3) in which we add a new variable. This new variable is an interaction between GST and a dummy that takes the value of 1 if the observation refers to a particular cultivar or 0 otherwise. We estimate this other version of model (3) for the three most planted cultivars in Australia: Syrah, Cabernet Sauvignon, and Chardonnay. The coefficients are not statistically significant for Syrah and Cabernet Sauvignon, while the coefficient for Chardonnay is positive and statistically significant at the 5% level. The results suggest that while an increase in GST leads to a lower price in these three cultivars, this price decrease is smaller for Chardonnay than for Syrah or Cabernet Sauvignon. Changes in GST due to climate change may also affect the price of grapes differently across cultivars.

3.4. Discussion

The progression of the results from model (1) to model (3) shows the importance of controlling for variables other than cultivar when estimating the impact of weather on grape prices. The results using LASSO reinforce this idea. The cross-sectional approach to estimating the impact of climate is susceptible to omitted variable bias. This can be addressed, to a certain extent, by including control variables in the model. However, an excessive number of control variables can also lead to multicollinearity and overcontrolling issues. This study shows how PCA can be used for dealing with these issues while still controlling for relevant variables in the model.

Nevertheless, while model (3) controls for GSP and characteristics of the production system, it still has at least four limitations. First, the estimate of GST may still be biased. This is because there are other characteristics that influence grape quality and that may be correlated with GST, but that are not accounted for in the model. Second, due to data limitations, the independent variables are based on regional characteristics rather than cultivar-by-region characteristics. Third, the impact of the weather variables may be nonlinear. We explore alternate model specifications, such as including square values of GST and/or GSP, but concluded that including only the GST and GSP without their square values or other specifications is preferred. Fourth, model (3) assumes that the impact of GST on (the natural logarithm of) grape prices does not vary across regions or cultivars. In reality, the impact of GST may differ across regions and cultivars, and the results of the comparative analysis between cultivars show evidence of these differences.

3.4.1. Implications for statistical analyses of the impact of climate change in grape and wine research

There are two major statistical approaches for estimating the impact of climate change on agriculture: the cross-sectional approach and the panel data approach (Blanc and Schlenker 2017). The cross-sectional approach is the oldest of these two. It gained relevance in the mid-1990s with the work of Mendelsohn et al. (1994). More than one decade later, the panel data approach gained prominence with the work of Deschênes and Greenstone (2007). The strength of the panel data approach is its strong identification properties, which makes this approach less susceptible to omitted variable bias (Hsiang 2016). Dell et al. (2014) referred to the large number of studies that use panel data methods to quantify the potential impact of climate change as 'the new climate-economy literature'. This literature has grown extensively in the past few years and, as a result, it is not considered new anymore.

To better explain the panel data approach and to facilitate a comparison with the cross-sectional approach, we describe how it could be applied in our study. A reduced-form panel data model for identifying the impact of GST on grape prices using the data available in this study could take the form:

$$lnPrice_{vrs} = \gamma GST_{rs} + \beta_1 GSP_{rs} + \beta_2 Yield_{rs} + \mu_{vr} + \tau_s + \varepsilon_{vrs}. \qquad (4)$$

$lnPrice_{vr}$ is the natural logarithm of the average price of cultivar v in region r and season s. The variable of interest, GST_{rs}, is the mean GST in region r and season s, and γ is the coefficient of interest. The control variables GSP_{rs} and $Yield_{rs}$ are the mean GSP and average regional yield, respectively, in region r and season s. ε_{vrs} is an error term.

The strong identification properties of model (4) are given by its fixed effects (Hsiang 2016). μ_{vr} are cultivar-by-region fixed effects that account for all time-invariant observable and unobservable characteristics of cultivar v in region r. As such, these fixed effects also control for characteristics of the production system of each cultivar-by-region combination, which in model (3) are controlled by the principal components. τ_s are season fixed effects that account for seasonal shocks that affect all cultivar-by-region combinations in season s. These seasonal shocks neutralise common trends and help to control for supply and demand imbalances that may impact all cultivar-by-region combinations.

Despite the role of the fixed effects in model (4) in decreasing the potential of omitted variable bias, the estimate of the impact of GST on grape prices could still be biased due to time-varying omitted variables that may be correlated with GST (Dell et al. 2014). That is the reason why model (4) includes GSP_{rs} and $Yield_{rs}$ as control variables.

The preference in the literature would be to estimate model (4) using the fixed effects estimator. (See Blanc and Schlenker (2017) for a discussion on why the fixed effects estimator is preferred to other estimators such as the random effects estimator.) This estimation strategy implies a joint demeaning of all variables. This means that the mean of each cultivar-by-region combination is subtracted from each observation that belongs to that cultivar-by-region combination. As a result, model (4) estimates the impact of GST shocks (weather shocks) on grape prices. The average weather across all seasons (or climate) is accounted for in the not-reported cultivar-by-region fixed effects (μ_{vr}).

It is worth noting that model (4) may have two other issues. The first issue is that the price of cultivar v in region r and season s may influence the price of that cultivar in that region in season $s + 1$. That, in turn, justifies the inclusion of the lag of the dependent variable in model (4). To avoid biased estimates, which would be the case if using a fixed effects estimator, this dynamic panel data model could be estimated using the system generalized method of moments (system GMM) estimator developed by Arellano and Bond (1991) and applying the bias correction method developed by Windmeijer (2005). The other issue is that, while the weather variables can be considered exogenous, $Yield_{rs}$ is endogenous. The Arellano-Bond estimation procedure allows one to treat the natural logarithm of yield as an endogenous variable and to instrument it using a predetermined number of lags of this variable.

While there are many differences in the strengths and limitations of cross-sectional and panel data models (see Blanc and Schlenker (2017) for a review), in this discussion we focus on two major differences. The first of these major differences is one of the main strengths of panel data methods, which is the strong identification properties and consequent lower potential for omitted variable bias, described above. The other major difference is one of the main strengths of cross-sectional methods: since they estimate the impact of climate instead of weather shocks, they account for medium- and long-run adaptation (Auffhammer 2018).

How important is it to account for adaptation? Grape growing is a capital-intensive activity with very long investment horizons (Ashenfelter and Storchmann 2016). Therefore, adaptation costs are higher, which translates into slower adaptation processes. Ineffective or limited adaptation and adjustments lead to smaller differences between short-run responses to weather shocks and long-run responses to changes in climate (Kolstad and Moore 2020). Based on this comparison between the strengths of model (3) and model (4), one could argue that model (4) may still represent a better statistical approach for quantifying the potential impact of future changes in GST than model (3).

However, in this study, there is an extra motivation for using a cross-sectional approach. Grape prices in Australia are usually reported before they are adjusted based on wine quality, and these quality adjustments are often influenced by the season's weather. These adjustments can also take the form of bonuses that are not included in the reported price of grapes. In addition, grape purchase contracts are usually multi-year and prices are established well before the season, so the variation in grape prices between seasons is more likely due to supply and demand imbalances rather than differences in weather.

As explained above, if we would use a fixed effects panel data model to estimate the impact of GST on grape prices, we would be estimating the impact of GST shocks (weather shocks), and the effect of the average GST (climate) would be captured by the cultivar-by-region fixed effects. Since grape prices are usually reported without adjustments due to the effect of GST among other variables, we may expect to get estimates of the impact of GST shocks that are not statistically significant. In fact, this is what happens in this particular case when we estimate model (4) with its suggested modifications (i.e., the dynamic instrumental variable panel data model described three paragraphs above). A cross-sectional approach allows us to avoid this issue by estimating the impact of climate instead of the impact of weather shocks.

A final concern related to model (3) that is worth commenting on is that it does not directly account for supply and demand imbalances. By contrast, the season fixed effects in model (4) help control for supply and demand imbalances that are common to all cultivar-by-region combinations. The fact that model (3) does not directly account for seasonal supply and demand imbalances that may affect the price of grapes would be a serious issue if this model were estimated with data for a short period of time, such as one or two seasons. However, since we estimate model (3) using average data for a relatively long period of time (i.e., average for ten years), we could argue that the length of this time period helps neutralising these supply and demand imbalances.

3.5. Conclusion

We have estimated the effect of GST on grape prices using cross-sectional data for Australia. Our results show how cross-sectional models can be susceptible to omitted variable bias. In particular, failing to control for characteristics of the production system that are influenced by GST can overestimate the true impact of GST on grape prices. Our results also show how price, due to changes in grape quality, is influenced by the production system. This finding suggests that changes in the production system may help reduce quality losses from climate change. From a statistical perspective, this study shows how PCA results can be used to control for numerous characteristics of the production system, reducing the susceptibility of cross-sectional analyses to omitted variable bias while avoiding issues of multicollinearity and overcontrol. The LASSO approach, such as the one that we have used as a robustness check, can also be used for getting estimates that are less susceptible to omitted variable bias. Further research could explore other variables affecting grape prices or quality, incorporate new control variables, and/or apply this or a similar approach to other countries.

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Supplementary material

Table S3.1: Explained variance by the first four principal components, and average values for each cluster of regions and for all the regions combined, for the 103 variables that relate to the characteristics of the production system of each region.

Variable	Explained (%)	Cluster of regions (average values)						
		1	2	3	4	5	6	All
Median age (years)	8	19	22	17	20	20	18	19
Median row spacing (m)	67	2.5	3.1	3.3	2.9	3.1	2.6	2.9
Median vine spacing (m)	66	1.5	1.9	2.1	1.8	1.7	1.6	1.8
Median plant density (vines/ha)	70	2839	1737	1451	1951	1950	2528	2091
Median row length (m)	56	118	208	293	259	191	158	199
Median row yield (kg/row)	85	117	417	2061	605	423	291	566
Single cordons	62	74	84	40	91	96	72	78
Multiple cordons	62	26	16	60	9	4	28	22
Row direction: N-S	47	64	49	33	45	62	59	53
Row direction: E-W	48	23	39	54	46	31	26	35
Row direction: NE-SW	35	0	2	10	6	4	10	5
Row direction: NW-SE	24	12	4	3	3	2	5	5
Row direction: contour	21	0	6	0	1	2	1	2
Post material: wood CCA treated	16	52	73	79	52	49	70	63
Post material: wood creosote treated	51	6	10	11	45	0	1	12
Post material: wood untreated	49	26	1	0	0	2	21	8
Post material: metal	66	15	15	9	1	49	8	16
Post material: plastic	22	2	1	0	3	0	0	1
Post material: other	17	0	1	0	0	0	0	0
Rootstocks	39	54	39	47	33	10	28	35
Pruning: cane	89	77	14	0	5	11	52	28
Pruning: spur	66	21	61	9	68	67	47	48
Pruning: mechanical	73	0	25	90	27	22	1	24
Pruning: minimal	11	2	0	0	0	0	0	0
Pruning wound treatment: local application	63	41	10	0	2	1	25	14
Pruning wound treatment: spray unit application	39	0	26	6	44	2	19	17
Fungicide and insecticide canopy sprays (average number per growing season)	40	9.7	7.2	7.7	7.0	8.8	9.5	8.3
Desuckering: hand	54	98	50	47	62	51	66	62
Desuckering: mechanical	5	0	14	0	2	1	0	4
Desuckering: chemically	56	1	15	33	5	39	15	17
Desuckering: other	6	1	6	0	1	5	4	3

Table S3.1 (cont.): Explained variance by the first four principal components, and average values for each cluster of regions and for all the regions combined, for the 103 variables that relate to the characteristics of the production system of each region.

Variable	Explained (%)	Cluster of regions (average values)						
		1	2	3	4	5	6	All
Shoot trims (average number per growing season)	21	0.8	1.1	1.0	1.2	0.9	1.5	1.1
Trellis system: VSP	77	72	25	10	49	72	94	55
Trellis system: SH SD	25	2	2	7	0	0	4	2
Trellis system: T-trellis	32	12	6	8	0	0	0	4
Trellis system: bush	19	0	1	0	0	0	0	0
Trellis system: other	26	13	1	6	1	0	1	3
Trellis system: sprawl	83	1	65	69	50	28	2	35
Shoot positioning: all shoots positioned	84	85	22	1	15	54	96	47
Shoot positioning: all shoots one side, some/none on other	23	0	1	1	22	3	2	5
Shoot positioning: other	24	0	1	0	0	0	0	0
Shoot thinned	77	80	18	1	18	16	51	32
Leaf plucking: both sides	49	5	0	0	1	7	23	6
Leaf plucking: one side	43	13	1	0	4	3	10	5
Leaf plucking: other	11	0	0	0	0	0	0	0
Irrigation method: drip or micro-spray	43	97	95	84	93	99	93	94
Irrigation method: spray or sprinkler	39	3	4	10	5	0	3	4
Irrigation method: furrow or flood	43	0	1	5	1	0	0	1
Irrigation method: other or not reported	10	0	0	1	1	1	4	1
Irrigation rate (ML per ha)	87	0.60	1.16	6.19	1.70	0.62	1.01	1.62
Irrigation rate (ML per t)	60	0.14	0.22	0.30	0.25	0.15	0.19	0.20
Crop thinning: preveraison	27	6	0	1	4	3	7	3
Crop thinning: veraison	41	24	8	0	13	3	7	9
Crop thinning: potveraison	59	0	1	0	2	0	15	3
Crop thinning: multiple times	18	13	5	0	0	3	5	5
At least one irrigation sensor	57	15	52	56	51	38	41	42
Regulated deficit irrigation	58	12	40	28	64	34	35	36
Partial rootzone drying	53	0	0	8	0	0	0	1
Leaching irrigation	62	0	6	28	27	2	4	10
Precision viticulture: multi-spectral imaging	26	3	6	9	21	10	12	10
Precision viticulture: soil mapping	38	0	5	5	2	12	5	5
Nutrition: tissue analysis	43	27	44	45	56	44	52	45
Nutrition: soil analysis	40	27	38	32	42	53	59	43

Table S3.1 (cont.): Explained variance by the first four principal components, and average values for each cluster of regions and for all the regions combined, for the 103 variables that relate to the characteristics of the production system of each region.

Variable	Explained (%)	Cluster of regions (average values)						
		1	2	3	4	5	6	All
Macronutrient application: N	60	45	60	88	76	55	65	64
Macronutrient application: P	41	51	47	56	73	61	62	58
Macronutrient application: K	78	37	44	54	53	71	71	55
Macronutrient application: Mg	66	17	17	58	58	56	56	42
Macronutrient application: S	53	6	18	39	29	34	33	26
Macronutrient application: Ca	68	17	23	57	36	48	51	37
Micronutrient application: Fe	73	11	14	31	29	14	41	23
Micronutrient application: Mn	62	11	32	56	47	21	43	34
Micronutrient application: Zn	79	9	28	62	55	51	58	42
Micronutrient application: B	59	35	29	42	23	57	59	40
Micronutrient application: Cu	42	12	15	29	29	22	31	22
Micronutrient application: Mo	53	9	10	20	43	34	38	25
Micronutrient application: Al	39	3	1	2	4	2	10	4
Undervine strip management: herbicide	34	65	88	89	93	89	92	86
Undervine strip management: cultivation	35	6	3	2	4	2	1	3
Undervine strip management: slashing	28	28	8	9	3	7	6	10
Undervine strip management: other	7	1	1	0	0	2	1	1
Undervine strip mulch added	40	34	31	15	39	27	37	32
Mid-row management: herbicide	22	7	6	21	0	8	3	7
Mid-row management: cultivation	52	13	6	20	1	4	2	7
Mid-row management: cover crops	53	77	85	53	99	84	95	84
Mid-row management: other	19	3	4	6	0	4	0	3
Management of grown cover-crops/swards: slashing/mowing	39	100	98	92	100	95	97	97
Management of grown cover-crops/swards: knockdown herbicide	47	0	12	29	4	0	1	7
Management of grown cover-crops/swards: rolling	45	0	2	2	5	0	0	2
Management of grown cover-crops/swards: cultivation	40	7	6	23	0	0	0	5
Management of grown cover-crops/swards: livestock grazing	43	21	31	8	60	51	36	36
Certified organic	34	1	1	6	1	1	8	3
Certified biodynamic and organic	16	2	6	0	0	2	1	2

Table S3.1 (cont.): Explained variance by the first four principal components, and average values for each cluster of regions and for all the regions combined, for the 103 variables that relate to the characteristics of the production system of each region.

Variable	Explained (%)	Cluster of regions (average values)						
		1	2	3	4	5	6	All
In 3-year transition to certified organic	29	0	1	1	3	1	0	1
Red: machine-harvested	84	6	84	100	92	89	61	71
Red: hand-picked	84	94	16	0	8	11	39	29
White: machine-harvested	76	18	85	100	70	86	66	70
White: hand-picked	76	82	15	0	30	14	34	30
Red: on-harvester destemming	50	0	3	0	13	1	29	9
White: on-harvester destemming	29	0	3	0	5	5	24	7
Side-arm discharge	62	50	95	100	88	93	51	79
On-harvester bins	61	0	5	0	12	7	49	14
Red: SO2 addition to machine-harvested grapes	79	0	86	88	95	93	67	72
White: SO2 addition to machine-harvested grapes	56	15	79	88	54	97	80	69

Notes: Explained is the percentage of the variance in the data on each of the 103 characteristics of the production system of the 26 regions that is explained by the first four principal components of the principal component analysis (PCA). The clusters of regions are described in Table 3.3. The average values for each cluster of regions and all the regions combined are percentages unless otherwise stated in brackets after the name of each variable. These values are the (unweighted) averages for the regions included in each cluster. The average value in each region is an area-weighted average across the vineyards included in the survey. Estimated with data from Nordestgaard (2019).

Explanation of the VIF results for model (3)

If we estimate model (3) using the first four principal components (PCs) as control variables, the VIF results for model (3) show that there is no VIF higher than 10 for any variable, except for a small number of variety fixed effects. These results suggest that multicollinearity is not an issue if we use the four PCs as control variables. By contrast, if we estimate model (3) using the 22 PCs with eigenvalues higher than 1 as control variables (rather than the first four PCs), many VIFs are substantially higher than 10. For example, the VIF of GST is 288, the VIF of GSP is 625, the VIF of average regional yield is 485, the VIF of the PC1 is 279, and the VIF of the other 22 PCs is higher than 10 (and sometimes 100) for all but two PCs. These results suggest that multicollinearity is an issue if we use the 22 PCs as control variables.

Estimation results of models (1) to (3) using OLS instead of WLS

Table S3.2 shows the results for the ordinary least squares (OLS) estimations (with robust standard errors clustered at the regional level) of models (1) to (3). We use these OLS estimations as robustness checks for the (preferred) weighted least squares (WLS) estimations.

Table S3.2: Estimation results using OLS instead of WLS.

Variable	**Model (1)**	**Model (2)**	**Model (3)**
GST	-0.2384***	-0.1828***	-0.1349***
	(0.0252)	(0.0247)	(0.0404)
GSP		-0.0009***	-0.0007**
		(0.0003)	(0.0003)
Yield		-0.0458***	-0.0191**
		(0.0071)	(0.0071)
PC1			-0.0256**
			(0.0123)
PC2			0.0225***
			(0.0076)
PC3			-0.0307***
			(0.0126)
PC4			-0.0067
			(0.0100)
Constant	10.7552***	10.42885***	9.3485***
	(0.4930)	(0.4503)	(0.8209)
R^2	0.7326	0.7919	0.8086

Notes: * = 10% significance level, ** = 5% significance level, and *** = 1% significance level. Standard errors are in brackets. GST is the growing season average temperature (°C), GSP is the growing season total precipitation (mm), Yield is the average regional yield (t/ha), and PC stands for principal component. The PCs intend to control for the characteristics of the production system of each region. Therefore, model (3) is the preferred model, as it is less susceptible to omitted variable bias. Models (1) to (3) include cultivar fixed effects (results omitted to save space).

Supplementary material reference

Nordestgaard, S. (2019). *AWRI Vineyard and Winery Practices Survey*. The Australian Wine Research Institute.

Chapter 4

Statement of authorship

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Principal author

Name of principal author (candidate)	German Puga		
Contribution to the paper	Led the study conception and design, reviewed the literature, prepared the data, performed statistical analyses, and interpreted the results. Wrote drafts/versions of the paper. Presented the paper at seminars and conferences to get feedback. Led the review/publication process.		
Overall percentage	65%		
Certification	This paper reports on original research I conducted during the period of my Higher Degree by Research candidature and is not subject to any obligations or contractual agreements with a third party that would constrain its inclusion in this thesis. I am the primary author of this paper.		
Signature		Date	11/07/2023

Co-author contributions

By signing the Statement of authorship, each author certifies that:

I. the candidate's stated contribution to the publication is accurate (as detailed above);
II. permission is granted for the candidate in include the publication in the thesis; and
III. the sum of all co-author contributions is equal to 100% less the candidate's stated contribution.

Name of co-author	Kym Anderson		
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Name of co-author	Wendy Umberger		
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Signature	**Signed form available at the end of this thesis.**	Date	

4. A climatic classification of the world's wine regions

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Abstract

Using a dataset with 16 climate variables for locations representing 813 wine regions that cover 99% of the world's winegrape area, we employed principal component analysis (PCA) for data reduction and cluster analysis for grouping similar regions. The PCA resulted in three components explaining 89% of the variation in the data, with loadings that differentiate between locations that are warm/dry from cool/wet, low from high diurnal temperature ranges, low from high nighttime temperatures during ripening, and low from high vapour pressure deficits. The cluster analysis, based on these three principal components, resulted in three clusters defining wine regions globally, with the results showing that premium wine regions can be found across each of the climate types. This is, to our knowledge, the first such classification of virtually all of the world's wine regions. However, with both climate change and an increasing preference for premium relative to non-premium wines, many of the world's winegrowers may need to change their mixes of varieties, or source more of their winegrapes from more appropriate climates.

Keywords: adaptation to climate change, cluster analysis, principal component analysis, viticultural zoning, winegrape varieties

4.1. Introduction

Climatic classifications of wine regions are important because they allow one to describe and compare wine regions that share similar characteristics. An example of a well-known climatic classification was developed by Tonietto and Carbonneau (2004) using three climatic indexes to create a multi-criteria climatic classification system. More recently, various studies have used multivariate statistical methods to group wine regions based on climatic indexes or climate variables. Examples of these studies are Herrera Nunez et al. (2011) in Italy, Montes et al. (2012) in Chile, Shaw (2012) in 25 Pinot Noir regions around the world, Fraga et al. (2016, 2017) in Portugal, Moral et al. (2016) in Spain, Karlík et al. (2018) in Austria, Cardoso et al. (2019) in Northwest Iberia, and Vianna et al. (2019) in Brazil. Except for Shaw (2012), who focused on selected Pinot Noir regions from eight countries, these studies focused on just one or two countries.

To our knowledge, there is no study describing and analysing the climate characteristics of virtually all of the world's wine regions using multivariate statistical methods. This research gap may be due to data availability issues. However, we have an opportunity to address this gap by obtaining location information on 16 climate variables for 813 wine regions that account for over 99% of the world's winegrape area (Anderson and Nelgen, 2020a, 2020b). This winegrape area database is an updated and expanded version of an earlier variety × region vineyard area database (Anderson, 2013).

The aim of this research is to classify virtually all of the world's wine regions in groups that share similar climate characteristics. Using a multivariate statistical approach allows for the grouping of similar characteristics into a smaller set of components, which is easier to do than examining all 813 regions with 16 climate variables. Because the dataset used for this classification includes information on the mix of varieties in each of these regions, it also allows us to infer the potential of the world's wine regions for high-quality wine production in the wake of climate change and a shifting demand towards premium wines.

4.2. Materials and methods

4.2.1. Data

The source of the data for the 813 wine regions is Anderson and Nelgen (2020a). These regions are sometimes legally defined geographical indications, but they are mostly delimited by political boundaries. A concordance between these regions and the ones in the *World Atlas of Wine* (Johnson and Robinson, 2019) is provided in Anderson and Nelgen (2020b). We use the locations reported in

Anderson and Nelgen (2020b), which represent municipalities within or close to each wine region, to extract climate data representing each region, for the 16 climate variables described in Table 4.1. The source of the climate data for the wine regions is TerraClimate (Abatzoglou et al., 2018). TerraClimate is built from multiple databases and uses climatically aided interpolation, combining high-spatial resolution (1/24°, ~4-km) climatological normals from the WorldClim dataset, with time-varying data from CRU Ts4.0 and the Japanese 55-year Reanalysis (JRA55). TerraClimate is updated annually, but at the time of this analysis it included the period of record 1958–2018. For our analysis we focused on the 30-year period from 1989 to 2018, but we also used data for the period 1959-1988 for comparisons of the evolution of climate between the two periods.

Table 4.1: Climate variables.

Variable	Description	Northern Hemisphere	Southern Hemisphere
AnnP (mm)	Annual precipitation	Year	Year
GSP (mm)	Growing season precipitation	April to October	October to April
HMP (mm)	Harvest month precipitation	September	March
AnnT (°C)	Annual average temperature	Year	Year
GST (°C)	Growing season average temperature	April to October	October to April
MJT (°C)	Mean January/July temperature	July	January
RPT (°C)	Ripening period average temperature	August to September	February to March
GDD (°C units)	Growing degree days	April to October	October to April
HI (°C units)	Huglin index	April to September	October to March
GSDTR (°C)	Growing season diurnal temperature range	April to October	October to April
RPDTR (°C)	Ripening period diurnal temperature range	August to September	February to March
CNI (°C)	Mean minimum March/September temperature	September	March
VPD_GS (kPa)	Growing season vapour pressure deficit	April to October	October to April
VPD_SU (kPa)	Summer vapour pressure deficit	June to August	December to February
SRAD_GS (W/m^2)	Growing season average day/night downward surface shortwave radiation	April to October	October to April
SRAD_SU (W/m^2)	Summer average day/night downward surface shortwave radiation	June to August	December to February

Notes: The base temperature for the GDD and HI calculations is 10°C, with no upper cut-off value.

The climate data extracted from TerraClimate for this study is based on one geographical location per region, usually a town or city within or adjacent to the region. The ideal climate data would be an average for the area devoted to vines within the qualified geographic boundaries of each region (spatial data). However, since such data are not available for all regions worldwide, we believe that a location extraction provides a general estimation of the area's climate and helps link these aspects to the varieties grown in each region. Other studies have encountered the same data availability issue, and they have also relied on one location for each region as a proxy of the spatial mean of each climate variable in each region. Examples are Tonietto and Carbonneau (2004) who examined 97 locations near or within wine regions, and Shaw (2012) who examined locations near or within 25 Pinot Noir wine regions.

4.2.2. Methods

Principal Component Analysis (PCA) is a dimensionality-reduction method that is often used to reduce the dimensionality of large datasets, by transforming a large set of variables into a smaller set that still contains most of the information in the larger set. PCA starts with the eigendecomposition of a correlation matrix. The eigenvectors from this decomposition are uncorrelated and normalised (orthonormal). We subjected the 16 climate variables for the 813 locations to PCA.

We used the principal components with eigenvalues greater than 1.0 resulting from the PCA as the input for doing a k-means cluster analysis. With too many variables (16 in our case), the k-means algorithm efficiency can be affected. This is because seeking neighbours (as is the case in the k-mean algorithm) in high dimensions is difficult as it may seem like the data points are too far away, even though all other dimensions are close to each other. For this reason, we performed PCA before the k-means cluster analysis.

K-means clustering allows observations to be classified in a predetermined (k) number of groups. This is a partition method and, unlike hierarchical cluster analysis methods, each observation is assigned to only one group. The process starts with all observations randomly assigned to the k groups. The mean for each group is calculated and each observation is re-assigned to the group with the closest mean. This process repeats until no observation changes group. K-means allows more than one variable to be employed by using a similarity or dissimilarity measure. For this study, we use the Euclidean distance, arguably the most used measure (Wu, 2012).

Stopping rules are helpful for choosing the optimal (k) number of groups. Milligan and Cooper (1985) evaluated a wide variety of stopping rules and concluded that the Calinski–Harabasz index is the best rule for non-hierarchical cluster analysis. Therefore, we used the Calinski and Harabasz (1974) pseudo-F index stopping rule to assist us in determining the optimal number of groups. A larger value of the Calinski–Harabasz index is preferred, as it signals a more distinct solution.

4.3. Results

The data for the 813 wine regions provide evidence of the diverse climates that exist in the world's wine regions. Table 4.2 shows the summary statistics for all the regions combined. This climatic variability is explained by latitudes that range from less than 10 degrees to almost 60 degrees from the equator, and elevations as low as sea level to as high as almost 3,000 meters above sea level. For example, annual precipitation (AnnP) ranges from basically zero in one of the driest regions of the world in northern Chile to 2996 mm in Taiwan. In addition, annual temperatures (AnnT) range from quite cold (less than 8°C) at higher latitude locations in Canada and Norway to above 26°C in regions such as India and Southeast Asia.

Table 4.2: Summary statistics and global weighted averages based on regional winegrape area as weights (period: 1989-2018).

Variable	Min	p25	p50	Mean	SD	p75	Max	Weighted mean
AnnP (mm)	0	510	685	730	362	931	2996	639
GSP (mm)	0	222	396	419	257	551	1974	334
HMP (mm)	0	32	56	62	43	85	338	51
AnnT (℃)	3.9	12.2	14.6	14.7	3.4	17.2	29.8	15.1
GST (℃)	9.9	17.2	19.3	19.4	2.8	21.3	30.8	19.8
MJT (℃)	14.2	21.5	23.6	23.6	2.8	25.7	33.6	24.4
RPT (℃)	12.0	19.4	21.3	21.5	2.9	23.5	32.5	22.3
GDD (℃ units)	314	1532	1973	1992	591	2383	4444	2097
HI (℃ units)	582	2079	2447	2453	516	2772	4380	2552
GSDTR (℃)	5.8	10.6	12.1	12.4	2.7	14.4	20.8	12.2
RPDTR (℃)	5.0	10.7	12.3	12.6	3.0	14.5	23.4	12.6
CNI (℃)	4.0	11.1	13.3	13.6	3.3	15.8	26.2	14.4
VPD_GS (kPa)	2.65	5.40	6.49	7.16	2.47	8.53	16.89	7.42
VPD_SU (kPa)	1.32	2.90	3.59	3.86	1.32	4.50	8.98	4.18
SRAD_GS (W/m^2)	1028	1420	1571	1575	187	1724	2072	1597
SRAD_SU (W/m^2)	510	723	792	790	86	856	996	816

Source: Authors' computation. Notes: The climate variables are described in Table 4.1.

Table 4.3 shows the results of the PCA. This table provides the eigenvalues and the explained variance of the components. The eigenvalue (or the proportion of the explained variance) of the first component is 8.52 and it explains 53% of the variation in the data. Choosing the components with eigenvalues greater than 1.0, which is the mean eigenvalue, is one of the most used objective criterion for selecting the number of components for data reduction (Jolliffe, 2002). Therefore, we chose the first three components (i.e., Comp1-3). These three components explain 89% of the variance in the data, demonstrating that PCA is a useful data-reduction technique in this case.

Table 4.3 also provides the principal component loadings. PC1 accounts for 53% of the variation in the data and distinguishes regions that are warmer and drier from regions that are cooler and wetter. The regions that are warmer and drier also have medium to high DTRs, and higher VPDs and SRADs. The regions that are cooler and wetter also have medium to low DTRs, and lower VPDs and SRADs. PC2 explains an additional 27% of the variation in the data with the loadings highlighting locations that have high GS and RP precipitation with lower DTR and warmer nights (+CNI) versus those that have low GS and RP precipitation, high DTR and cooler nights (-CNI). The wetter locations also tend to have warmer temperatures and relatively low VPD, while the drier locations have cooler temperatures and higher VPD. The first two PCs account for most of the variation in the data (80%), with PC3 accounting for an additional 9% with loadings appearing to distinguish between locations that are wet and have high DTRs and those that are dry and have low DTRs (Table 4.3).

Table 4.3: Components' eigenvalues and explained variance, and principal components' loadings and unexplained variance (period: 1989-2018).

	Comp1	**Comp2**	**Comp3**	**Sum**
Eigenvalue	8.52	4.28	1.48	14.28
Explained variance	0.53	0.27	0.09	0.89
Loadings				**Unexplained**
AnnP (mm)	-0.16	0.29	0.35	0.25
GSP (mm)	-0.16	0.33	0.42	0.05
HMP (mm)	-0.12	0.37	0.37	0.08
AnnT (℃)	0.28	0.19	-0.08	0.18
GST (℃)	0.31	0.21	0.01	0.02
MJT (℃)	0.29	0.19	0.08	0.14
RPT (℃)	0.30	0.21	-0.03	0.05
GDD (℃ units)	0.30	0.22	0.01	0.02
HI (℃ units)	0.32	0.13	0.14	0.05
GSDTR (℃)	0.16	-0.33	0.43	0.04
RPDTR (℃)	0.14	-0.35	0.42	0.04
CNI (℃)	0.22	0.34	-0.24	0.02
VPD_GS (kPa)	0.31	-0.14	0.19	0.07
VPD_SU (kPa)	0.29	-0.16	0.20	0.11
SRAD_GS (W/m^2)	0.27	-0.13	-0.10	0.28
SRAD_SU (W/m^2)	0.24	-0.18	-0.14	0.33

Source: Authors' computation. Notes: The climate variables are described in Table 4.1. Sum is the sum of the three principal components (Comp1-3). Unexplained is the proportion of the variance for each climate variable that is unexplained by the three principal components.

The eigenvectors in Table 4.3 are small and never greater than 0.5. For testing the significance of the eigenvectors, we estimated the PCA with the standard errors and related statistics (results not shown). This estimation relies on the assumption that the data have a multivariate normal distribution. This assumption can be justified by the relatively large sample size, thus the central limit theorem applies, and because PCA itself uses the central limit theorem implicitly by transforming the variables so that they have zero mean and unit variance. The results of this estimation show that, while the eigenvectors are small, all but two are statistically significant, which justifies the inclusion of all the climate variables in the analysis.

The last column in Table 4.3 shows the proportion of the variance for each climate variable that is unexplained by the three principal components. The variance of each of the 16 variables is well explained, with only 11% unexplained on average. The least explained variables are SRAD_SU and SRAD_GS, followed by AnnP and AnnT, which extend beyond the growing season, meaning they are arguably less relevant for this analysis. Even so, a large proportion of these variables is explained by the first three components.

We used the three principal components from the PCA for the k-means cluster analysis. To choose the k number of groups, we calculated the Calinski–Harabasz index for k-means cluster solutions with two to 14 groups based on the three principal components. The results suggest that a solution with three groups indicates the most distinct clustering. Figure 4.1 is a score plot based on the first and second principal components, where each of the 813 points represents a region and each of the three colours represents a group of regions. A similar interpretation can be inferred from graphs for the first and third and for the second and third principal components (not shown).

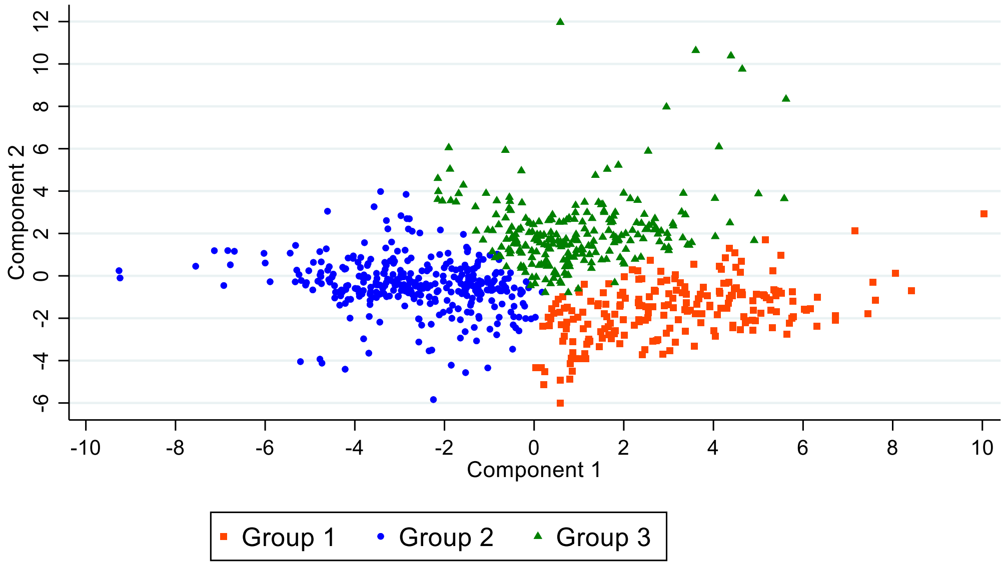

Figure 4.1: Score plot of three-group classification (period: 1989-2018).
Source: Authors' computation.

Figure 4.2A shows the regions plotted against their GST and GSP. Groups 1 and 3 are warmer than Group 2. Group 3 is, on average, wetter than Group 1, while a wide range of GSP is observed for Group 2. A large degree of overlap between Groups 1 and 3 is evident in Figure 4.2A. These two groups would appear more distinct in a three-dimensional graph with GSDTR on the third axis. That is because part of the difference between the regions that overlap is given by their difference in GSDTR. The regions in Group 1 have a higher GSDTR (Figure 4.2B). A wide range of GSDTR is observed for Group 2.

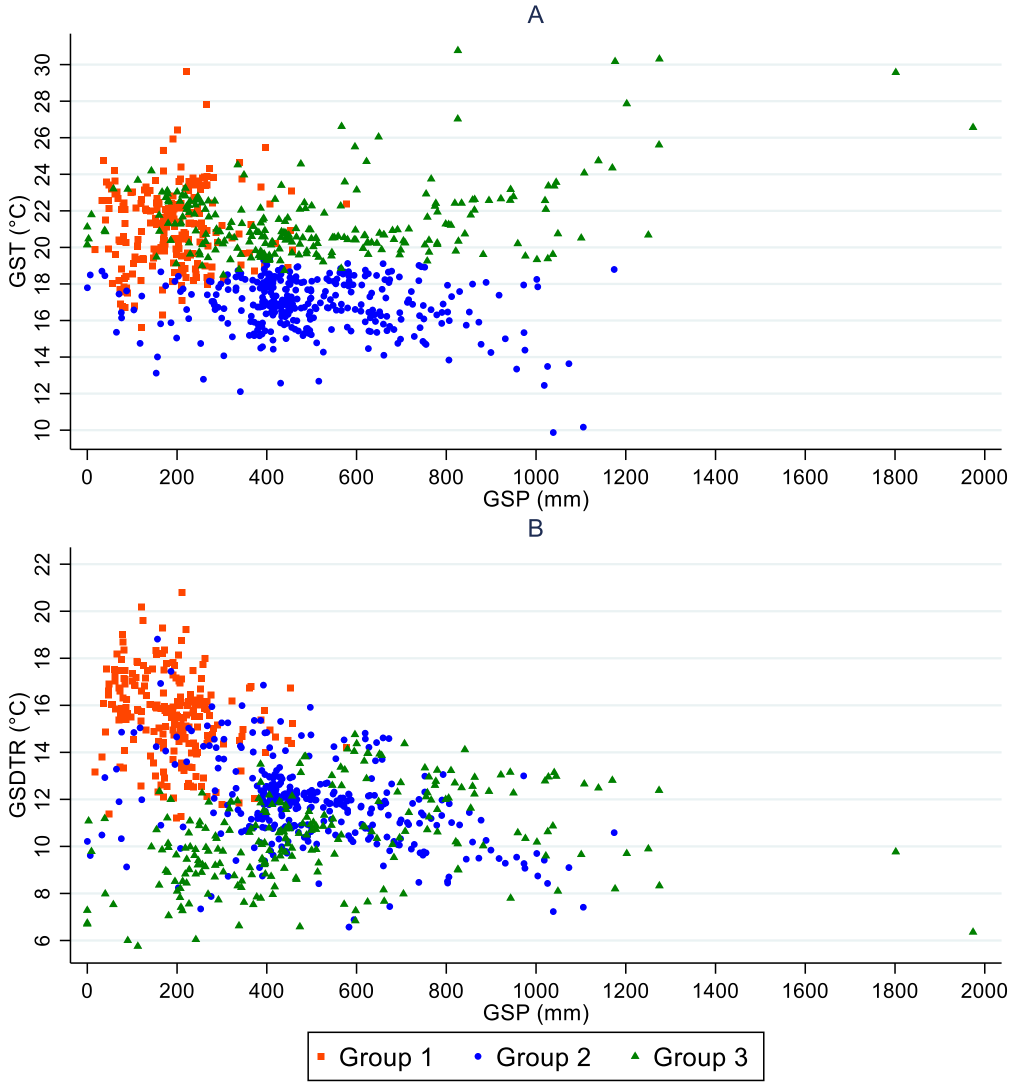

Figure 4.2: Scatter plots of three-group classification (period: 1989-2018).
Source: Authors' computation. Notes: GSP = growing season precipitation; GST = growing season average temperature; GSDTR = growing season diurnal temperature range.

Figure 4.3A shows the regions plotted against their VPD_GS and GSP. Group 1 has higher VPD_GS than Groups 2 and 3. This also explains part of the overlap between Groups 1 and 3 in Figure 4.2A. Figure 4.3B shows the regions plotted against their SRAD_GS and GSP. A wide range of SRAD_GS is observed in the three groups, although the average SRAD_GS is highest for Group 1 and lowest for Group 2.

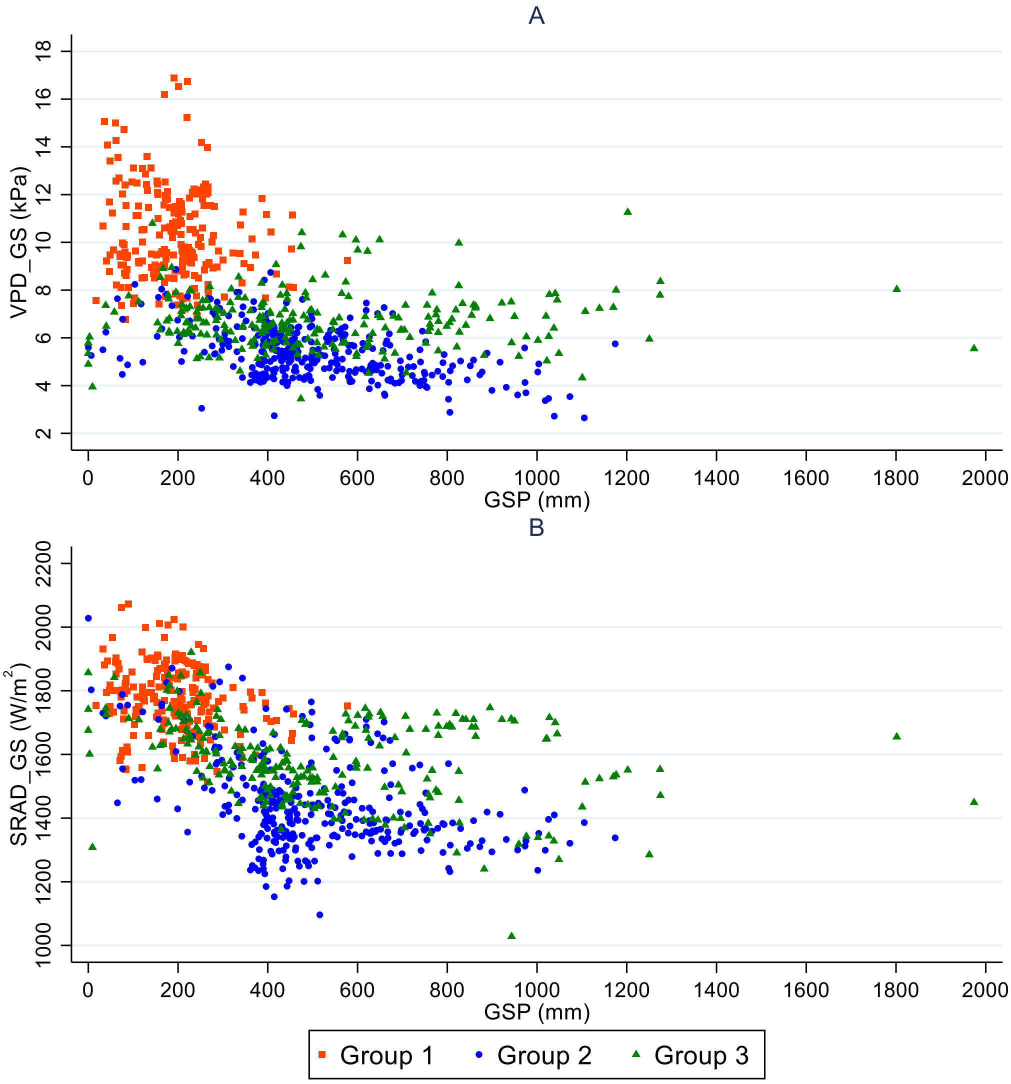

Figure 4.3: Scatter plots of three-group classification (period: 1989-2018).
Source: Authors' computation. Notes: GSP = growing season precipitation; VPD_GS = growing season vapour pressure deficit; SRAD_GS = growing season average day/night downward surface shortwave radiation.

Table 4.4 provides the summary statistics for the three almost equal-sized groups of regions. Group 1 is the smallest by number of regions (221) but the largest by surface (34.6% of the total winegrape area). Group 2 is the largest by number of regions (346) but the smallest by surface (31.5%). Group 3 includes 246 regions that cover 33.9% of the total winegrape area. Table 4.4 also provides the summary statistics for elevation. While there are wide ranges of elevation across the three groups, on average, Group 1 has the highest elevations and Group 3 the lowest.

Table 4.4: Summary statistics for the three groups (period: 1989-2018).

Cluster	Group 1					Group 2					Group 3				
Variable/Statistic	**Mean**	**Median**	**SD**	**Max.**	**Min.**	**Mean**	**Median**	**SD**	**Max.**	**Min.**	**Mean**	**Median**	**SD**	**Max.**	**Min.**
AnnP (mm)	433	374	225	1340	17	839	784	303	1865	7	844	746	387	2996	0
GSP (mm)	192	193	93	578	17	496	452	198	1174	0	515	445	302	1974	0
HMP (mm)	25	23	17	89	0	68	62	31	209	0	85	78	50	338	0
AnnT (°C)	16.6	16.8	2.4	24.9	8.6	12.0	11.8	2.0	17.8	3.9	16.9	16.8	2.8	29.8	12.4
GST (°C)	21.1	21.2	2.2	29.6	15.6	16.8	16.9	1.5	19.4	9.9	21.4	20.8	2	30.8	18.5
MJT (°C)	25.2	25.2	2.3	33.6	20.1	21.2	21.3	1.9	25.4	14.2	25.5	25.5	1.7	30.9	21.3
RPT (°C)	23.1	23.0	2.2	32.5	18.0	18.9	19.1	1.6	22.8	12.0	23.6	23.4	1.8	30.1	20.2
GDD (°C units)	2334	2342	461	4201	1256	1471	1480	290	2005	314	2417	2295	420	4444	1732
HI (°C units)	2864	2838	392	4380	2076	2009	2032	302	2636	582	2710	2647	345	4261	1907
GSDTR (°C)	15.6	15.8	1.8	20.8	11.2	11.8	11.8	1.8	18.8	6.6	10.4	10.4	1.9	14.8	5.8
RPDTR (°C)	15.9	15.6	2.2	23.4	11.2	12.1	12.1	2.0	19.9	6.7	10.4	10.6	1.9	14.4	5.0
CNI (°C)	13.7	14.0	2.7	25.0	6.0	11.1	11.1	1.8	16.4	4.0	16.9	16.6	2.4	26.2	12.3
VPD_GS (kPa)	10.36	9.90	1.94	16.89	6.77	5.40	5.33	1.08	8.87	2.65	6.75	6.63	1.17	11.26	3.45
VPD_SU (kPa)	5.55	5.45	1.08	8.98	3.04	2.96	2.90	0.62	4.85	1.32	3.63	3.66	0.65	6.38	1.60
SRAD_GS (W/m^2)	1774	1773	105	2072	1513	1444	1417	145	2028	1096	1581	1579	129	1921	1028
SRAD_SU (W/m^2)	876	880	58	996	713	737	730	65	950	566	789	804	70	961	510
Elevation (m)	484	398	412	2045	2	307	201	397	2952	2	180	65	272	1896	-3

Source: Authors' computation. Notes: The climate variables are described in Table 4.1.

The first map in Figure 4.4 shows that there are regions in the three groups across the globe. Regions from Group 1 account for most of the surface in the New World, which is evident from the second map in Figure 4.4, where the size of each region is proportional to its area. Group 1 includes most of the winegrape area in Argentina, central Chile, and South Africa, and a big proportion of the area in the United States, Australia, and Chile. Group 2 is mainly represented by New Zealand, some regions in Chile, and most of southern Australia, and by New York and coastal and northern regions in western North America. Last, Group 3 comprises most of Brazil and Uruguay.

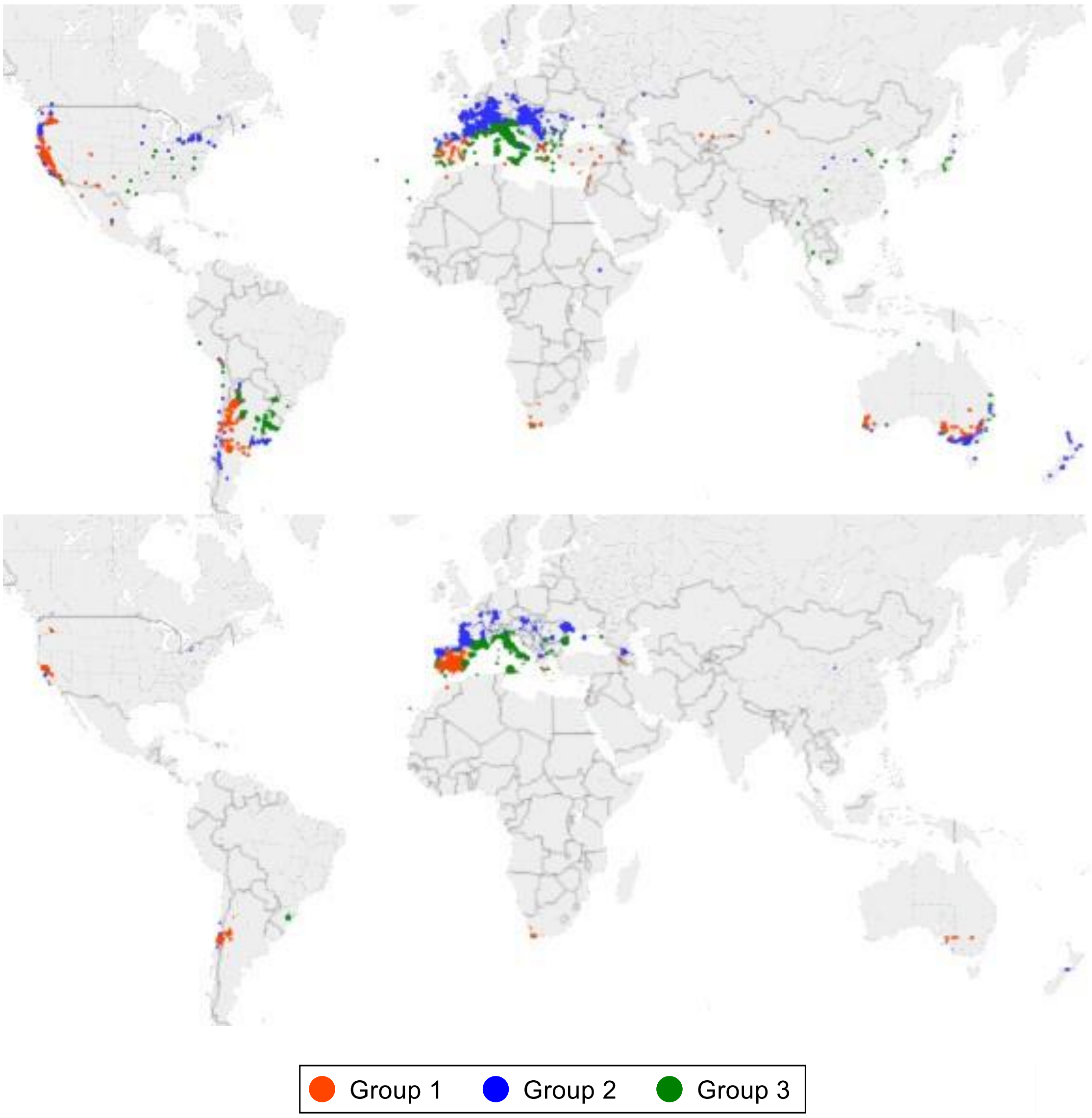

Figure 4.4: Classification maps in which all regions are the same size (first map), and in which the size of each region is proportional to the region's winegrape area (second map). Source: Authors' computation.

The winegrape area outside of the Old World has a larger share of its area in Group 1, whereas the Old World winegrape area is distributed more evenly across the three groups. Group 1 includes large regions in the centre of the Iberian Peninsula, as well as other regions in Greece, North Africa, and some countries in Asia. Group 2 comprises regions in the north of Spain and Portugal, the middle and north of France, inland countries with regions at higher elevations such as Germany and Austria, as well as Georgia and countries in Eastern Europe. Group 3 includes mostly coastal regions in the Iberian Peninsula, the south of France, a large portion of regions in Italy, and some Eastern European countries. An animated video of the world in which the area of each region is represented by the length of each location's bar is available at https://universityofadelaide.box.com/v/ClimaticClassification3DMap

We also explored the differences in the PCA between this period (1989-2018) and the previous period (1959-1988). The results for the first period (not shown) are very similar to those for the second period. When using the first three principal components from the first period to cluster the regions into three groups using k-means, only 35 out of the 813 regions change their cluster membership. Some regions that are part of Group 1 (e.g., Valparaiso in Chile) and Group 3 (e.g., Great Southern in Western Australia) in the first period become part of Group 2 in the second period, and some regions that are part of Group 2 become part of Group 3 (e.g., Rioja in Spain and Cuneo in Italy).

Besides looking at the differences in the PCA and cluster memberships between the two periods, we explored climatic differences between these periods. Table 4.5 provides the mean values and differences in mean values for the two periods for each of the three groups of regions and for all observations. Annual precipitation has decreased slightly in all groups, while the precipitation in the growing season has decreased slightly in the driest group (Group 1) and increased in the wetter groups (Groups 2 and 3). In all groups, temperatures have increased, especially in the warmest months, and daily temperature ranges have decreased. These changes in temperatures explain part of the changes in the vapour pressure deficits, which have increased across the three groups. As expected, average day/night downward surface shortwave radiation has not changed much over the two 30-year periods. The changes in medians rather than changes in means (results not shown) suggest some slight differences in the interpretation of these changes, but they reinforce the observation that the three groups of regions are warmer and have higher vapour pressure deficits.

We conducted paired t-tests on the equality of the means between the first and second period, for each climate variable, and for each group of regions and all the regions combined. The results show that these differences are all statistically significant at a 1% level except for the differences in GSDTR and RPDTR for Group 2, and SRAD_GS for Group 1. The last column in Table 4.5 shows the differences in climates between the two periods for all observations combined, all of which are statistically significant. Overall, both GSP and GSDTR increased (and decreased) in about half of the regions. GST, instead, increased in all but two regions. The increases in GST were higher than 0.5℃ in 76% of the regions, and higher than 1℃ in 46% of the regions. VPD_GS increased in 93% of the regions, while SRAD_GS increased in 72% of the regions.

Table 4.5: Mean values and differences in mean values for the two periods (P1: 1959-1988; P2: 1989-2018) for each group and for all regions.

Group	1			2			3			All		
Variable/Period	**P1**	**P2**	**Diff.**	**P1**	**P2**	**Diff.**	**P1**	**P2**	**Diff.**	**P1**	**P2**	**Diff.**
AnnP (mm)	447	433	-14	849	839	-11	861	844	-17	744	730	-14
GSP (mm)	195	192	-3	488	496	7	503	515	12	413	419	6
HMP (mm)	26	25	-2	66	68	3	80	85	5	59	62	2
AnnT (℃)	16.0	16.6	0.6	11.1	12.0	0.9	16.2	16.9	0.8	14.0	14.7	0.8
GST (℃)	20.4	21.1	0.6	15.9	16.8	0.9	20.5	21.4	0.9	18.5	19.4	0.8
MJT (℃)	24.5	25.2	0.7	20.1	21.2	1.1	24.5	25.5	1.0	22.6	23.6	1.0
RPT (℃)	22.5	23.1	0.6	18.1	18.9	0.9	22.8	23.6	0.8	20.7	21.5	0.8
GDD (℃ units)	2221	2334	113	1287	1471	184	2245	2417	172	1831	1992	161
HI (℃ units)	2779	2864	85	1825	2009	184	2564	2710	146	2308	2453	146
GSDTR (℃)	15.8	15.6	-0.3	11.8	11.8	0.0	10.6	10.4	-0.2	12.5	12.4	-0.1
RPDTR (℃)	16.3	15.9	-0.3	12.1	12.1	0.0	10.6	10.4	-0.2	12.8	12.6	-0.1
CNI (℃)	13.0	13.7	0.7	10.6	11.1	0.5	16.3	16.9	0.6	13.0	13.6	0.6
VPD_GS (kPa)	10.05	10.36	0.30	4.83	5.40	0.57	6.23	6.75	0.52	6.67	7.16	0.48
VPD_SU (kPa)	5.38	5.55	0.17	2.59	2.96	0.37	3.29	3.63	0.33	3.56	3.86	0.31
SRAD_GS (W/m^2)	1776	1774	-1	1418	1444	26	1566	1581	15	1560	1575	15
SRAD_SU (W/m^2)	879	876	-3	721	737	16	780	789	9	782	790	9

Source: Authors' computation. Notes: The climate variables are described in Table 4.1.

4.4. Discussion

This classification provides a description of the climates of the world's wine regions across a wide range of variables, including precipitation, average temperature, diurnal temperature range, vapour pressure deficit, and surface shortwave radiation. Compared to prior research classifying climates in wine regions, this classification utilises site locations across a wider range of regions that together encompass virtually all the world's winegrape area.

Despite its advantages, this classification has at least two limitations. First, the climate variables are based on extracting location data from one point in or near wine regions. A better representation would come from using approved wine region boundaries (e.g., GI, PDO, AVA, etc.) summarising spatial climate data across the wine regions, but these boundaries are not available for the majority of the regions studied. Second, there may be other climate variables that are also relevant, but which were not available in the spatial data used to extract the location data. Furthermore, the spatial climate data is aggregated to the time periods, so models that use daily data inputs could not be used. In addition, having phenological data for the main varieties in the region would allow for the application of novel models, such as Grapevine Flowering Véraison and Grapevine Sugar Ripeness (Parker et al., 2020). The impact of temporal variability in grapevine phenology (Hall and Blackman, 2019) is therefore not accounted for in this analysis. Moreover, considering that terroir is important for winegrape production and quality (van Leeuwen et al., 2020, 2018), the interactions between soils and climates are not reflected in this climatic classification.

This classification reveals that premium regions (i.e, those with relatively high wine prices) can be found in each of the three groups of regions. Group 1 includes Sonoma and Napa Valley (California), Uco Valley (Argentina), and Barossa Valley (Australia). Group 2 includes Bordeaux and Burgundy (France), Mosel Valley (Germany), and Marlborough (New Zealand). Group 3 includes Piemonte and Toscana (Italy), and Rioja (Spain). These are just some examples of premium regions that can be found across the climate types identified in this research, depending on style criteria and other factors.

The comparison between the two periods in our analysis reveals evidence of a changing climate in the wine regions. The increase in average temperature during the growing season (GST increased by 0.8℃) and the decrease in temperature range are perhaps the most concerning changes in relation to winegrape quality. The influence of temperature on berry composition makes it the key climatic factor affecting winegrape quality (Davis et al., 2019; Hall and Jones, 2009; Pons et al., 2017). Temperature range variables (e.g., GSDTR) also are often related to winegrape quality, as cooler nights can be positive for aroma and colour development due to a decrease in carbon use by respiration (Schultz, 2016).

Figure 4.5 shows the estimated GST ranges for producing high-quality winegrapes in the Northern Hemisphere, according to Jones et al. (2011). In parentheses on the vertical axis is the share of the global area of each variety (Anderson and Neglen, 2020) that is planted within that temperature range. The 21 varieties in this graph account for 45% of the global winegrape area and a much higher share of premium regions. In aggregate, 44% of that area is cultivated outside those temperature ranges identified for high-quality winegrape production in Figure 4.5. Most of that share which is not within those temperature ranges comprises regions that are too hot, rather than too cold. The vertical lines in Figure 4.5 show the mean GST for each group. Groups 1 and 3 have mean GSTs that are higher than the ideal temperatures for producing high-quality wine from the varieties represented in the figure. Combined, these regions accounted for 60% of the world's winegrape area in 2016. van Leeuwen et al. (2013), however, argues that the upper limits from Figure 4.5 are underestimated, and our research here indicates that as well.

It is also likely that some form of adaptation in grapevines to changes in climate has already occurred (van Leeuwen et al. 2013). However, with additional warming in the future, further adaptation, either in the plant system or in vine management, will likely be necessary as the share of the global winegrape area within the GST ranges for high-quality winegrape production will continue to decline. Most regions will need to adapt to further changes in climate, including some of the premium regions that may be subject to deteriorating quality (Santos et al. 2020). While warmer growing seasons are sometimes beneficial in some of the coolest regions, such as the Mosel Valley in Germany (Ashenfelter and Storchmann, 2010), years with significantly higher temperatures are associated with a decrease in quality in most of the world's current wine regions. Decreases in quality that may be induced by climate change are happening at a time when the preference for premium wine is increasing (Anderson et al., 2018). Should this trend continue, the need to adapt to climate change will only intensify (see Santos et al. (2020) for a review).

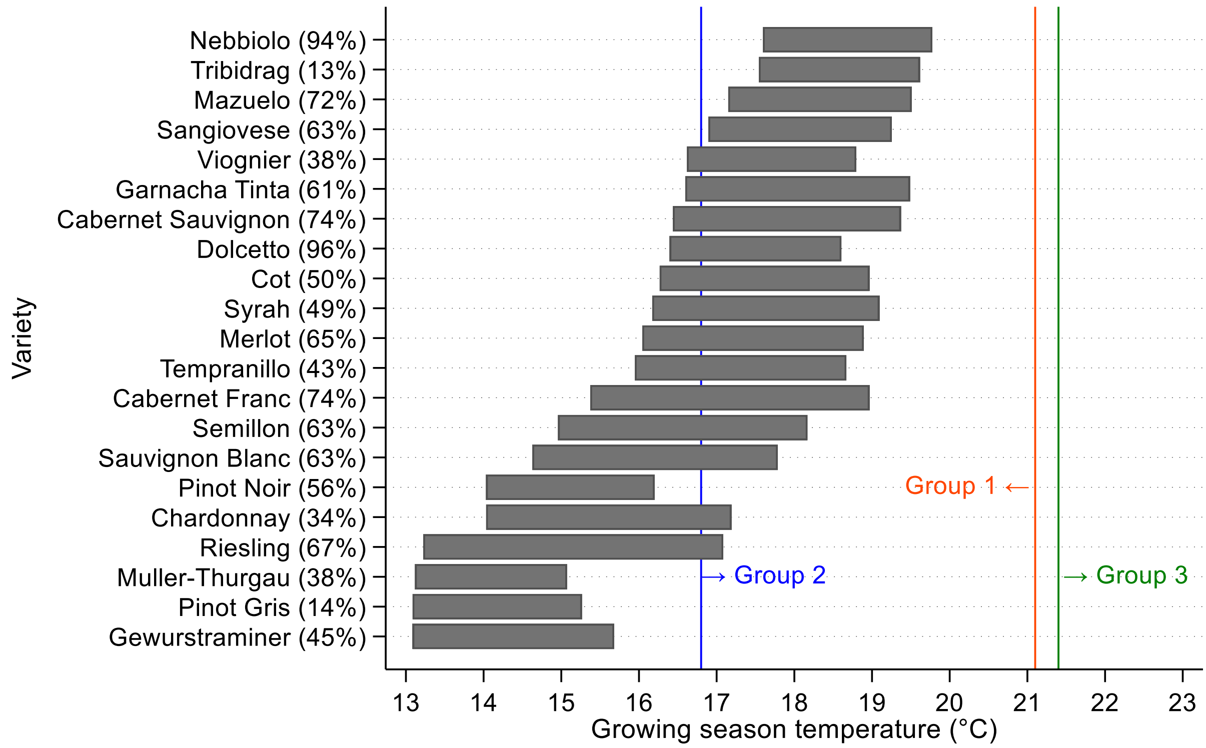

Figure 4.5: Optimal GST ranges for high-quality winegrape production (shares of world winegrape area under the grey ranges are shown in parentheses on the vertical axis).
Source: Jones et al. (2011) and authors' computation. Notes: The vertical lines show the mean GSTs for each group.

Much of the adaptation to climate change can take place in wineries. For example, oenological advances can help lower alcohol concentrations and increase acidity in wines – two issues that will intensify in some wine regions due to future warming (Dequin et al., 2017). However, part of the adaptation process will need to take place in the vineyards. Vineyard management techniques, such as alterations in training systems, canopy management, soil management and irrigation strategies, can help maintain production and quality levels in less-than-ideal climates (van Leeuwen et al., 2019), but further action may be required in some regions. Besides changing their vineyard management strategies, grape growers can adapt to climate change by selecting either different plant materials or different sites (van Leeuwen and Destrac-Irvine, 2017).

Modifications in plant material include using different rootstocks or clones. New breeding technologies that rely on genome editing techniques have a promising potential to produce plant material that can mitigate the effects of climate changes, but that potential is currently limited by the state of advancements and the perception that winegrowers and consumers have about these technologies (Dalla Costa et al., 2019). Therefore, winegrowers may need to diversify their production towards varieties that can produce high-quality wines in warmer growing seasons. There is little evidence, however, that the latter is happening at a global scale; between 2000 and 2016, the share of global area for the 21 varieties in Figure 4.5 that are cultivated within the temperature ranges shown there decreased from 60 to 56%. Another option for winegrowers who wish to retain their varietal mix is to source more winegrapes from regions with more-appropriate climates.

4.5. Conclusions

We used information on 16 climate variables to classify 813 wine regions that account for over 99% of the world's winegrape area using multivariate statistics, namely PCA and k-means clustering. The 813 regions were clustered into three groups of regions that are characterised by precipitation, average temperature, diurnal temperature range, vapour pressure deficit, and surface shortwave radiation variables. This is, to our knowledge, the first classification of wine regions that covers virtually all of the world's winegrape area. By grouping the regions into clusters that share similar climates, we provide an easy-to-interpret description of the climates of the world's wine regions. This classification reveals that premium regions can be found across all three climate types.

The comparison between the two time periods (1959-1988 and 1989-2018) suggests that the climate of each of the three groups has already changed. Current and further increases in temperature, detailed by the AR6 (IPCC, 2021) and others, may be the most concerning changes in terms of winegrape quality when the global demand for wine is likely to continue shifting towards more premium products. Therefore, winegrowers in some regions may need to use varieties that are more appropriate for warmer climates and/or to purchase or plant vineyards in cooler regions to maintain the typicity of wine styles.

The present analysis could be enhanced by using spatial climate data as opposed to location data, and by including additional climate variables that may prove useful in better understanding vine growth, productivity, and fruit quality. To do so would require a global database of governmentally approved wine region boundaries, allowing for a spatial assessment of all regions, and a robust global climate dataset with spatial resolutions and a wide range of variables suitable for assessing viticulture and wine production. In addition, having spatial climate data that reflects temporal variability (i.e., monthly or daily data), as well as variables that are not climatic but relate to the terroir, the vine, and winegrape quality (i.e., soils, phenology and fruit composition) would enhance this type of analysis. Further research could also incorporate climate change projections across all wine regions globally and consider the implications of future climate scenarios on the wine production sector. This would allow an analysis of the potential for some winegrape growing to shift to potentially more appropriate climates and regions. Future studies could also identify winegrape varieties growing successfully in regions with a similar climate to what any particular region is expecting its climate to become in the decades ahead. The database analysed for this research can also be used for that purpose because it includes the area by variety for more than 1,700 prime varieties for all the 813 regions we have classified (Anderson and Neglen, 2020).

Furthermore, the results of this study indicate that more research needs to be done on climate thresholds for winegrapes varieties worldwide. While Jones et al. (2011) provide a framework for a small subset of the varieties planted worldwide, further work is needed to examine the temperature thresholds for a wider range of economically important varieties. Enhanced models using phenological observations (Parker et al. 2020) are clearly useful in this regard, yet data availability across both regions worldwide and a larger set of varieties (Anderson and Neglen, 2020) would be needed to refine our understanding of climate limits to vine growth, productivity, and quality.

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Further information on the data used in this study

The version of this paper published in the journal *OENO One* includes an Excel file with supplementary material that is not included in this thesis because it is too long. That file contains: (a) PCA estimations with standard errors and related statistics for testing the significance of the eigenvectors; (b) a table with the climate and elevation data and cluster classification for each region; (c) more detailed maps for different world regions; (d) PCA results for the 1959-1988 period; (e) a table with median values and differences in median values for the two periods (1959-1988 and 1959-2018), for each group and for all regions; and (f) a table with 1,565 winegrape varieties ranked from highest to lowest area-weighted average GST in the world, which may be useful for identifying varieties that might be better adapted to warmer climates. Since this paper is published open access, this Excel file is freely available at https://doi.org/10.20870/oeno-one.2022.56.2.4627

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Chapter 5

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Contribution to the paper	Led the study conception and design, reviewed the literature, prepared the data, performed statistical analyses, and interpreted the results. Wrote drafts/versions of the paper. Led the review/publication process.		
Overall percentage	80%		
Certification	This paper reports on original research I conducted during the period of my Higher Degree by Research candidature and is not subject to any obligations or contractual agreements with a third party that would constrain its inclusion in this thesis. I am the primary author of this paper.		
Signature		Date	11/07/2023

Co-author contributions

By signing the Statement of authorship, each author certifies that:

I. the candidate's stated contribution to the publication is accurate (as detailed above);
II. permission is granted for the candidate in include the publication in the thesis; and
III. the sum of all co-author contributions is equal to 100% less the candidate's stated contribution.

Name of co-author	Kym Anderson		
Contribution to the paper	Contributed to the study conception and design, and to the interpretation and discussion of the results. Edited drafts/versions of the paper and helped responding reviewers' questions.		
Signature	**Signed form available at the end of this thesis.**	Date	

5. Concentrations and similarities across countries in the mix of winegrape cultivars

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Abstract

Background and goals: This study empirically summarizes the extent of similarities and concentrations in the mixes of winegrape cultivars across countries. It also seeks to determine by how much these mixes are becoming more or less similar and more or less concentrated in terms of area by winegrape cultivar.

Methods and key findings: Using a database of area by cultivar that accounts for 99% of the world's winegrape area, we analyse similarities and concentrations in the mixes of winegrape cultivars using two indexes (including a new cultivar concentration index) in innovative ways. The results show a great diversity across countries in terms of both similarities and concentrations, while providing robust evidence that the mixes of winegrape cultivars are tending to become more similar across countries and between countries and the world as a whole, and that these mixes are also tending to become more concentrated within countries and globally.

Conclusions and significance: The results point to the increasing scope for grape growers to diversify and differentiate their product by choosing less-planted cultivars, but they also suggest most winegrowers have found it more profitable to move toward mainstream cultivars.

Keywords: biodiversity, grape cultivar, winegrape concentration, winegrape similarities

5.1. Introduction

What winegrape cultivars (i.e., varieties) are planted and where they are planted is often influenced by two sometimes simultaneous but opposing forces. On the one hand, winegrowers often plant profitable cultivars that are well-known by consumers. This has been a common strategy in non-European countries. On the other hand, winegrowers also plant less-well-known cultivars to diversify and differentiate their offering, to better suit their particular terroir, or in response to expected changes in their climate.

The mix of winegrape cultivars has been the subject of a recent set of studies that started with Anderson (2010). These studies have all used a global database on winegrape cultivars by region that has been updated three times, Anderson and Nelgen (2020a) being the most recent version. Over time, this database has led to studies that analyse the mix of winegrape cultivars at the global level (e.g., Anderson and Nelgen (2020b, 2021a,b)), as well as country-specific studies, such as Anderson (2015) for Australia and Alston et al. (2015) for the United States.

The present paper extends those studies by empirically summarizing the extent of similarities and concentrations in the mixes of winegrape cultivars across countries, and by determining by how much these mixes are becoming more or less similar and more or less concentrated. Specifically, we contribute to the abovementioned literature on the mix of winegrape cultivars in four ways.

First, we provide an alternative way of looking at similarities in the mixes of winegrape cultivars. Previous research has relied on large matrices of similarity indexes between regions or countries. Our alternative method uses hierarchical clustering to present a large matrix of similarity indexes in one figure that helps uncover some relationships that are otherwise difficult to visualise.

Second, we introduce a new index that allows us to measure how concentrated a region (or country, or the world) is in terms of its mix of winegrape cultivars. Previous research has relied on summary statistics as well as indexes of cultivar intensity and internationalization to study cultivar concentration or diversity. Unlike those indexes, our index summarises how concentrated a mix of winegrape cultivars is in just one value with a straightforward interpretation.

Third, we classify countries based on two variables: how similar their mix of winegrape cultivars is relative to the world, and how concentrated their mixes are. This allows us to provide a more holistic picture of the extent of similarities and concentrations for 53 countries that cover 99% of the world's winegrape area.

Finally, we analyse whether the mixes of winegrape cultivars in the different countries and the world as a whole are becoming more or less similar and more or less concentrated. We do this by using average and area-weighted average indexes, and exploring the time series dimension of the database. This leads to the robust conclusion that the mix of winegrape cultivars became more similar across countries and more concentrated globally between 2000 and 2016.

5.2. Materials and methods

5.2.1. Data

We use a recently-revised database on area by region and cultivar that covers 99% of the world's winegrape area (Anderson and Nelgen, 2020a). This database contains information for 53 countries in 2016, and for 38 of these 53 countries in 2000, including all major nations in terms of wine production (Anderson and Nelgen, 2020b). The database includes a total of 1,733 DNA-distinct cultivars based on their prime names according to their perceived country of origin as provided in Robinson et al. (2012) or otherwise JKI (2019).

5.2.2. Cultivar similarity index

We use the cultivar similarity index (CSI) for analysing similarities in the mix of winegrape cultivars between two countries. This index was first introduced by Anderson (2010) and it is also known as the regional similarity index. The CSI for countries i and j takes the form:

$$CSI_{ij} = \frac{\sum_{c=1}^{C} f_{i,c} f_{j,c}}{\left(\sum_{c=1}^{C} f_{i,c}^2\right)^{1/2} \left(\sum_{c=1}^{C} f_{j,c}^2\right)^{1/2}}. \quad (1)$$

$f_{i,c}$ ($f_{j,c}$) is the area of cultivar c in country i (j) as a proportion of the total winegrape bearing area in that country.

The CSI ranges between 0 and 1. The closer the index is to 1, the more similar is the mix of cultivars between two countries. An index of 0 indicates a completely different mix of winegrape cultivars, while an index of 1 means that both countries have exactly the same cultivars and the same proportional area for each of those cultivars. We also use equation (1) to compute CSIs between countries and the world as a whole.

5.2.3. Hierarchical cluster analysis based on CSIs

We provide an innovative way of visualising similarities in the mixes of winegrape cultivars which we explain with a simple example that involves the three largest countries in terms of winegrape area: Spain, France, and Italy. This matrix of CSIs is:

	Spain	France	Italy
Spain	1	0.04	0.15
France	0.15	1	0.41
Italy	0.04	0.41	1

With this matrix, we construct a dissimilarity matrix in which each dissimilarity index between two countries is simply 1 minus their CSI. This dissimilarity matrix allows us to cluster the countries using an average-linkage hierarchical clustering method, as shown in Figure 5.1. This process starts with all countries assigned to three different groups, each group being just one country. The two groups with the lowest dissimilarity index (highest CSI) are merged into one group: Italy and France. The vertical line that links Italy and France is at a dissimilarity level of 0.59 because their CSI is 0.41. The process continues combining groups until all countries are part of the same group (the three countries in this case). The average-linkage clustering method gives equal weight to each country in each group. That explains why the vertical line that links Spain and the other two countries is at a dissimilarity level of 0.9: the average CSI between Spain and the two other countries is 0.1.

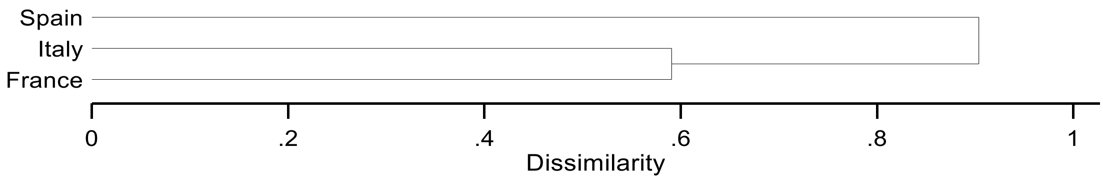

Figure 5.1: Dendrogram based on winegrape CSIs for the top three countries by winegrape area in 2016.
Notes: CSI is the cultivar similarity index. Dissimilarity = 1 - CSI.

Besides being a useful way of visualising CSI data, this method allows one to classify the countries into clusters by simply drawing a vertical line at any level of dissimilarity. The Calinski-Harabasz and the Duba-Hart stopping rules can help in identifying more distinct cluster solutions.

5.2.4. Cultivar concentration index

For analysing concentrations in the mix of winegrape cultivars, we use a novel index that we call the cultivar concentration index (CCI), given by:

$$CCI_i = 100\left(\sum_{c=1}^{C} f_{i,c}^2\right). \tag{2}$$

The same formula has been used in other disciplines: the Herfindahl–Hirschman index for analysing concentration in economics, the Simpson index in ecology (Simpson, 1949), the Hunter–Gaston index in microbiology (Hunter and Gaston, 1988), and the effective number of parties index in politics (Laakso and Taagepera, 1979). The interpretation of the CCI is that if two different winegrape blocks are randomly chosen, the probability in percentage of those winegrape blocks having the same cultivar is equal to the value of the index.

5.2.5. K-means cluster analysis based on the CSIs relative to the world and the CCIs

We use both the CSIs between each country and the world as a whole and the CCIs to cluster the countries using a k-means method with data for 2016. To choose the optimal number of clusters, we rely on the Calinski- Harabasz stopping rule.

5.2.6. Further details regarding the methods, indexes, and data

We also use the time dimension of our data to analyse changes in similarities and concentrations across time, based on our indexes. Further, we do correlation analyses to derive insights into how similarities and concentrations vary based on the countries' winegrape areas.

The supplementary material comments on the implication of minor not-reported cultivars on the indexes computation, and provides a detailed explanation of the cluster analysis methods used in this study. The data and the Stata code used in the cluster analyses are also available in the supplementary material.

5.3. Results

5.3.1. Hierarchical cluster analysis based on CSIs

Figure 5.2 is a dendrogram that shows how the top 20 countries by winegrape area group together at various levels of dissimilarity based on their winegrape CSIs as of 2016. The interpretation is the same as explained above in the example for Spain, France, and Italy (Figure 5.1). That is, longer horizontal lines between countries or clusters indicate larger differences between them in their mix of winegrape cultivars.

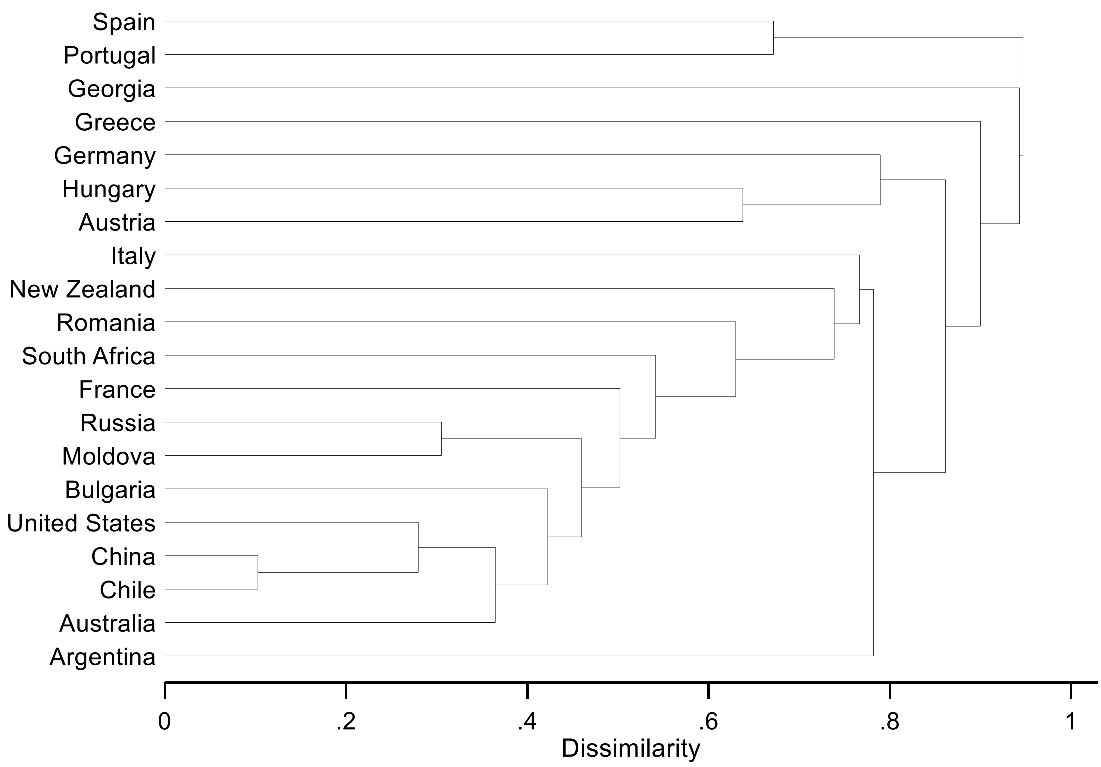

Figure 5.2: Dendrogram based on winegrape CSIs for the top 20 countries by winegrape area in 2016.
Notes: CSI is the cultivar similarity index. Dissimilarity = 1 - CSI.

Figure 5.2 gives insights into what may make countries have a more-similar cultivar mix. While this figure does not allow us to support any causal relationship, it shows that countries that are part of the same cluster are often geographically close (e.g., Spain and Portugal) or have similar climates (e.g., the regions within the cluster of Germany, Hungary, and Austria have the same broad climate type, see Puga et al. (2022a)). The dendrogram for 53 countries provided in Figure S5.1 suggests other types of characteristics such as colonial ties (e.g., France and Algeria, Italy and Ethiopia) also may affect the extent of similarities in the mix of winegrape cultivars between countries.

5.3.2. CSIs relative to the world

Besides looking at the CSIs between countries, it is also useful to look at the CSI between each country and the world as a whole to analyse how the mix of winegrape cultivars of a country compares to that of all countries combined. As with the CSI between two countries, the CSI relative to the world takes values between 0 and 1, and is higher the more similar is the mix of winegrape cultivars of a country to that of the world as a whole. The fifth column of Table 5.1 shows these indexes for 2016 for the top 20 countries by winegrape area, as well as for all 53 countries in our dataset combined.

The mean CSI between each country and the world is 0.33, with a standard deviation of 0.22. Across countries, there is a correlation of 0.44 between CSI relative to the world and winegrape vineyard area (Table S5.1), meaning that the larger a winegrape-producing country the more similar tends to be its cultivar mix to that of the world.

5.3.3. CCIs

The seventh column of Table 5.1 shows the CCI in 2016 for the top 20 countries by winegrape area, as well as for all 53 countries in our dataset combined. The mean CCI is 17.28, with a standard deviation of 13.30. On average, if two different winegrape blocks in a country are randomly chosen, the probability of those winegrape blocks having the same common cultivar is 17.28%. Overall, there is a correlation of -0.30 between CCI and winegrape vineyard area (Table S5.1), meaning that smaller winegrape-producing countries tend to have a more concentrated cultivar mix.

The mean CCI in the world as a whole in 2016 is 2.23, lower than the CCI for any country and barely one-eighth of the mean CCI across countries. If two different winegrape blocks are randomly chosen anywhere in the world, the probability of those winegrape blocks having the same common cultivar is 2.23%.

Table 5.1: Area, CSI relative to the world, and CCI for each country in 2000 and 2016, and cluster classification based on both CSIs relative to the world and CCIs in 2016, for the top 20 countries by area in 2016.

Country	Area 2000 (ha)	Area 2016 (ha)	CSI 2000	CSI 2016	CCI 2000	CCI 2016	Cluster 2016
Spain	1181806	883558	0.70	0.58	13.5	11.8	Green
France	864846	814882	0.67	0.76	6.6	5.7	Green
Italy	636662	604551	0.37	0.46	3.2	3.3	Green
United States	175693	239632	0.48	0.72	9.2	8.9	Green
Argentina	197418	206342	0.28	0.39	7.6	9.1	Orange
Romania	222173	182762	0.33	0.42	1.7	2.0	Green
Portugal	205003	182649	0.09	0.28	2.0	4.0	Orange
China		178000		0.65		6.8	Green
Chile	113966	145873	0.46	0.68	14.3	12.7	Green
Australia	130602	132435	0.48	0.67	12.0	15.6	Green
South Africa	93656	95775	0.34	0.53	10.6	9.7	Green
Germany	104233	94501	0.12	0.19	11.0	10.0	Orange
Moldova	89844	82600	0.37	0.52	10.0	6.7	Green
Hungary	86886	63881	0.22	0.32	2.5	4.3	Orange
Bulgaria	95997	52974	0.34	0.58	10.5	11.5	Green
Greece	50915	50845	0.06	0.17	9.4	8.8	Orange
Russia	56332	50794	0.17	0.55	6.6	8.0	Green
Georgia	37419	48000	0.10	0.08	32.2	32.2	Blue
Austria	48496	45439	0.10	0.14	16.2	13.8	Orange
New Zealand	9942	35463	0.36	0.31	16.5	37.3	Blue
WORLD average	90706	84587		0.33		17.28	
WORLD total	4807408	4483130				2.23	

Notes: CSI is the cultivar similarity index relative to the world. CCI is the cultivar concentration index. 'WORLD average' is a simple average (i.e., not area weighted). Both 'WORLD average' and 'WORLD total' refer to the 53 countries in the dataset, which include the top 20 countries by area. The green cluster includes countries with high cultivar similarity index (CSI) relative to the world and low cultivar concentration index (CCI). The orange cluster encompasses countries with low CSI relative to the world and low CCI. The blue cluster includes countries with low CSI relative to the world and high CCI.

5.3.4. K-means cluster analysis based on CSIs relative to the world and CCIs

The Calinski–Harabasz stopping rule suggests that the most-distinct solution for our k-means cluster analysis consists of three clusters shown in different colours in Figure 5.3. While only 20 out of 53 countries are in the green cluster (high CSI, low CCI), these countries account for 79% of the world's winegrape area. The orange cluster includes another 20 countries that cover 18% of the world's winegrape area (low CSI and CCI). The remainder 3% of the world's winegrape area belongs to the nine countries in the blue cluster (low CSI, high CCI). Table 5.1

specifies which of the top 20 countries by winegrape area belong to each cluster, and Table S5.1 provides the same information for all other countries.

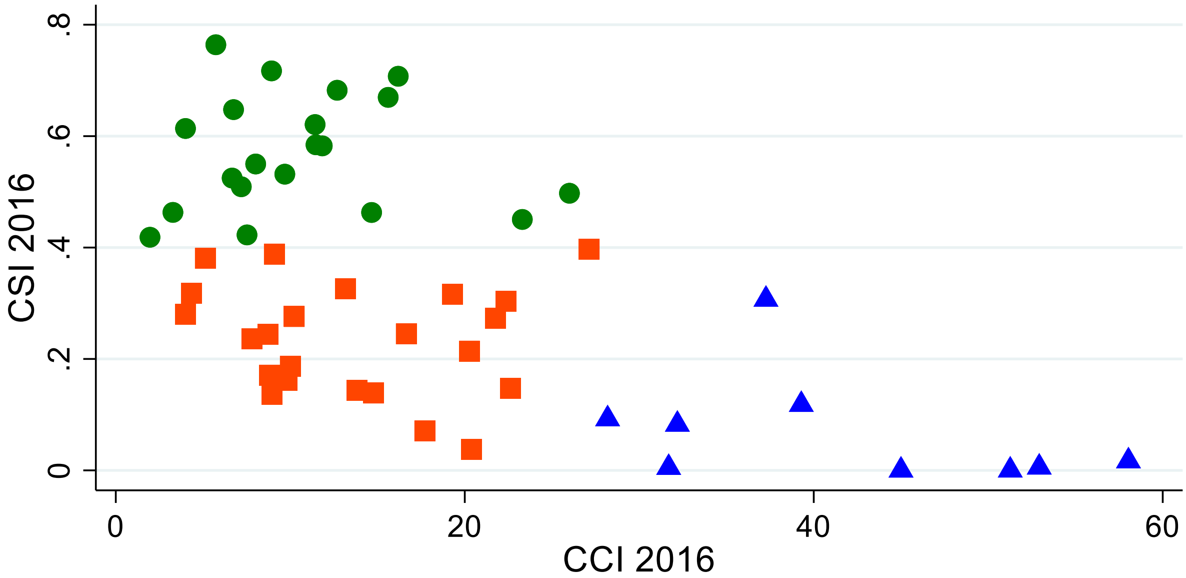

Figure 5.3: K-means cluster classification of countries based on their CSI relative to the world and their CCI.

Notes: CSI is the cultivar similarity index relative to the world. CCI is the cultivar concentration index. The green cluster (dots) includes countries with high cultivar similarity index (CSI) relative to the world and low cultivar concentration index (CCI). The orange cluster (squares) encompasses countries with low CSI relative to the world and low CCI. The blue cluster (triangles) includes countries with low CSI relative to the world and high CCI.

5.3.5. Changes in similarities and concentrations

Table 5.2 presents average values across countries of the CSIs relative to the world and the CCIs in 2000 and 2016, for the 38 countries for which there are data in both years. The CSI relative to the world has increased in 28 of those 38 countries, while the CCI has increased in 21 of them. As countries are tending to become more similar to the world in their cultivar mix, that mix is also becoming more concentrated within each country.

Table 5.2: Simple average and area-weighted average CSIs and CCIs across countries for 2000 and 2016, and world's CCI for 2016, using only the countries for which there are data on area by cultivar for both years.

Index	Calculated for	2000	2016
CSI	Countries – simple average	0.101	0.149
CSI	Countries – area-weighted average	0.145	0.165
CCI	Countries – simple average	13.99	15.80
CCI	Countries – area-weighted average	9.38	8.83
CCI	World – as a whole	1.90	2.25

Notes: CSI is the cultivar similarity index relative to the world. CCI is the cultivar concentration index.

The average CSI relative to the world across those 38 countries has increased by half, from 0.10 to 0.15. Even considering an area-weighted average, this index has increased by one-seventh, from 0.145 to 0.165. These results suggest that the mixes of winegrape cultivars have become more similar across countries.

A parallel analysis for cultivar concentrations is less straightforward. The average CCI across these countries has increased by 13%, but the area-weighted average has decreased by 6%. However, the CCI can be calculated for the world as a whole in 2000 and 2016 using countries for which there is information in both years, to provide an answer to the question on whether the mix of winegrape cultivars has become more or less concentrated. The last row of Table 5.2 shows that the world's CCI has increased by 18% (considering only the 38 countries for which there are data in 2000 and 2016). This, in turn, suggests that the mix of winegrape cultivars has become more concentrated globally.

5.4. Discussion

5.4.1. Industry and policy implications

The results of this study show that there are large variations in similarities and concentrations of winegrape cultivars across countries. Variables such as geographic proximity and climate type may influence these similarities. However, the cluster analysis of countries based on their CSI relative to the world and their CCI show that there is no clear pattern in terms of where the countries in each cluster are located. All clusters are represented both in Europe and in other continents. Overall, countries are becoming more similar and concentrated in their mix of winegrape cultivars.

Anderson and Nelgen (2021b) argue that the change towards a less diverse cultivar mix is in part explained by a rise in the plantings of 13 key premium cultivars from France (Cabernet Franc, Cabernet Sauvignon, Chardonnay, Malbec, Merlot, Pinot Gris, Pinot Noir, Sauvignon Blanc, and Syrah), Germany (Riesling), Italy (Nebbiolo and Sangiovese), and Spain (Tempranillo). These cultivars have been among the highest priced in important non-European wine countries such as the United States (Alston et al., 2015), Australia (Anderson, 2015), and Argentina (Puga et al., 2019). The area covered by these cultivars rose 51% between 2000 and 2016.

The fact that nine of the 13 abovementioned cultivars are French explains in part why France has the highest CSI relative to the world (0.76). Many non-European countries have increasingly focused on some well-known French cultivars, often for the ease of marketing (Anderson and Nelgen, 2021b).

The increasing similarities and concentrations in the mixes of winegrape cultivars do not translate into less diversity for consumers, however (Anderson and Nelgen, 2021a). This is because these changes in similarities and concentrations in the cultivar mix have been slower than the increase in wine exports that has taken place in the last few decades, which in turn has increased choices for consumers. In recent years, global wine imports have increased and more than two of every five bottles that are consumed are imported (Anderson and Pinilla, 2018).

Nevertheless, countries that have a more similar mix of winegrape cultivars tend to trade more wine between them (Puga et al., 2022b). This may also be explained in part by the ease of marketing wine of better-known cultivars.

Overall, our results signal that most growers and wine producers have found it more profitable to move toward mainstream cultivars. However, they also suggest that there is increasing scope for grape growers to diversify and differentiate their products by choosing less-planted cultivars. Winegrowers should make their own assessment as to which cultivars to discontinue and which to expand. Their decisions should depend on how profitable the next-best alternative cultivars would be on their particular site’s terroir and with their particular management skills.

Meanwhile, a large share of some widely-planted winegrape cultivars seems to be grown in climates (and projected climates) that may not be ideal for producing high-quality wine with those cultivars (van Leeuwen et al., 2019; Puga et al., 2022a). Since ease of marketing may be driving part of these trends in cultivar choices, grower organizations could analyse whether it is worth investing in marketing programs of less-known cultivars that do well in the (expected future) climates of their regions.

Changes in regulations may also help. For example, in countries where winegrowers usually market their wines by cultivar, there is usually a minimum percentage of wine of a particular cultivar for the wine to be labelled as made of that cultivar. Policymakers could consider decreasing that minimum percentage.

An interesting finding of this research is that there does not seem to be an association between how concentrated countries are (based on their CCIs) and the flexibility that growers have in the different countries in choosing the cultivars to plant (or even in having the right to plant). In fact, the least-concentrated countries include Italy (CCI = 3.3), Portugal (CCI = 4), and France (CCI = 5.7). These are countries with quite rigid cultivar regulations. This suggests that a focus on marketing by geographical indications (as many European countries do) instead of marketing by cultivars (as many non-European countries do) may help increase the share of a region that has more-appropriate cultivars for the (expected) climate of that region.

5.4.2. Further applications of the methods used in this study

The main advantage of our hierarchical method based on dissimilarities in the mix of winegrape cultivars is that it provides an easier-to-interpret representation of these dissimilarities. Figure S5.1 provides a dendrogram for all 53 countries in our dataset, hence summarising in a single figure a matrix of CSIs of more than 2,809 cells.

Another advantage of this method is that it allows one to classify countries by drawing a vertical line in the dendrogram at any level of dissimilarity. In this study, since there are some countries with a unique mix of winegrape cultivars, a classification of this type leads to heterogeneous clusters in terms of the number of countries. Using our proposed method to classify regions within countries may be more useful, as it sometimes leads to more homogeneous clusters.

A classification of regions based on their CSIs may be useful for policymakers seeking to determine which regions or sub-regions could be part of a same geographical indication. Viticultural zoning often relies on classifications that are usually related to the climates and other characteristics of the terroir of wine regions (Puga et al., 2022a). The degree of similarity in the mixes of winegrape cultivars could also be considered in zoning exercises using our proposed method.

The CCI could be applied in other analyses too. For example, it could be used as an independent variable in modelling exercises seeking to determine how different regulations influence the degree of concentration in the mix of winegrape cultivars.

5.4.3. Phylogenetic blindness of the CSI and the CCI

Perhaps a limitation of both indexes is that they do not account for genetic similarities between cultivars, as only the cultivar type is considered in the computations. Therefore, these indexes are phylogenetically blind. Characterizing the biodiversity of a crop often requires a phylogenetically informed approach, which incorporates the notion of cultivar relatedness in the index (Chai et al., 2022). If pertinent data became available, analyses of diversity using phylogenetically informed indexes may provide useful complementary insights to the ones provided in this study.

It would also be interesting to develop indexes that consider clonal differences. In viticulture, clones differ in numerous characteristics such as fruit composition (Reynolds et al., 2022) or the response to abiotic stress (Hébert-Haché et al., 2021).

5.5. Conclusions

This study introduces a new index for quantifying the degree of concentration in the mix of winegrape cultivars, and provides an innovative use of this index and a previously-defined similarity index to analyse similarities and concentrations in the world's winegrape cultivar mix. The results show a great diversity across countries in terms of both similarities and concentrations, while providing robust evidence that the mixes of winegrape cultivars are tending to become more similar across countries and between countries and the world as a whole, and that these mixes are also tending to become more concentrated within countries and globally. Further research could look into similarities and concentrations in the cultivar mixes at the regional level using the database used in this study, and investigate changes in diversity using phylogenetically informed rather than phylogenetically blind indexes.

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Supplementary material

Comment on the implication of minor not-reported cultivars on the indexes computation

Not all cultivars are reported in Anderson and Nelgen (2020a,b). Some countries provide a list of ‘other’ cultivars that are not separately identified. These ‘other’ cultivars, which may differ in number between 2000 and 2016, are not accounted for in the indexes’ computation. As well, new cultivars are occasionally discovered and reported (Pastore et al., 2020).

How important is this limitation? The data in Anderson and Nelgen (2020a,b) is reported at a great level of detail. While more cultivars have been reported in 2016, most of these newly reported cultivars are minor in terms of area coverage. The formulas for both the CSI and the CCI give little weight to the least-planted cultivars. For illustrating this, we calculated the CCI for the world in 2016 using only the top 150 cultivars in terms of area, i.e., less than 10% of all the cultivars in that year. At two decimal points, the CCI is the same (2.23) whether we use the top 150 cultivars or all cultivars. Therefore, we argue that this first limitation is not quantitatively important in our study, but it may be more relevant in other studies in which the number and relevance of reported cultivars changes considerably across countries or regions, or between time periods.

More detailed explanation of the cluster analyses methods used in this study

Hierarchical cluster analysis based on CSIs

We compute a matrix of CSIs for all the countries for which there are winegrape area data in 2016. We then transform this matrix into a dissimilarity matrix in which the dissimilarity index between two countries i and j is $1 - CSI_{ij}$. With this dissimilarity matrix, we clustered the countries using an average-linkage hierarchical clustering method.

Hierarchical clustering starts with all countries assigned to N separate groups, each group containing one country. The two countries with the highest CSI (lowest dissimilarity index) are merged into one group, leading to $N - 1$ groups. The closest two groups are then merged so that the total number of groups becomes $N - 2$. This process continues until all countries are merged into one single group of size N. Average-linkage clustering determines the closest two groups based on the average dissimilarity between countries in the two groups, and gives equal weight to each country.

We use this clustering method to classify the countries based on their CSIs in 2016. Theoretically, it is possible to classify the countries into up to N clusters by choosing a dissimilarity level as the threshold. For choosing the number of clusters, we rely on the Calinski-Harabasz and the Duba-Hart stopping rules. The Calinski-Harabasz stopping rule provides a pseudo F-index. Higher pseudo-F indexes indicate more distinct clustering. The Duba-Hart stopping rule gives a Je(2)/Je(1) index and a pseudo-T^2 value. Higher Je(2)/Je(1) and lower pseudo-T^2 values point out more distinct cluster solutions.

K-means cluster analysis based on the CSIs relative to the world and the CCIs

We use both the CSIs relative to the world and the CCIs to cluster the countries using a k-means method with data for 2016. We use the Minkowski distance metric with argument 2 (Euclidean distance) for comparing the observations (countries) based on two variables (CSI relative to the world and CCI). The process starts with all countries randomly assigned to the (k) number of groups. The mean for each group is calculated based on the Euclidean distance between countries, and each country is re-assigned to the group with the closest mean. This process repeats until no country changes group. Since the Duba-Hart stopping rule only applies to hierarchical clustering methods and k-means is a partition method, we rely on the Calinski-Harabasz stopping rule to choose the (k) number of clusters.

Stata codes for the cluster analyses performed in this study

Code for hierarchical cluster analysis based on CSIs

We use Stata 17 to perform this analysis. Here we are pasting its corresponding code:

```
**# CSIs 2016 dendogram and classification
*This code is to perform an average linkage cluster analysis of all countries using data for 2016, and to create Figure S5.1.
```

***Perform cluster analysis:

clustermat averagelinkage D, add name(alink)

*D is a the dissimilarity matrix.

***Use stopping rules to determine appropiate number of clusters:

cluster stop alink, rule(calinski) groups(3/30) variables(v*)

cluster stop alink, rule(duda) groups(3/30) variables(v*)

*The Calinski-Harabasz stopping rule provides a pseudo F-index. Higher pseudo-F indexes indicate more distinct clustering.

*The Duba-Hart stopping rule gives a Je(2)/Je(1) index and a pseudo-T2 value. Higher Je(2)/Je(1) and lower pseudo-T2 values point out more distinct cluster solutions.

*Therefore, the results of these stopping rules suggest that nine cluster is the most distinct cluster solution.

***Generate nine clusters:

cluster generate g9 = group(9)

***Order and sort observations in the dataset:

order g9, after(Countryofplanting)

sort g9 Country

***Generate graph (same as Figure S5.1):

cluster dendrogram alink, horizontal labels(Countryofplanting) ylabel(, angle(0) labsize(*.45)) xtitle("Dissimilarity", size(11.5pt)) xlabel(, labsize(*.4)) color(black) lwidth(vvthin) graphregion(color(white)) xsize(8.25) ysize(11.75) xline(.936, lwidth(1pt) lcolor(black) lpattern(dash)) title("")

Code for k-means cluster analysis based on the CSIs relative to the world and the CCIs

We use Stata 17 to perform this analysis. Here we are pasting its corresponding code:

**# K-means cluster analysis using 2016 CSIs and CCI

*This code is to perform a k-means cluster analysis of all countries using data for 2016, and to create Figure 5.3.

***Standarize variables

generate CSI2016z = std(CSI2016)

generate CCI2016z = std(CCI2016)

*The new variables are the standarized CSIs and CCIs.

***Perform cluster analysis:

```
cluster kmeans CSI2016z CCI2016z, k(2) name(CS2) s(kr(1234))
cluster kmeans CSI2016z CCI2016z, k(3) name(CS3) s(kr(1234))
cluster kmeans CSI2016z CCI2016z, k(4) name(CS4) s(kr(1234))
cluster kmeans CSI2016z CCI2016z, k(5) name(CS5) s(kr(1234))
cluster kmeans CSI2016z CCI2016z, k(6) name(CS6) s(kr(1234))
cluster kmeans CSI2016z CCI2016z, k(7) name(CS7) s(kr(1234))
cluster kmeans CSI2016z CCI2016z, k(8) name(CS8) s(kr(1234))
cluster kmeans CSI2016z CCI2016z, k(9) name(CS9) s(kr(1234))
cluster kmeans CSI2016z CCI2016z, k(10) name(CS10) s(kr(1234))
cluster kmeans CSI2016z CCI2016z, k(11) name(CS11) s(kr(1234))
cluster kmeans CSI2016z CCI2016z, k(12) name(CS12) s(kr(1234))
```

*1234 is a seed for replicability.

***Use stopping rule to determine appropiate number of clusters:

```
cluster stop CS2
cluster stop CS3
cluster stop CS4
cluster stop CS5
cluster stop CS6
cluster stop CS7
cluster stop CS8
cluster stop CS9
cluster stop CS10
cluster stop CS11
cluster stop CS12
```

*The Calinski-Harabasz stopping rule provides a pseudo F-index. Higher pseudo-F indexes indicate more distinct clustering.

*Therefore, the results of these stopping rule suggest that three cluster is the most distinct cluster solution.

***Order and sort observations in the dataset:

```
order Country CS3
sort CS3 Area
```

***Generate graph (same as Figure 5.3):

```
graph twoway (scatter CSI2016 CCI2016 if CS3==1, color(orange_red) msize(medlarge) msymbol(square)) (scatter CSI2016 CCI2016 if CS3==2, color(green) msize(medlarge)) (scatter CSI2016 CCI2016 if CS3==3, color(blue) msize(medlarge) msymbol(triangle)), aspect(0.425) graphregion(color(white)) legend(off) xtitle("CCI 2016", size(11.5pt)) ytitle("CSI 2016", size(11.5pt))
```

Supplementary table and figure

Table S5.1: Area, CSI relative to the world, and CCI for each country in 2000 and 2016, and cluster classification based on both CSIs relative to the world and CCIs in 2016.

Country	Area 2000 (ha)	Area 2016 (ha)	CSI 2000	CSI 2016	CCI 2000	CCI 2016	Cluster 2016
Algeria	30200	8300	0.42	0.45	18.5	23.3	Green
Argentina	197418	206342	0.28	0.39	7.6	9.1	Orange
Armenia	11206	14705	0.09	0.02	7.8	58.0	Blue
Australia	130602	132435	0.48	0.67	12.0	15.6	Green
Austria	48496	45439	0.10	0.14	16.2	13.8	Orange
Brazil	52840	33205	0.09	0.07	14.7	17.7	Orange
Bulgaria	95997	52974	0.34	0.58	10.5	11.5	Green
Cambodia		10		0.50		26.0	Green
Canada	8498	12600	0.39	0.42	5.9	7.5	Green
Chile	113966	145873	0.46	0.68	14.3	12.7	Green
China		178000		0.65		6.8	Green
Croatia	59448	11746	0.12	0.21	11.3	20.3	Orange
Cyprus	18282	5133	0.02	0.01	38.3	52.9	Blue
Czechia	11331	13600	0.16	0.24	7.7	7.8	Orange
Ethiopia		169		0.12		39.3	Blue
France	864846	814882	0.67	0.76	6.6	5.7	Green
Georgia	37419	48000	0.10	0.08	32.2	32.2	Blue
Germany	104233	94501	0.12	0.19	11.0	10.0	Orange
Greece	50915	50845	0.06	0.17	9.4	8.8	Orange
Hungary	86886	63881	0.22	0.32	2.5	4.3	Orange
India		2700		0.30		22.4	Orange
Israel	4851	5000	0.46	0.62	9.6	11.4	Green
Italy	636662	604551	0.37	0.46	3.2	3.3	Green
Japan		3869		0.14		9.0	Orange
Kazakhstan		6938		0.09		28.2	Blue
Korea, Rep.	5400	5400	0.01	0.00	31.7	31.7	Blue
Lebanon		4000		0.71		16.2	Green
Luxembourg	1348	1300	0.09	0.14	19.0	14.8	Orange
Mexico		5465		0.51		7.2	Green

Table S5.1 (cont.): Area, CSI relative to the world, and CCI for each country in 2000 and 2016, and cluster classification based on both CSIs relative to the world and CCIs in 2016.

Country	Area 2000 (ha)	Area 2016 (ha)	CSI 2000	CSI 2016	CCI 2000	CCI 2016	Cluster 2016
Moldova	89844	82600	0.37	0.52	10.0	6.7	Green
Morocco	49600	17590	0.09	0.28	13.2	10.2	Orange
Myanmar		70		0.40		27.1	Orange
New Zealand	9942	35463	0.36	0.31	16.5	37.3	Blue
North Macedonia		24777		0.15		22.6	Orange
Norway		13		0.00		45.0	Blue
Peru		3831		0.04		20.4	Orange
Portugal	205003	182649	0.09	0.28	2.0	4.0	Orange
Romania	222173	182762	0.33	0.42	1.7	2.0	Green
Russia	56332	50794	0.17	0.55	6.6	8.0	Green
Serbia	68999	22014	0.14	0.61	28.3	4.0	Green
Slovakia	15580	7748	0.18	0.16	12.6	9.8	Orange
Slovenia	23472	15989	0.29	0.38	3.8	5.1	Orange
South Africa	93656	95775	0.34	0.53	10.6	9.7	Green
Spain	1181806	883558	0.70	0.58	13.5	11.8	Green
Switzerland	15042	14793	0.14	0.25	24.4	16.6	Orange
Taiwan	2833	149	0.01	0.00	39.6	51.3	Blue
Thailand		208		0.27		21.8	Orange
Tunisia	16836	3400	0.31	0.28	22.6	10.2	Orange
Turkey		13704		0.24		8.7	Orange
Ukraine		25166		0.46		14.7	Green
United Kingdom	873	1839	0.07	0.32	7.0	19.3	Orange
United States	175693	239632	0.48	0.72	9.2	8.9	Green
Uruguay	8880	6743	0.17	0.33	20.3	13.2	Orange
WORLD average	90706	84587		0.33		17.28	
WORLD total	4807408	4483130				2.23	
Correlation with area			0.64	0.44	-0.25	-0.30	

Notes: CSI is the cultivar similarity index relative to the world. CCI is the cultivar concentration index. 'WORLD average' is a simple average (i.e., not area weighted). Both 'WORLD average' and 'WORLD total' refer to the 53 countries in the dataset, which include the top 20 countries by area. 'Correlation with area' is the correlation coefficient between the indexes (either CSIs or CCIs) and the areas in the respective year, based on the information for all the countries for which there is area data for that year. The green cluster includes countries with high cultivar similarity index (CSI) relative to the world and low cultivar concentration index (CCI). The orange cluster encompasses countries with low CSI relative to the world and low CCI. The blue cluster includes countries with low CSI relative to the world and high CCI.

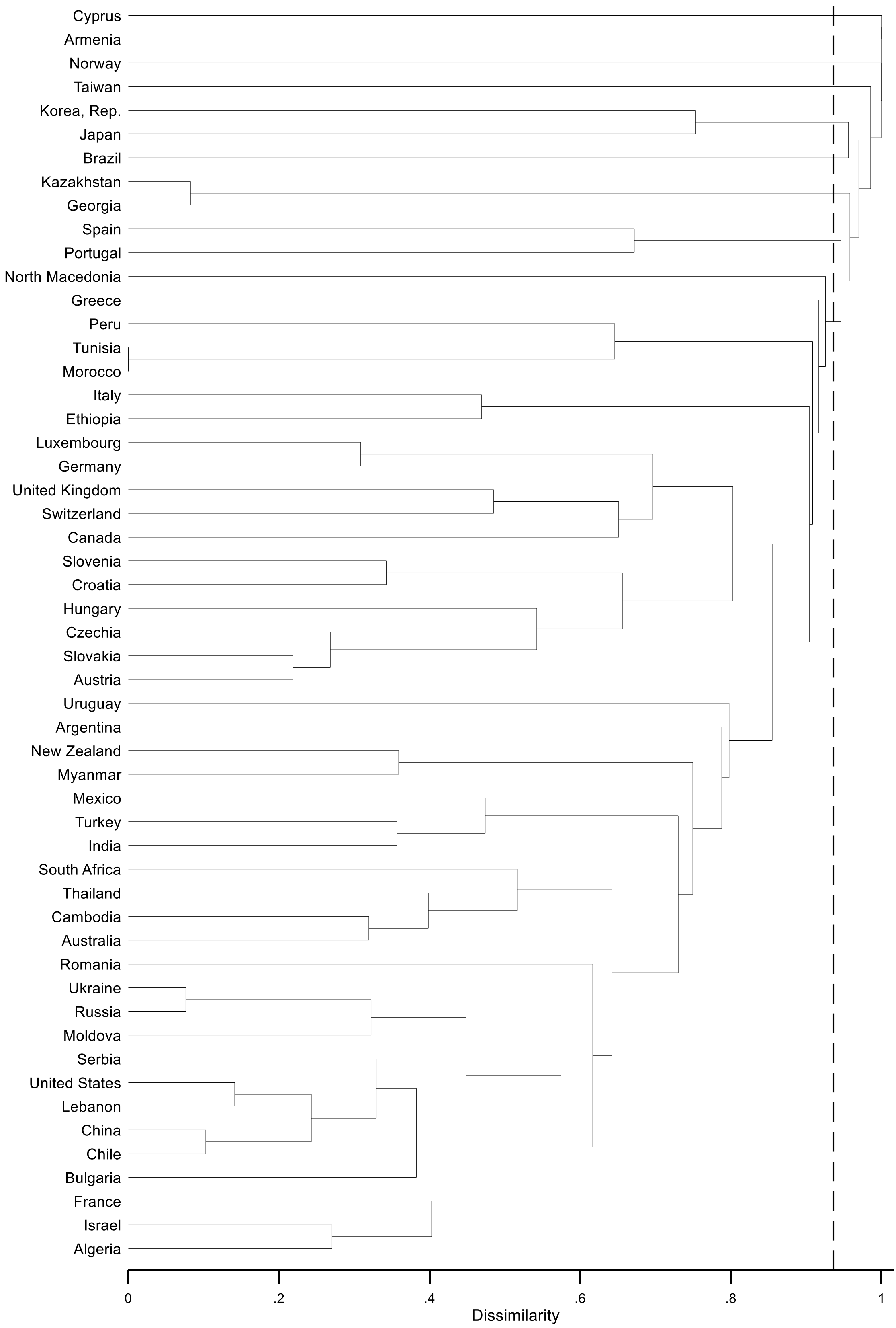

Figure S5.1: Dendrogram based on winegrape CSIs, 2016.

Notes: CSI is the cultivar similarity index. Dissimilarity = 1 - CSI. The clustering method is average linkage. The dashed vertical line shows a nine-cluster classification based on CSIs between countries.

Supplementary material references

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Chapter 6

Statement of authorship

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Principal author

Name of principal author (candidate)	German Puga		
Contribution to the paper	Led the study conception and design (including the econometric models), reviewed the literature, prepared part of the datasets for analysis, and interpreted the results. Wrote drafts/versions of the paper. Presented the paper at a conference to get feedback. Led the review/publication process.		
Overall percentage	70%		
Certification	This paper reports on original research I conducted during the period of my Higher Degree by Research candidature and is not subject to any obligations or contractual agreements with a third party that would constrain its inclusion in this thesis. I am the primary author of this paper.		
Signature		Date	11/07/2023

Co-author contributions

By signing the Statement of authorship, each author certifies that:

I. the candidate's stated contribution to the publication is accurate (as detailed above);
II. permission is granted for the candidate in include the publication in the thesis; and
III. the sum of all co-author contributions is equal to 100% less the candidate's stated contribution.

Name of co-author	Alfinura Sharafeyeva		
Contribution to the paper	Prepare data for analysis and performed econometric estimations. Contributed to the study conception and design, and to the interpretation and discussion of the results. Edited drafts/versions of the paper and helped responding reviewers' questions.		
Signature	**Signed form available at the end of this thesis.**	Date	

Name of co-author	Kym Anderson		
Contribution to the paper	Contributed to the study conception and design, and to the interpretation and discussion of the results. Edited drafts/versions of the paper and helped responding reviewers' questions.		
Signature	**Signed form available at the end of this thesis.**	Date	

6. Explaining bilateral patterns of global wine trade, 1962-2019

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Abstract

This study uses gravity models to explain bilateral patterns of global wine trade since 1962. This is, to our knowledge, the first study on global wine trade covering the second wave of globalisation as a whole. The results suggest that the impact of distance, common language, and common coloniser post-1945 on wine trade was lower in the 1991-2019 period than in the 1962-1990 period. We also use gravity models to explain the impact on bilateral wine trade patterns of similarities across countries in the mix of winegrape varieties in their vineyards. The results suggest that countries trade more wine with each other the closer their mix of winegrape varieties, although our models do not allow us to identify causality.

Keywords: gravity model, second wave of globalisation, varietal similarity index, wine trade

6.1. Introduction

The great boom in wine trade over the past six decades can be decomposed into two 3-decade periods (Figure 6.1). The first period started in the 1960s, when traditional European wine-producing countries dramatically increased their wine exports, something that was influenced by a decrease in their domestic demand. The second period began in the 1990s, when several wine-producing countries in the Southern Hemisphere increased their exports at an accelerated rate in an explicit drive for export-led growth (Figure 6.1), raising the New World's share of global wine exports from less than 3% prior to 1990 to one-quarter in the 2010s.

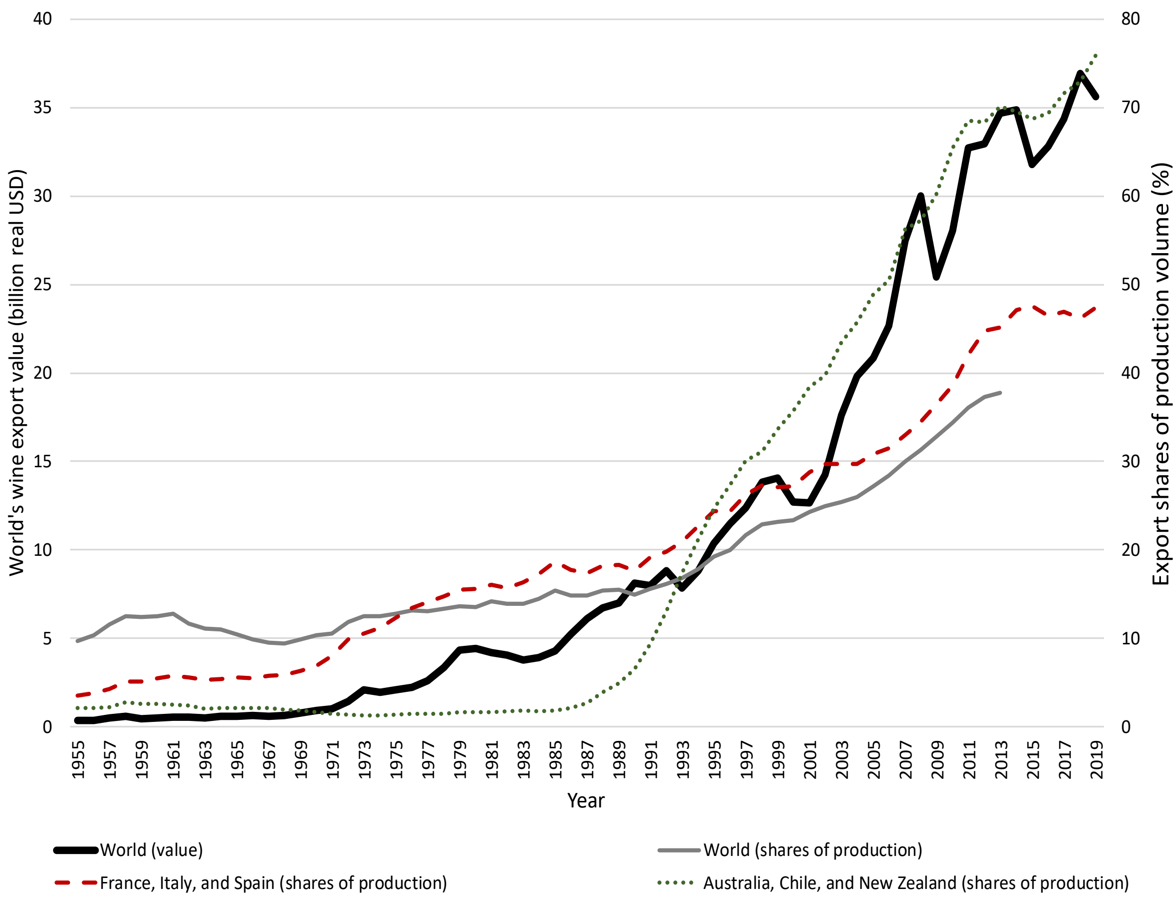

Figure 6.1: World's wine export values and export shares of production volume, 1995 to 2019.

Notes: Authors' computation based on data from Anderson and Pinilla (2020, 2021). Exports values are deflated by US CPI where 2015 = 1.00. The export shares of production volume are averages of the previous five years. For both three-country groups, the export shares of production volume are simple averages between the three countries of each group.

The aim of this study is to explain, econometrically, the impact of key variables affecting wine trade since the 1960s. We divide the second wave of globalisation into two periods (1962-1990 and 1991-2019), which allows us to test how the influence of these key variables affecting wine trade has changed due to the impact of globalisation. Our study is, to our knowledge, the first of its kind covering the second wave of globalization as a whole, complementing previous research that has focused on the first wave of globalisation (Ayuda et al., 2020). Previous studies focusing on world wine trade use datasets that begin in the 1990s (Santeramo et al., 2019; Dal Bianco et al., 2016) or early 2000s (Balogh and Jámbor, 2018). We limit the time series to 2019 to avoid the following two years in which wine trade was disrupted by COVID-19, Brexit, and the imposition by China of punitive tariffs on its imports of Australian wine (Wittwer and Anderson, 2020, 2021).

Further, we analyse the influence on wine trade of similarities across countries in the mix of their vineyards' winegrape varieties, something that has not previously been analysed. We do so to test two contrary hypotheses from empirical trade research. One draws on the home-country bias phenomenon: because consumers enjoy most the varieties they are familiar with from domestic production (Friberg et al., 2011), they seek them also from among those that can be imported. The opposite hypothesis draws on the consumers' love of diversity phenomenon: their choice of imports complements what is available locally (Krugman, 1980; Broda and Weinstein, 2004) and so its varietal mix is dissimilar to the mix of domestically produced winegrapes.

6.2. Gravity models

The gravity model constitutes the theoretical and empirical framework of our analysis (see Head and Mayer (2014) and Yotov et al. (2017) for reviews). We estimate two sets of models. The first set allows us to compare the influence of key variables on wine trade between the first and second half of the second wave of globalisation. The second set of models allows us to test the influence of similarities in the mix of winegrape varieties on wine trade.

The first set of models is given by:

$$X_{ij,t} = \exp\left[\rho_{i,t} + \upsilon_{j,t} + \beta_1 lnD_{ij} + \beta_2 RTA_{ij,t} + \beta_3 CL_{ij} + \beta_4 CC_{ij} + \beta_5 CB_{ij}\right] \times \epsilon_{ij,t}. \qquad (1)$$

The dependent variable, $X_{ij,t}$, is the trade flow from country i to country j, in year t (FOB USD). $\rho_{i,t}$ ($\upsilon_{j,t}$) are exporter-time (importer-time) fixed effects that account for time-varying country-specific characteristics such as macroeconomic variables, exchange rates, and wine production. Importantly, these fixed effects also account for multilateral resistances (Olivero and Yotov, 2012). lnD_{ij} is the natural logarithm of the physical distance between country i and country j. The dichotomous variables $RTA_{ij,t}$, CL_{ij}, CC_{ij}, and CB_{ij}, take the value of one if countries i and j have at least one regional trade agreement (RTA), common official or primary language, common coloniser post-1945, and common borders, respectively. The β_s are parameters to be estimated, and $\epsilon_{ij,t}$ is an error term. We estimate this first set of models separately for the 1962-1990 period and the 1991-2019 period.

The second set of models is given by:

$$X_{ij,t} = \exp\left[\rho_{i,t} + \upsilon_{j,t} + \alpha_1 VSI_{ij,t} + \beta_1 lnD_{ij} + \beta_2 RTA_{ij,t} + \beta_3 CL_{ij} + \beta_4 CC_{ij} + \beta_5 CB_{ij}\right] \times \epsilon_{ij,t}. \qquad (2)$$

The difference between equations (1) and (2) is that equation (2) incorporates a new variable, the varietal similarity index between countries i and j in year t ($VSI_{ij,t}$). The VSI between two countries takes values between 0 and 1, where 0 means that the mix of winegrape varieties (in terms of bearing area of these varieties) is totally different and 1 means that the mix of winegrape varieties is exactly the same for both countries. Anderson (2010) introduces this index and its formula. We estimate this second set of models for all countries, but also for those that have a wine self-sufficiency index higher than 33%, 50%, and 100% (to reduce the sample to countries that are themselves significant wine producers). We use data for the three years in which we have VSI data: 2000, 2010, and 2016.

We estimate the two sets of models using the Poisson pseudo maximum likelihood (PPML) estimator, which works well in the presence of heteroskedasticity and a large proportion of zero trade flows (Santos Silva and Tenreyro, 2006, 2011). Trefler (2004) argues that using data for all years does not allow for adjustments to changes in trade policy. Therefore, Olivero and Yotov (2012) propose using 3- to 5-year interval data. As a robustness check, we estimate the models given by equation (1) using 3-year interval data.

6.3. Data

We use export data from Harvard's Atlas of Economic Complexity available at www.atlas.cid.harvard.edu/. We use VSI data from Anderson and Nelgen (2020) and wine self-sufficiency data from Anderson and Pinilla (2022). The source of distance in km between the most populous cities of each country, common official or primary language, common colonizer post-1945, and common borders is the CEPII gravity database, available at www.cepii.fr/cepii/en/bdd_modele/bdd.asp.

6.4. Results and discussion

The first set of models reveals differences between the 1962-1990 period and the 1991-2019 period (see 'Continuous data' columns in Table 6.1). These results are consistent whether we estimate equation (1) using yearly data or using 3-year interval data, which we use as a robustness check (see 'Interval data' columns in Table 6.1). The impacts of distance, common language, and common coloniser post-1945 are smaller for the latter period. This is consistent with trade theory and the findings of previous studies (e.g., Borchert and Yotov, 2017), and it relates to the decline in trade costs over time (Anderson and van Wincoop, 2004). RTAs, on the other hand, have a greater influence in the latter period, consistent with the dramatic growth in the number of such agreements since the early 1990s (currently more than 350, see https://www.wto.org/english/tratop_e/region_e/region_e.htm).

Table 6.1: Estimation results of the gravity models given by equation (1) for 1962-1990 and 1991-2019, with continuous data (preferred) and 3-year interval data.

Variable	Continuous data		Interval data	
	1962-1990	**1991-2019**	**1962-1990**	**1991-2019**
(ln) Distance	-0.465^{***}	-0.351^{***}	-0.477^{***}	-0.350^{***}
	(0.116)	(0.089)	(0.114)	(0.089)
RTA	0.061	0.400^{**}	0.029	0.419^{***}
	(0.243)	(0.195)	(0.225)	(0.198)
Common language	1.228^{***}	0.935^{***}	1.269^{***}	0.926^{***}
	(0.163)	(0.166)	(0.169)	(0.167)
Common colonizer post-1945	2.214^{***}	1.310^{**}	2.009^{***}	1.450^{***}
	(0.290)	(0.532)	(0.295)	(0.535)
Common borders	-0.154	0.169	-0.228	0.141
	(0.212)	(0.245)	(0.209)	(0.245)
Constant	20.772^{***}	20.807^{***}	21.006^{***}	20.763^{***}
	(0.921)	(0.760)	(0.904)	(0.760)
Exporter-year fixed effects	Yes	Yes	-0.477^{***}	-0.350^{***}
Importer-year fixed effects	Yes	Yes	(0.114)	(0.089)
Observations	63,435	161,273	24,528	54,876
R^2	0.941	0.923	0.943	0.924

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are in parentheses. The dependent variable is the natural logarithm of wine trade between two countries (FOB USD). RTA denotes the presence of a regional trade agreement. The preferred model uses continuous data, while the model with 3-year interval data serves as a robustness check.

The second set of models suggests that the VSI has a statistically significant positive effect on wine trade flows (see Table 6.2). This result is consistent whether the model is estimated for all countries or for those who have a wine self-sufficiency index higher than 33%, 50%, or 100%. This suggests those countries with a similar mix of winegrape varieties tend to trade more wine with each other, which is consistent with the home-country bias hypothesis and not with the hypothesis that consumers' choice of imports complements the varietal mix available from local producers. However, our models do not allow us to imply a causal relationship as there may be potential endogeneity issues due to reverse causality. For example, the specifics of the international demand for wine may influence decisions in exporting countries as to which varieties to plant.

Table 6.2: Estimation results of the gravity models given by equation (2) for all countries, as well as for countries with a wine self-sufficiency index higher than 33%, 50%, and 100%.

Variable	Countries included in the model			
	All	**SSI > 33%**	**SSI > 50%**	**SSI > 100%**
VSI	0.187***	0.205***	0.245***	0.237***
	(0.068)	(0.072)	(0.083)	(0.085)
(ln) Distance	-0.331***	-0.316**	-0.317**	-0.284**
	(0.122)	(0.127)	(0.129)	(0.126)
RTA	0.358	0.362	0.375	0.420
	(0.291)	(0.295)	(0.299)	(0.315)
Common language	0.874***	0.886***	0.864***	0.864***
	(0.202)	(0.209)	(0.214)	(0.249)
Common colonizer post-1945	2.994***	2.997***	2.986***	3.251***
	(0.605)	(0.620)	(0.631)	(0.698)
Common border	-0.089	-0.073	-0.103	-0.152
	(0.248)	(0.255)	(0.256)	(0.253)
Constant	21.703***	21.657***	21.809***	21.621***
	(1.073)	(1.114)	(1.136)	(1.090)
Exporter-year fixed effects	Yes	Yes	Yes	Yes
Importer-year fixed effects	Yes	Yes	Yes	Yes
Observations	3,988	3,335	2,996	2,024
R^2	0.938	0.938	0.939	0.935

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are in parentheses. The dependent variable is the natural logarithm of wine trade between two countries (FOB USD). VSI denotes the varietal similarity index and RTA denotes the presence of a regional trade agreement. SSI stands for the wine self-sufficiency index. For example, a SSI > 50% means that the only countries included in the analysis are those that produce at least half of the wine quantity they consume. Estimated with data for 2000, 2010, and 2016.

Unfortunately, comprehensive time series data on national expenditure on the various varieties of domestically produced wine are not available for most countries. If they were, more-robust models would be able to be estimated because those data would help solve the missing globalisation puzzle (Borchert and Yotov, 2017) and to better identify the impact of trade variables (Heid et al., 2021). Further, such models could use country-pair fixed effects to account for any resistance (preference) towards imported (domestically produced) wine.

6.5. Conclusion

We have used a gravity approach to estimate the impact of important variables influencing wine trade for two time periods: 1962-1990 and 1991-2019. The results suggest that the impact of distance, common language, and common coloniser post-1945 on wine trade has decreased in the latter period. These results are consistent with previous studies focused on other industries and with the expected impact of globalisation. We have also used a gravity approach to estimate the impact of similarities in the mix of winegrape varieties on wine trade flows. The results suggest that countries that have a more similar mix of winegrape varieties tend to trade more wine with each other. However, potential endogeneity issues do not allow us to imply a causal relationship. We argue that a database with intra-national trade flows would allow wine economists to estimate more-robust gravity models that could yield important insights.

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Chapter 7

Statement of authorship

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Principal author

Name of principal author (candidate)	German Puga		
Contribution to the paper	Led the study conception and design, reviewed the literature, cleaned the data and prepared the dataset for analysis, performed econometric estimations, and interpreted the results. Wrote drafts/versions of the paper. Led the review/publication process.		
Overall percentage	80%		
Certification	This paper reports on original research I conducted during the period of my Higher Degree by Research candidature and is not subject to any obligations or contractual agreements with a third party that would constrain its inclusion in this thesis. I am the primary author of this paper.		
Signature		Date	11/07/2023

Co-author contributions

By signing the Statement of authorship, each author certifies that:

I. the candidate's stated contribution to the publication is accurate (as detailed above);
II. permission is granted for the candidate in include the publication in the thesis; and
III. the sum of all co-author contributions is equal to 100% less the candidate's stated contribution.

Name of co-author	Wendy Umberger		
Contribution to the paper	Contributed to the study conception and design, and to the interpretation and discussion of the results. Edited drafts/versions of the paper and helped responding reviewers' questions.		
Signature	**Signed form available at the end of this thesis.**	Date	

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Contribution to the paper	Contributed to the study conception and design, and to the interpretation and discussion of the results. Edited drafts/versions of the paper.		
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7. The impact of the European grapevine moth on grape production: Implications for eradication programs

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Abstract

The European grapevine moth is one of the most pertinent viticulture pests. In recent years, the moth extended to New World countries, some of which started eradication programs. We used a dataset for Mendoza and a county-fixed effects regression model to estimate the impact of the moth on grape production across the province's counties. Our results suggest that the moth led to a decrease of up to 8% of Mendoza's grape production; however, this may have been worse without strong eradication efforts. We conclude that moth eradication programs are economically justified in Argentina, and perhaps in other countries.

Keywords: Lepidoptera, *Lobesia botrana*, pest management, viticulture, weather

7.1. Introduction

The European grapevine moth (EGVM), also known by its scientific name of *Lobesia botrana* (Lepidoptera: Tortricidae) (Denis and Schiffermüller), is arguably the most important insect affecting vineyards globally. The EGVM has up to four generations throughout the whole grapevine growing season (Heit et al., 2019). In its larval stage, the pest eats vines' flowers or bunches, decreasing grape production and quality. Although endemic throughout Europe and common in some countries outside of Europe, the EGVM did not extend to the United States (US), Chile, and Argentina until 2008-2010 (Mutis et al., 2014). The US government successfully implemented an EGVM eradication program, and programs are ongoing in Chile and Argentina.

The eradication program in Argentina was established through a national law and is funded by both the government and the private sector. While the eradication program targets all Argentinian provinces, this study focuses specifically on Mendoza, which is the most important wine-producing province in Argentina, accounting for 70% of the country's vineyard surface area (i.e., 153 thousand hectares). The scientific literature related to the EGVM is extensive; however, we failed to identify any study looking at the impact of the EGVM at the regional level. The aim of this research is to estimate the impact of the EGVM on Mendoza's grape production, controlling for other relevant factors that may affect production, and to develop implications for eradication programs, both in Argentina and in other countries.

7.2. Data

We used data provided by the Argentinian Wine Observatory, Mendoza's Institute for Agricultural Sanitation and Quality, and the Government of Mendoza. With these data, we constructed a dataset covering the 2001-02 season to the 2018-19 season, for all 15 of Mendoza's grape-producing counties (totalling 270 observations). The dataset includes information on grape yield, the percentage of area 'completely damaged' by frost and hail (as defined by Mendoza's Climate Department), and the population density of EGVM. The dataset also includes information on the growing season average temperature (GST) and total growing season precipitation (GSP), based on averages from two to five weather stations in each of the three contiguous regions of Mendoza (i.e., Lujan-Maipu and the Northeast, Uco Valley, and the Southern region). Using weather stations' data for wine regions is the most common approach in studies quantifying the impact of weather on grape or wine production, as meso-weather data are usually unavailable (Niklas, 2018). Table 7.1 shows the descriptive statistics.

Table 7.1: Descriptive statistics.

Variable	Obs.	Mean	SD	Min.	Max.
Yield (t/ha)	270	10.19	3.60	1.24	21.85
Frost (total damage %)	270	2.86	6.43	0.00	46.29
Hail (total damage %)	270	5.81	7.85	0.00	42.56
GST (°C)	270	19.28	1.22	16.66	21.15
GSP (mm)	270	170.22	84.42	63.40	521.50
EGVM (captures/ha)	270	2.18	6.23	0.00	49.90

Notes: GST = growing season average temperature, GSP = total growing season precipitation, EGVM = European grapevine moth density.

Table 7.2 shows the evolution of yield, percentage of area 'completely damaged' by frost and hail, GST and GSP, and the density of EGVM. The average yield in Mendoza between 2001-02 and 2018-19 was 11.3 tons per hectare, with a standard deviation of 2.3 tons per hectare. The area 'completely damaged' by frost or hail represents 2.5% and 6.4%, respectively, of the total surface. The average GST (19.4°C) and GSP (166 mm) provide evidence of the warm and dry climate that predominates in the province. The average number of moths captured per hectare by Mendoza's trapping system provides a measure of the pest's population density. The number of captures per hectare increased considerably between 2010-11 and 2015-16. Strong eradication efforts started after the 2015-16 growing season, leading to a substantial drop in the EGVM density.

Table 7.2: Evolution of yield, area 'completely damaged' by frost and hail, area-weighted average GST and GSP, and EGVM density in Mendoza, 2001-02 to 2018-19.

Season/s	Yield (t/ha)	Frost (total damage %)	Hail (total damage %)	GST (°C)	GSP (mm)	EGVM (captures/ha)
2001-02	9.70	0.17	7.14	19.3	165	0.00
2002-03	11.23	4.41	7.13	19.5	101	0.00
2003-04	12.15	0.35	4.43	20.6	102	0.00
2004-05	11.92	2.38	9.44	18.9	209	0.00
2005-06	12.41	0.03	7.37	19.5	77	0.00
2006-07	12.95	0.10	7.03	19.6	145	0.00
2007-08	11.45	1.54	7.96	19.3	176	0.00
2008-09	8.98	0.00	10.30	20.4	143	0.00
2009-10	11.29	1.81	6.22	19.1	88	0.00
2010-11	12.30	6.43	3.31	19.3	138	0.31
2011-12	9.35	0.03	11.42	20.2	130	0.63
2012-13	12.53	0.00	4.53	19.9	144	2.56
2013-14	16.73	4.96	1.67	19.4	293	3.80
2014-15	13.23	5.07	3.28	20.3	200	9.17
2015-16	6.43	1.77	12.24	18.3	369	9.69
2016-17	8.10	9.85	4.81	18.6	168	6.50
2017-18	11.21	4.33	1.40	19.4	176	0.92
2018-19	11.03	1.25	5.54	18.1	158	0.83
From 2001-02	11.28	2.47	6.40	19.4	166	1.91
From 2010-11	11.21	3.74	5.36	19.3	197	3.82

Notes: GST = growing season average temperature, GSP = total growing season precipitation, EGVM = European grapevine moth density.

7.3. Methods

The aim of our model is to estimate the impact of the EGVM on grape production. Our baseline model is:

$$\log(Yield_{is}) = \alpha_i + \gamma EGVM_{is} + \delta Frost_{is} + \zeta Hail_{is} + \sigma GST_{rs} + \theta GST_{rs}^2 + \lambda GSP_{rs} + \varphi GSP_{rs}^2 + e_{is}\,. \quad (1)$$

$Yield_{is}$ is the average yield per hectare for county i in season s; α_i is an intercept specific for county i; $EGVM_{is}$ is the average number of moths captured (through Mendoza's trapping system) per hectare for county i in season s; $Frost_{is}$ and $Hail_{is}$ are the percentages of the vineyard area in county i that were 'completely damaged' due to frosts and hail, respectively, in season s; GST_{rs}, GST_{rs}^2, GSP_{rs}, and GSP_{rs}^2 are the GST and GSP and their squared values, in season s, for the contiguous region r that includes county i; and e_{is} is an error term.

Mendoza's Climate Department defines the percentage of area 'completely damaged' by frost and hail for every season. This is not a direct measure of the impact of frost and hail, as vineyards not considered as 'completely damaged' may still have been affected by frost and/or hail damage.

In addition to being influenced by vineyard and pest management strategies, the EGVM population density depends on weather-related variables, such as temperature and precipitation (Heit et al., 2019). Since in this research the EGVM variable is the observed density of EGVM itself, we do not account for the potential effects that weather and other variables may have on the prevalence of the pest. In fact, between 2010-11 and 2018-19, the correlation between GST (GSP) and the EGVM density was just -0.01 (0.01).[2]

However, we included the control variables GST and GSP as these are important weather variables affecting grape production (van Leeuwen and Darriet, 2016; Schultz, 2016; Ollat et al., 2016). Including the square of GST, which is a common approach in studies that model the impact of temperature on grape or wine quality (Ashenfelter, 2017), is also justified when modelling grape yields. While higher temperatures are often correlated with higher yields, extreme temperatures can decrease yields (Ashenfelter and Storchmann, 2016). Perhaps, more importantly, higher temperatures increase evapotranspiration, often creating water deficits (Gambetta, 2016). Including the square of GSP is also justified in the context of Mendoza. While higher precipitation has the potential to mitigate the water constraints that Mendoza's growers often face when irrigating their vineyards, precipitation enhances the most relevant grape diseases (i.e., powdery and downy mildew, and rot). If precipitation is too high, these diseases become harder for grape growers to control, often leading to lower yields.

We estimated the within transformation of the model shown in equation (1) using a county-fixed effects model with heteroskedasticity robust standard errors. Unlike random effects, the fixed effects estimator allows correlation between counties, the explanatory variable (EGVM), and the control (weather) variables. Since some of these correlations may occur in practice, and considering that we are not interested in the county-specific effects, a fixed effects estimator is preferred over random effects. Still, the fixed effects estimator accounts for unobserved heterogeneities that are assumed to be constant over time. This

[2] These correlations are based on weather and EGVM density data specific for each county, and considering only those seasons and counties in which there was presence of the pest.

unobserved heterogeneity includes the varietal mix of each county (some varieties are more productive than others are), the predominant trellis system, the age distribution of the vineyards, the efficiency of the irrigation systems, and the knowledge and experience of grape growers, among other county-specific characteristics.

We also estimated model (1) using a first difference estimator with Newey-West standard errors. We used the first difference estimation as a robustness check, as the fixed effects estimator tends to be more efficient than the first differences estimator, especially when the idiosyncratic errors are serially uncorrelated.

7.4. Results

The model provides a good fit to the data. The variable of interest, EGVM, as well as the control variables are highly significant and with the expected signs (see ‘Fixed effects’ column in Table 7.3). The results are similar to the estimated by first differences with standard errors robust to heteroskedasticity and third order autocorrelation, which we used as a robustness check (see ‘First differences’ column in Table 7.3).

Table 7.3: Impact of EGVM density and weather on the logarithm of grape yields in Mendoza.

Variable	Fixed effects	First differences
EGVM	-0.0075**	-0.0083*
	(0.0022)	(0.0039)
Hail	-0.0230***	-0.0174***
	(0.0016)	(0.0023)
Frost	-0.0148***	-0.0092*
	(0.0020)	(0.0036)
GST	0.5855*	0.7337*
	(0.2397)	(0.3191)
GST^2	-0.0132•	-0.0184*
	(0.0063)	(0.0083)
GSP	0.0017***	0.0013*
	(0.0003)	(0.0005)
GSP^2	-0.0000***	-0.0000**
	(0.0000)	(0.0000)
Intercept	-1.8054	0.0068
	(2.2785)	(0.0165)
Goodness of fit:	$R^2_{\text{within}} = 0.4495$	$R^2 = 0.3741$

Notes: ***$p < 0.001$; **$p < 0.01$; *$p < 0.05$; •$p < 0.1$. Robust standard errors in (.). GST = growing season average temperature, GSP = total growing season precipitation, EGVM = European grapevine moth density.

We used our regression coefficients (shown in Table 7.3), the average yield and the average density of EGVM in each county and year to estimate the average impact of the EGVM on the average yield (and hence total grape production) in each county, and in Mendoza as a whole (see Table 7.4). The onset of the pest varies by county. The EGVM was first detected in Maipu, and quickly expanded to Lujan de Cuyo and the counties in the Northeast. Lujan-Maipu and the Northeast are part of the same contiguous region, and the pest had an important incidence in all counties except for Santa Rosa and La Paz, which are further away. In Uco Valley the estimated impact of the EGVM was higher in the counties that are closest to Lujan-Maipu and the Northeast (i.e., Tupungato, followed by Tunuyan). The Southern region is distant from all other regions and the pest did not spread widely in the counties of that region. Overall, in Mendoza, there have been annual losses of up to 8% of the total grape production volume.

Table 7.4: Estimated grape production losses (%) due to the EGVM by county and harvest year.

Region and county	2011	2012	2013	2014	2015	2016	2017	2018	2019
Lujan-Maipu									
Lujan de Cuyo	0.19	0.57	3.89	6.21	11.84	7.96	3.12	0.23	0.22
Maipu	2.57	4.43	13.97	12.23	17.29	10.19	5.89	1.44	2.45
Northeast									
Guaymallen	0.00	0.15	1.12	3.40	27.47	33.15	37.22	2.07	13.19
Junin	0.00	0.28	2.91	8.72	15.60	8.35	1.19	0.13	0.25
La Paz	0.02	0.00	0.00	0.00	0.01	0.06	0.13	0.00	0.03
Las Heras	0.00	0.01	0.02	0.44	7.46	14.78	16.52	0.00	1.00
Lavalle	0.00	0.00	0.01	0.13	2.20	9.28	9.86	0.86	0.96
Rivadavia	0.00	0.18	0.35	1.93	11.24	10.43	4.88	0.96	0.10
San Martin	0.00	0.02	0.14	0.78	5.17	8.43	5.12	0.94	0.79
Santa Rosa	0.00	0.00	0.01	0.02	0.36	0.79	0.83	0.14	0.38
Uco Valley									
San Carlos	0.00	0.00	0.01	0.03	0.13	1.66	5.27	0.13	0.16
Tunuyan	0.06	0.30	0.27	0.11	0.66	4.39	6.65	0.73	0.38
Tupungato	0.07	0.01	2.14	3.70	9.29	13.80	9.01	1.89	0.49
South									
General Alvear	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00
San Rafael	0.00	0.00	0.00	0.00	0.00	0.01	0.06	0.00	0.00
MENDOZA	0.24	0.48	2.05	3.06	7.39	7.97	5.26	0.75	0.70

Higher GSTs have positive but diminishing effects on yields, and these effects are only expected to become negative in seasons with a GST higher than 22.2°C, which is higher than any GST value in our sample. Higher GSP also has positive but diminishing effects on yields, and these effects are expected to become negative in wetter years (i.e., GSP > 266 mm). These negative effects of GSP may be explained by growers facing issues in managing diseases in growing seasons with high precipitation.

Very relevant has been the effect of the other weather variables, Frost and Hail. Between the 2002 and 2019 harvests, the estimated average grape loss in production due to frosts (hail) has been 3.5% (18.4%). As expected, these values are higher than the area 'completely damaged' by frosts and hail (see Table 7.2), which we used as control variables in the model, as there are also areas that are partially damaged by frost and hail. Further, hail often enhances rot, and these diseases can also lead to lower yields.

From 2011 to 2019, in Mendoza alone, an estimated 490 thousand tons of grapes were lost due to the EGVM. The quantity of grape production lost was equivalent to approximately USD 182.2 million (nominal value). Within this period, the highest impact of the EGVM was felt in the 2015 harvest, when an estimated 169 thousand tons or USD 45.1 million (nominal value) were lost due to the incidence of the EGVM. While 2015-16 was the season with the greatest incidence of the EGVM, a strong eradication program started after that season. Without the program, the incidence of the pest would have been greater, as the area affected and the density of the pest was still increasing when the program started.

7.5. Discussion and conclusions

We estimated the value of grape production in Mendoza that was lost due to the EGVM based on the average farm gate prices of grapes. It is important to consider that grape prices in Mendoza tend to be higher when the total harvest in the province is lower (Puga et al., 2019). As such, the average grape prices may have been higher due to the moth decreasing production. On the other hand, the EGVM results in quality losses as it provides a way of entry for *Botrytis cinerea* and other fungi that cause rot (Kiaeian Moosavi et al., 2020). These quality losses are likely to negatively impact grape prices.

Further, there are other economic impacts not accounted for in the calculation. First, most of the EGVM control relies on the use of pesticides, which can sometimes have negative health-related externalities. Second, the use of pesticides, which was uncommon before the arrival of the EGVM, has led to perverse unintended outcomes including an increase in the incidence of pests such as mites and *Naupactus xanthographus*, an insect that eats vines' roots. Third, there are logistical issues caused by policies and regulations which were put in place to prevent the pest from spreading further. For example, grape growers in Lujan-Maipu and the Northeast cannot sell their grapes to wineries in Uco Valley or the Southern region. Fourth, table grapes must go through a chemical process that diminishes their shelf life, making Argentinian table grapes less valuable for export markets. Fifth, there are important costs of controlling the EGVM for both grape growers and the government. As such, the economic impact of the pest may well be greater than the estimated value of production lost.

Nevertheless, controlling for other variables, the results of this research suggest that a successful eradication program is likely to be cost-effective. The estimated value lost the year before the strongest efforts started (i.e., 2016) was enough to cover 1.7 times the whole vineyard surface of Mendoza with mating disruption disposals. Mating disruption is arguably the most effective and socially accepted control method, and it is the most environmentally friendly (Lance et al., 2016).

In Mendoza, the program has already been successful in lowering the moth's population density and even eradicating the pest from many sub-counties. This success suggests eradication is achievable. The situation in Argentina could end up being similar to what happened in California, where a panel of experts doubted the feasibility of eradicating the EGVM at the beginning (Gutierrez et al., 2012), but then the pest was eradicated. The eradication program in California was very similar to the ongoing program in Argentina, with the use of quarantine areas, and controlling the pest with mating disruption and insecticides (Schartel et al., 2019). Perhaps, the EGVM is easier to eradicate than what the scientific community originally believed. Further research could analyse the impact of the EGVM at the regional level in other countries, in order to derive implications on the feasibility of eradicating the EGVM from other wine regions.

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Chapter 8

8. Concluding remarks

Chapter 1 ('Introduction') summarises the structure and content of this thesis. In addition, each chapter includes summary and conclusion sections, and discusses the limitations of the methods and significance of the results. This chapter comments on the main implications of this thesis and on research efforts that have not been included as chapters or appendixes. In doing so, it also provides additional recommendations and ideas for future research.

Chapters **2** and **3** use climate econometrics to quantify part of the potential impact of climate change on Australia's viticulture. More specifically, they analyse the impact that climate change projections could have in the future. This is different to the impact that climate change has had to date, as well as to the degree to which the industry has adapted to climate change. It would be possible to estimate econometric models (e.g., using a long differences approach) that account for adaptation, but these models would require longer time series than the ones currently available. Even so, it would be difficult to distinguish how much of that adaptation could be attributed to a response to climate change.

In **Chapter 2**, 'Impact of climate change on grape yields: evidence from Australia' (Puga et al., 2023), we estimated the impact of weather on grape yields and used those estimates to quantify the potential implications of the climate change projections of Remenyi et al. (2020). The conclusion is that climate change may affect yields very little overall, but some regions gain while others lose. This conclusion is subject to a wide range of assumptions that are discussed in the chapter itself.

Besides having an impact on grape production, climate change can also have an impact on grape (and wine) quality. While grape and wine quality are difficult to define, grape prices constitute a more objective measurement that partially depends on quality. In **Chapter 3**, 'Impact of growing season temperature on grape prices in Australia' (Puga et al., 2022a), we estimated the impact of growing season temperature on grape prices and used those estimates to quantify the potential impact of the climate change forecasts of Remenyi et al. (2020). Subject to a no-change scenario and other assumptions, by 2050, the average price of grapes is expected to decrease by 12% on average across Australia's wine regions.

In investigating the potential impact of climate change on viticulture, we estimated some models that we ended up not using in the analyses. One of these models is given by equation (4) in **Chapter 3**. Subsection **3.4** explains why we opted for the cross-sectional model given by equation (3) in **Chapter 3** rather than this other dynamic model. We believe that this cross-sectional model is more appropriate despite acknowledging some potential endogeneity issues.

Another model that we did not use in our analyses consists of a dynamic panel data model of the impact of weather on grape yields. Such a model takes a similar form to the one in equation (1) in **Chapter 2** but includes a lag of the dependent variable. The reasoning behind estimating a dynamic model of this type is that there are persistent events and dynamic phenomena that take place in the current season but affect yields of both the current and subsequent seasons in the same direction (positive or negative). This, in turn, could allow one to get the long-run effect of weather on grape yields. However, it is unclear whether this model is appropriate as perennial crops are often affected by alternate bearing.

Alternate bearing is a phenomenon in which a year with high yields is followed by a lower-yielding year, and vice versa. Since this phenomenon is induced by weather events, regional weather tends to synchronize alternate bearing in farms that are located within the same region, leading to (usually) biennial differences in yields (Samach and Smith, 2013). Alternate bearing is very evident in perennial crops such as apple, olive, mango, citrus, pistachio, litchi, dates, and avocado (Sharma et al., 2019). Grapes, instead, do not exhibit a great degree of alternate bearing due to canopy management and other strategies (Smith and Samach, 2013).

Accounting for alternate bearing can be difficult because, even if this phenomenon exists, there are persistent events and dynamic phenomena that take place in the current season but affect yields of both the current and subsequent seasons in the same direction. With this in mind, we tried to develop a statistical model for identifying the effect of alternate bearing on perennial crops in which this phenomenon is less evident, such as winegrapes. However, we were not confident regarding the appropriateness of these models. Not knowing the degree in which alternate bearing is present in winegrape production, we chose the static model given by equation (1) in **Chapter 2** rather than an alternative dynamic model.

Another econometric consideration relates to the length of the growing season, which in Chapters **2** and **3** goes from October through April. The motivation for using this seven-month period is that it is the same period as the one used in the climate projections of Remenyi et al. (2020). This period, however, may be too long considering that grapes are been harvested earlier than in the past (Cameron et al., 2021). Future research could use a more appropriate growing season length, such as October through March, equivalent to the approach of Zito et al. (2023) in the Northern Hemisphere. Another even more appropriate option could be to use weather variables consistent with the grapevines' phenophases such as in Roucher et al. (2022) and Sgubin et al. (2023).

Leaving the econometrics aside, Chapters **2** and **3** seem to indicate that a decrease in grape (and wine) quality may be one of the most challenging consequences of climate change for the Australian wine industry. That leads to the question of whether the varieties grown in Australia are appropriate for the regions where they are grown. This is the topic of **Appendix 1**, 'Climate change and the evolving mix of grape varieties in Australia's wine regions' (Puga et al., 2022b). The take-home message of this short appendix is that for maintaining wine styles, Australian winegrowers may need to adjust their mix of winegrape varieties so that it is better suited to warmer climates, or to source more grapes from regions (or part of regions) with cooler climates.

While analysing viticulture data for Australia, it was evident that these data were sometimes inconsistent through time and regions, with periods of missing data for some regions, and with data belonging to diverse sources that had applied different data-gathering methodologies. This led first to a database for South Australia (Anderson and Puga, 2021) and a non-peer-reviewed paper summarising this database (Anderson and Puga, 2022a). That database and that paper are not included in this thesis. Instead, a subsequent non-peer-reviewed paper describing a newer database for all of Australia (Anderson and Puga, 2022b) is included in this thesis (i.e., **Appendix 2**, 'Two decades of grape variety trends in Australia's wine regions' (Anderson and Puga, 2023)).

Appendix 2 shows the index of tables of this database. Creating this database was a time-consuming effort due to concordance issues between regions and varieties across sources, differences in the data-gathering process for different sets of often the same variable, and periods with no data. For example, there were no data on the area by region and variety outside South Australia since this information has not been surveyed in recent years. **Appendix 2** describes the methodology that we used to estimate these missing areas.

Appendix 2 provides insights into the viticulture developments that have taken place over the last two decades. In an attempt to better understand these developments, we thought of estimating an acreage response model. However, estimating supply models for perennial crops can be difficult (Alston et al., 2015). Unlike with annual crops, the short-run acreage elasticity of perennial crops is expected to be extremely small. Indeed, we estimated a Nerlovian partial adjustment model and got short-run and long-run acreage elasticities close to zero.

The data for South Australia includes plantings, and we were able to get removals using that data. Therefore, we thought about estimating new plantings and removals acreage response models. Unfortunately, we then realised that these data are not reliable enough for conducting these types of econometric analyses. As a result, we stopped working on the idea of estimating acreage response models for winegrapes in Australia.

Besides analysing the potential impact of climate change on the wine industry and the mix of winegrape varieties in Australia, this thesis gives insights on these topics for the world as a whole (i.e., Chapters **4** to **6**). **Chapter 4**, ‘A Climatic classification of the world’s wine regions’ (Puga et al., 2022c), shows an easy-to-interpret classification of virtually all the world’s wine regions into three clusters based on 16 climate variables. Each of these clusters contains premium regions, showing that high-quality wine can be produced in a wide range of climate types.

However, further analysis in **Chapter 4** shows two reasons for concern. The first is that the climate changed between 1959–1988 and 1989–2018, the latter period being warmer than the former. The second reason for concern is that two of the three groups have average growing season temperatures that may be too high for producing high-quality wine of the most planted varieties. This issue may become even more challenging with ongoing climate change and if the global demand for wine continues shifting towards more premium products. Similar to what **Appendix 1** concludes for Australia, **Chapter 4** argues that for maintaining wine styles, winegrowers in many regions may need to shift towards varieties that are more appropriate to the climates of their regions or plant more vines in regions (or part of regions) with more appropriate climates.

Perhaps a limitation of the climatic classification of **Chapter 4** (not mentioned in that chapter) is that every region has the same weight. While this is a common approach in viticultural zoning (e.g., Shaw (2012), Tonietto and Carbonneau (2004)), it means that very small regions affect the classification as much as very large regions. For example, Gironde (France), which has 123,023 hectares of winegrapes has no more influence in this climatic classification than each of 17 other regions with a winegrape area below 1 hectare.

This potential limitation motivated us to develop a method that indirectly assigns a weight to each region based on its area planted to winegrapes. More specifically, we assumed that each hectare of vines has the same climate as the region it belongs to, and applied the same methodology as in **Chapter 4**, but with each observation being a hectare of vines rather than a region itself. This area-weighted method leads to very similar results. However, when estimating new standard and area-weighted climatic classifications for the top ten wine-producing countries by winegrape area, the differences in results between the two approaches are sometimes significant. It seems that area-weighted climatic classifications offer advantages over standard climatic classifications, even though sometimes both approaches can lead to very similar results. That said, we are still investigating the advantages and limitations of this alternative approach, which is why this work is not included in this thesis.

The mix of winegrape varieties is analysed in more detail in **Chapter 5**, 'Concentrations and similarities across countries in the mix of winegrape cultivars' (Puga and Anderson, 2023). The methods used in this study include two contributions: (a) the use of hierarchical clustering to simplify the visualisation of complex matrices of variety similarity indexes, and (b) an index that shows how concentrated the mix of winegrape varieties is. The results show that countries are often quite diverse in terms of how similar their mixes of winegrape varieties are compared to the world and how concentrated their mixes are. However, they also show that countries are tending to become more similar in their mixes of winegrape varieties, and also more concentrated on a few popular varieties.

While **Chapter 5** gives some possible explanations regarding the similarity levels across countries in their mix of winegrape varieties, it does not do it econometrically. In **Chapter 6**, 'Explaining bilateral patterns of global wine trade, 1962-2019' (Puga et al., 2022d), we analysed (econometrically) the link between similarities in the mix of winegrape varieties across countries and bilateral wine trade. While our gravity models do not allow us to uncover a causal relationship due to potential endogeneity issues, the results signal that countries trade more wine with each other the closer their mix of winegrape varieties.

Another set of quite-different gravity models in **Chapter 6** analyses how the impacts of some trade variables have changed during the second wave of globalization. The results suggest that the impact of distance, common language, and common colonizer on wine trade was lower in the 1991–2019 period than in the 1962–1990 period. This is consistent with trade theory and the findings of previous studies (e.g., Borchert and Yotov, 2017), and it relates to the decline in trade costs over time (Anderson and van Wincoop, 2004).

Chapter 6 mentions a limitation that we encountered while estimating gravity models: the lack of time-series data on national expenditure on the various varieties of wine for many countries. If that type of data was available, as it is for many other industries, more complex gravity models could be estimated and more interesting research questions could be answered. These data could even help in estimating models of the impact of similarities on the mix of winegrape varieties across countries on bilateral wine trade that could potentially uncover causal relationships.

In **Chapter 7**, 'The impact of the European grapevine moth on grape production: Implications for eradication programs' (Puga et al., 2020), we estimated an econometric model of the impact of the European Grapevine Moth on grape production. We used those results to advise on whether it may make sense to continue with a program to eradicate this pest from Argentina. Based on the results of this model and the experience in countries with eradication programs including Argentina itself, we suggest that it may well be profitable to eradicate this pest. This is a very pertinent study for Argentina and has been recently used in the Argentinian government's assessment of whether it is worth continuing with the ongoing eradication program. Further, while this analysis is based on Argentina, its conclusion regarding the economic viability of eradicating this pest might also apply to other countries.

Chapter 7 also relates to the impact of weather on grape yields, although indirectly. This is because there are four weather variables included in its model. As is the case for Australia (**Chapter 2**), both growing season temperature (GST) and growing season precipitation (GSP) have an inverse-U shape effect on grape yields. However, the inflexion point is higher for Mendoza than Australia for GST (22.2°C vs 20.6°C) and lower for GSP (266mm vs 392mm). What is very interesting is the projected yearly losses due to frost and hail in Mendoza, estimated to be about 3.5% and 18.4% of the province's grape production.

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Appendix 1

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Name of principal author (candidate)	German Puga		
Contribution to the paper	Contributed to the study conception and design, prepared the data, performed statistical analyses, and interpreted the results. Wrote parts of drafts/versions of the paper. Presented the paper at a conference to get feedback.		
Overall percentage	40%		
Certification	This paper reports on original research I conducted during the period of my Higher Degree by Research candidature and is not subject to any obligations or contractual agreements with a third party that would constrain its inclusion in this thesis. I am the primary author of this paper.		
Signature		Date	11/07/2023

Co-author contributions

By signing the Statement of authorship, each author certifies that:

I. the candidate's stated contribution to the publication is accurate (as detailed above);
II. permission is granted for the candidate in include the publication in the thesis; and
III. the sum of all co-author contributions is equal to 100% less the candidate's stated contribution.

Name of co-author	Kym Anderson		
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Signature	**Signed form available at the end of this thesis.**	Date	

A1. Climate change and the evolving mix of grape varieties in Australia's wine regions

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Abstract

The aim of this paper is to examine the climates and the changing mix of winegrape varieties in Australia to determine how well suited this mix of winegrape varieties is in light of recent climate change projections. We first do a cluster analysis of the Australian wine regions based on their climates. This analysis shows that while there is a wide range of climates across wine regions in Australia, most regions are warm and dry. We then analyse the potential implications of climate change forecasts. If the mix of winegrape varieties remains the same, projected changes in growing season temperature will make it hard to maintain current wine styles and/or quality in most regions. We also show that the share of hot regions in the national vineyard bearing area has declined and the most-widely planted varieties have a higher share under more-appropriate climates for high-quality winegrape production. However, these adjustments have been relatively small and lower than in other New World countries. We conclude that for adapting to climate

change, many Australian winegrowers will need to change their mix of winegrape varieties and/or plant vineyards in more-appropriate cooler climates.

Keywords: adaptation, Australia's viticulture, climate change, growing season average temperature, mix of winegrape varieties, wine regions' climate

A1.1. Introduction

It has long been claimed that Australia's mix of winegrape varieties is less than ideal for expressing and exploiting the terroir of its various wine regions. The purpose of this paper is to examine the climates and the changing mix of winegrape varieties in Australia so as to address the question: How well suited are the winegrape varieties planted in Australia's wine regions, and what is the nation's vulnerability to climate change?

A1.2. Materials and methods

This study draws on two main databases. The first database (Remenyi et al., 2020) provides spatial data for the major Australian wine regions for the 1997-2017 period. We use these data to perform a k-means cluster analysis based on four climate variables: growing season average temperature (GST), growing season precipitation (GSP), frost risk days, and aridity. This cluster analysis allows us to catalogue the climates of the Australian wine regions. The data in Remenyi et al. (2020) also provide climate change projections for each of those regions to 2041-2060 and 2081-2100, which we use in our analysis in combination with another database (Anderson and Nelgen, 2020). The latter database contains information on the area by variety and region for 2000 and 2016, as well as information on climate variables for the 1958-2019 period. The data in Anderson and Nelgen (2020) cover more than 99% of the world's winegrape area, which allows us to make comparisons between Australia and the rest of the world.

A1.3. Results and discussion

The k-means cluster analysis of the climates of the wine regions reported by Remenyi et al. (2020) leads to a four-group classification (see Table A1.1). Group 1 and Group 4 have the lowest GSP, but Group 4 has a higher average GST than Group 1. Group 1 includes McLaren Vale and Margaret River. Group 4 includes the major hot irrigated regions (i.e., Riverland, Riverina, and Murray Darling – Swan Hill), as well as other regions with GSTs lower than 20℃ (e.g., Barossa Valley and Clare Valley) but that are more arid than those with similar GSTs in Group 1. The regions in Groups 2 and 3 have higher GSP and are usually less arid than those in Groups 1 and 4. The difference between Groups 2 and 3 is given by the GST, which is lower in Group 2, the coolest of all groups and the most affected by frosts. Group 2 includes the Tasmanian regions and Yarra Valley.

Table A1.1: Summary statistics for the climatic classification based on Remenyi et al. (2020) spatial data for 1997-2017.

Group	Statistic	GSP (mm)	GST (℃)	Frost risk days	Aridity index
1	Min.	188	15.5	0.0	0.34
N = 33	Mean	267	18.0	1.6	0.48
	Max.	370	19.8	6.7	0.85
2	Min.	353	12.7	1.9	0.53
N = 15	Mean	443	15.9	7.3	0.83
	Max.	549	18.1	18.8	1.17
3	Min.	448	18.0	0.0	0.45
N = 8	Mean	616	19.7	1.2	0.67
	Max.	982	22.4	3.5	1.08
4	Min.	148	19.0	0.0	0.14
N = 15	Mean	205	20.5	0.9	0.28
	Max.	349	21.9	2.9	0.46
TOTAL	Min.	148	12.7	0.0	0.14
N = 71	Mean	331	18.2	2.6	0.53
	Max.	982	22.4	18.8	1.17

Source: Authors' compilation from data in Remenyi et al. (2020).

Overall, this classification reveals that there is a wide range of climates across wine regions in Australia, but most regions are warm and dry. A recent classification of the world's wine regions (Puga et al., 2022) suggests that when compared to the rest of the world, most Australian wine regions are warm and dry, with high diurnal temperature ranges and high vapour pressure deficits. The average winegrape hectare is hotter and drier than the average wine region, as the major hot irrigated regions account for about 43% of Australia's winegrape area.

The forecasts from Remenyi et al. (2020) indicate that by 2041-2060 (2081-2100) frost risk days will decrease by 46% (80%) across regions. While this decrease in frost risk is positive for winegrape production, it is presently only a minor threat in most regions in Australia. Rainfall patterns will change in various seasonal directions, but more significantly, all regions will become more arid. By 2041-2060 (2081-2100) aridity is projected to increase by 15% (29%) across regions due to increases in evaporation. This increase in aridity will challenge both non-irrigated and irrigated regions, because of stress on the available water in the Murray-Darling river system and in regions with other sources of irrigation water.

Rising temperatures will challenge high-quality wine production in most of Australia's wine regions, as GSTs will increase in all regions (1.3℃ by 2041-2060 and 3℃ by 2081-2100, on average). Figure A1.1 reproduces GI regional outlines with colour coding of GST word descriptions for 1ºC intervals by Smart (2021) for continental Australia. Note that some regions are very large: the GI area is not proportional to vineyard area but rather determined by the decision to have contiguous GI boundaries. By 2041-2060, 90% of Australia's present vineyard surface will be within regions in the 'hot' or 'very hot' classifications, and 45% will be 'extremely hot'. Temperatures are predicted to keep rising towards the end of this century, such that by 2081-2100, only 1% of Australia's present vineyard area will be 'warm'. The rest of the area will be 'moderately hot' (3%), 'hot' (16%), 'very hot' (21%), or 'extremely hot' (58%). Tasmania (not shown in Figure A1.1) is the only presently 'very cool' region and the only one that will not be classified as 'hot' by 2081-2100.

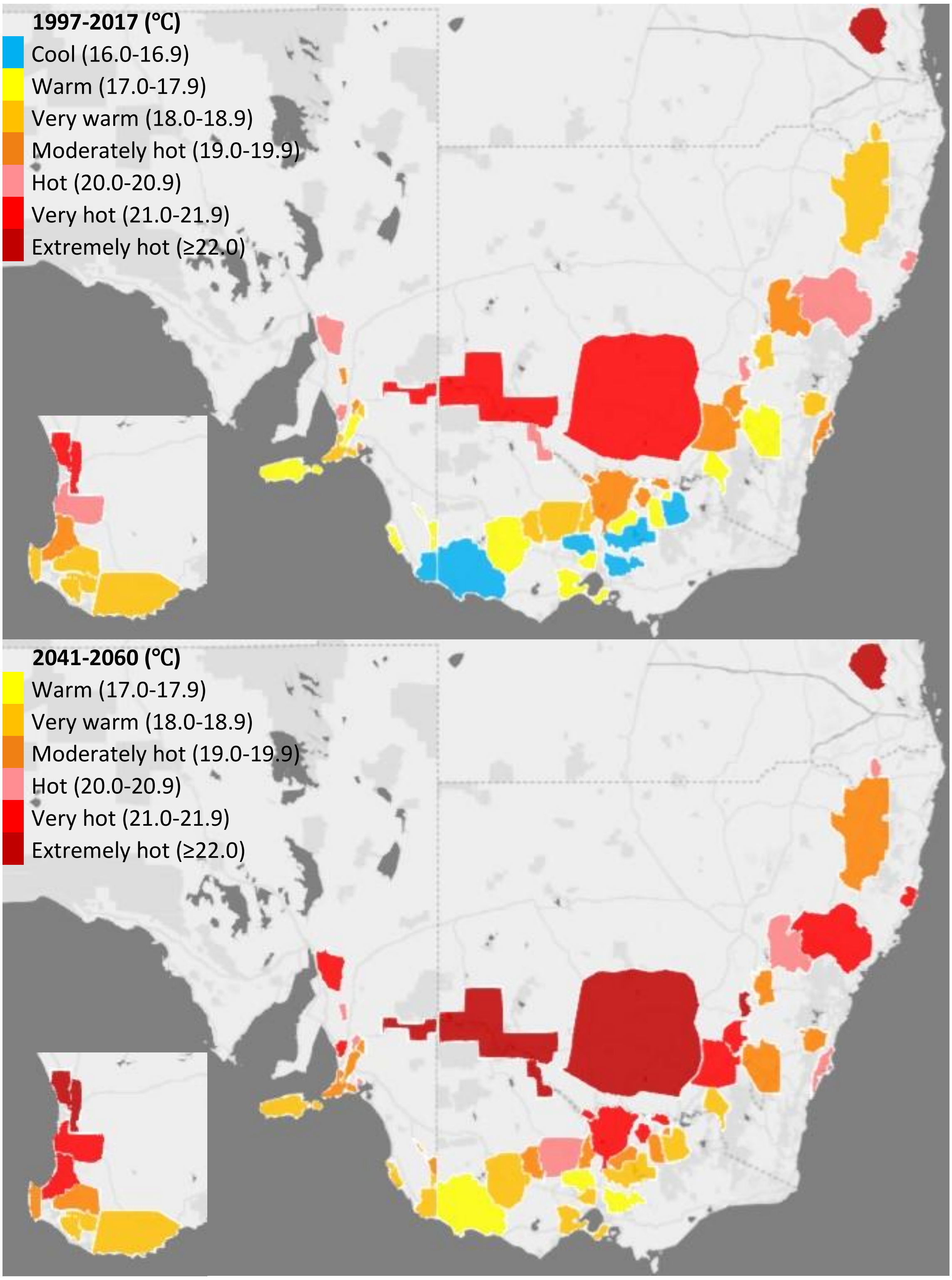

Figure A1.1: Smart (2021) classification for the continental Australian wine regions based on Remenyi et al. (2020) spatial data on GSTs for 1997-2017 and GST projections for 2041-2060.

Source: Authors' compilation from data in Remenyi et al. (2020). Notes: Western Australia is shown on the bottom left corner of the maps.

Without substantial new plantings of varieties in cooler regions, projected increases in GSTs mean that Australia will not be able to maintain current wine styles and quality levels in most regions. Table A1.2 shows the percentage of vineyard area planted in the GST ranges suggested by Jones (2012) as providing high-quality winegrapes for each of 12 key varieties. Except for Merlot, no other key varieties decreased their proportions under ideal GSTs for high-quality wine production between 2000 and 2016. This rate of desirable adjustment, however, will not be sufficient to offset the decrease in winegrape area planted within ideal GST ranges that would take place with projected future warming. If the current proportional areas of those key varieties in each Australian region were not to change, a much bigger share of their area would be hotter than ideal by mid-century, and an even bigger share by the end of the century.

Table A1.2: Shares of Australian winegrape area in 2000 and 2016 for what Jones (2012) considers the ideal GST range for high-quality wine production, 12 key varieties[1].

Climate data: Surface year:	1997-2017 2000	1997-2017 2016	2041-2060 2016	2080-2100 2016	% of Aust production, 2020
Cabernet Franc	51%	60%	24%	1%	0.1
Cabernet Sauvignon	56%	63%	29%	1%	19.9
Chardonnay	6%	6%	2%	2%	12.0
Côt (Malbec)	45%	49%	9%	0%	0.4
Garnacha Tinta (Grenache)	56%	75%	1%	0%	1.7
Merlot	35%	30%	11%	0%	4.8
Pinot Gris	0%	3%	0%	0%	4.0
Pinot Noir	6%	14%	13%	0%	5.2
Riesling	3%	5%	3%	0%	3.4
Sangiovese	42%	59%	24%	4%	0.5
Sauvignon Blanc	14%	14%	5%	3%	6.9
Syrah (Shiraz)	42%	47%	10%	0%	32.5
TOTAL OF ABOVE	35%	36%	12%	1%	91.4

Source: Authors' compilation from data in Anderson and Nelgen (2020a) and Remenyi et al. (2020), and GST ranges from Jones (2012). Notes: [1]These are the top dozen varieties whose winegrape prices averaged above AUD 1000 in 2020 in all but the very hot irrigated regions. In a hedonic analysis of Australian wines, Oczkowski (2016) calculates the optimal GST for high-quality production of seven of these 12 key varieties and shows that the optimal GST falls within the ranges suggested by Jones (2012), except for Sauvignon Blanc which falls 0.2°C from the upper limit. However, van Leeuwen et al. (2013) argue that high-quality wine can be produced at higher temperatures than the upper limits of Jones (2012) optimal GST ranges.

Australia's vineyards have already made some adjustments this century when looking at Jones (2012) climate ranges, i.e.: 'cool' (<15°C), 'temperate' (15-19°C), 'warm' (17-19°C), and 'hot' (>19°C). However, these adjustments have been small. Between 2000 and 2016, the share of ‘cool’ regions in the total bearing area remained unchanged at a very small 1.2%, while the ‘hot’ regions fell by one-eleventh to a still dominating 49%. The decline in the ‘hot’ regions’ share was considerably greater in other New World countries, and the bias toward the ‘hot’ end of the spectrum remains much greater for Australia compared with the Old World.

A1.4. Conclusion

This study shows that the climates of the Australian wine regions are relatively warm (or hot) and dry, and that climate change represents a major threat to high-quality wine production. The situation may become more challenging if the global demand for wine continues to shift towards higher-quality products. Therefore, the Australian wine industry should consider more-appropriate plant materials and relocating vineyards as long-term adaptation strategies. More-appropriate plant materials include shifting towards currently underrepresented varieties that may be useful for producing high-quality wine in warmer climates. Relocating vineyards may imply planting at higher elevations or in cooler regions with higher water availability such as Tasmania, which currently accounts for only 1% of the country’s vineyard area.

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Appendix 2

Statement of authorship

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Co-author

Name of co-author (candidate)	German Puga		
Contribution to the paper	Prepared the data used in the analyses. Wrote parts of drafts/versions of the paper.		
Overall percentage	20%, but a much larger share of the database in which this appendix draws. The index of that database is available at the end of this appendix.		
Certification	This paper reports on original research I conducted during the period of my Higher Degree by Research candidature and is not subject to any obligations or contractual agreements with a third party that would constrain its inclusion in this thesis. I am NOT the primary author of this paper.		
Signature		Date	11/07/2023

Principal author contributions

By signing the Statement of authorship, each author certifies that:

I. the candidate's stated contribution to the publication is accurate (as detailed above);
II. permission is granted for the candidate in include the publication in the thesis; and
III. the sum of all co-author contributions is equal to 100% less the candidate's stated contribution.

Name of co-author	Kym Anderson		
Contribution to the paper	Contributed to the study conception and design, and to the interpretation and discussion of the results. Wrote drafts/versions of the paper.		
Signature	**Signed form available at the end of this thesis.**	Date	

A2. Two decades of grape variety trends in Australia’s wine regions

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A2.1. Introduction

Over the past two decades, Australia’s vignerons have both produced and exported around 180 winegrape varieties from 70+ regions and sub-regions, but the main varieties have changed little. This is despite the industry being on a huge roller-coaster ride since the turn of the century.

Having more than trebled its vine bearing area in the previous decade, Australia’s average winegrape price peaked in 2001 before halving over the next decade. The expansion in bearing area continued until 2008, making that 22-year boom in area nearly twice as long as the average of Australia’s four previous booms of 12 years (Anderson, 2015).

The global financial crisis of 2008 followed six years of rapid appreciation of the AUD, and since then there have been numerous extreme weather events possibly associated with climate change (drought, floods, and heat waves that led to huge bushfires), plus disruptions to supply chains thanks to COVID-19 and Russia’s invasion of Ukraine, China’s decline in wine consumption since 2017 and imposition of prohibitive tariffs on Australian wine since late

2020, and a new era of higher inflation, interest rates, and global economic and policy uncertainty.

Particularly with the loss of sales to China plus high yields in 2021, Australia's wine stocks-to-annual-sales ratio rose above two in 2022, which is one-third above the average of the past four decades. More than two-thirds of those stocks are red varieties, a historic record (Wine Australia, 2022c and earlier).

Each of Australia's four previous booms was followed by a longer plateau period, averaging 21 vintages. This begs the question as to how long it might be before the next boom, it now being 15 years since the 2008 peak in the nation's vine bearing area.

The present article does not address that unanswerable question, but it does provide a brief summary of Australia's winegrape developments over the past two decades by drawing on a comprehensive new dataset that includes, for the first time, estimates of the bearing area of winegrapes in each of Australia's wine regions outside of South Australia for the numerous years when surveys were not conducted.

Fortunately South Australia, which accounts for almost half the national vineyard area, is well served with data because of the required annual reporting by SA growers to Vinehealth Australia (previously the Phylloxera and Grape Industry Board of South Australia). Those data, which are now published annually by Wine Australia (2022a and earlier), were analysed in a recent *Wine and Viticulture Journal* article by Anderson and Puga (2022a).

For the rest of Australia, there have been no data on the bearing area of winegrapes by variety and region since 2015. That was when the Australian Bureau of Statistics stopped collecting data on national, state and regional vine areas. Neither did it collect them in 2009, 2011, 2013, and 2014 (see ABS (2015 and earlier)). So it has not been possible to trace changes in that basic statistic outside of South Australia since then to see how growers have been altering their area of each variety in different wine regions in response to the above-mentioned macro shocks plus changes in demand for various varieties, and in the expected climate of each region.

To compile a database for wine regions outside South Australia and thus also for each of the other states and for the nation as a whole, Anderson and Puga (2022b) have brought together available annual data from various sources for winegrape crush volumes and prices by variety and region, and then made a series of assumptions (detailed under 'Further information on the data used in this study' at the end of this article) to estimate the missing bearing area data. This new dataset also includes some national varietal data back to 1956, building from and updating the historic varietal data reported in Anderson (2015).[3]

In total, there are 72 regions in the database, a little more than the 65 legally defined Geographic Indicators (GIs) because of changes in definitions of GIs over time including the emergence of some sub-regions, and despite needing to aggregate some small new regions. Area, crush, and price data are available for 118 'prime' varieties (prime as defined by Anderson and Nelgen (2020b) based on Robinson et al. (2012) or otherwise www.vivc.de). There are also another 64 more-minor prime varieties whose data are aggregated into 'other red' or 'other white' for confidentiality reasons. Of that total of 183 varieties, 178 of them have been exported at some time in the past 22 years (but just five accounted for around four-fifths of the total volume of Australia's wine exports in the past five years).

This article first summarizes what this new dataset – enhanced by our new estimates of bearing area data that used to be provided annually by the Australian Bureau of Statistics (ABS) – suggests has been happening at the national and state levels leading up to and during the 21st century. It then focuses in more detail on varietal developments at the regional level from 2001.

A2.2. National and state data

While interest in expanding Australia's winegrape area began shortly after the mid-1980s' subsidized vine-pull, the bearing area began to grow most rapidly from the mid-1990s, in a delayed reaction to rising prices of winegrapes which in turn shadowed rising wine export prices (Figure A2.1). That expansion was stimulated also by the industry's long-term strategy that was laid out in 1995 (WFA, 1995). The plan had targets of exporting $1 billion worth of wine by the turn of the century (up from $470 million in 1995-96 and less than $100 million a decade prior) and of trebling the real value of wine production within 30 years. As it turned

[3] To validate the assumptions used to estimate the missing non-SA area data, we applied the same assumptions to the SA data and compared them with the actual SA area data by region and variety for those same vintages. As reported in the supplementary information, there is a close match, which gives us confidence in our estimates for non-SA regions.

out, exports reached $1.4 billion by 2000, and the trebling of wine production target was met in one rather than three decades.

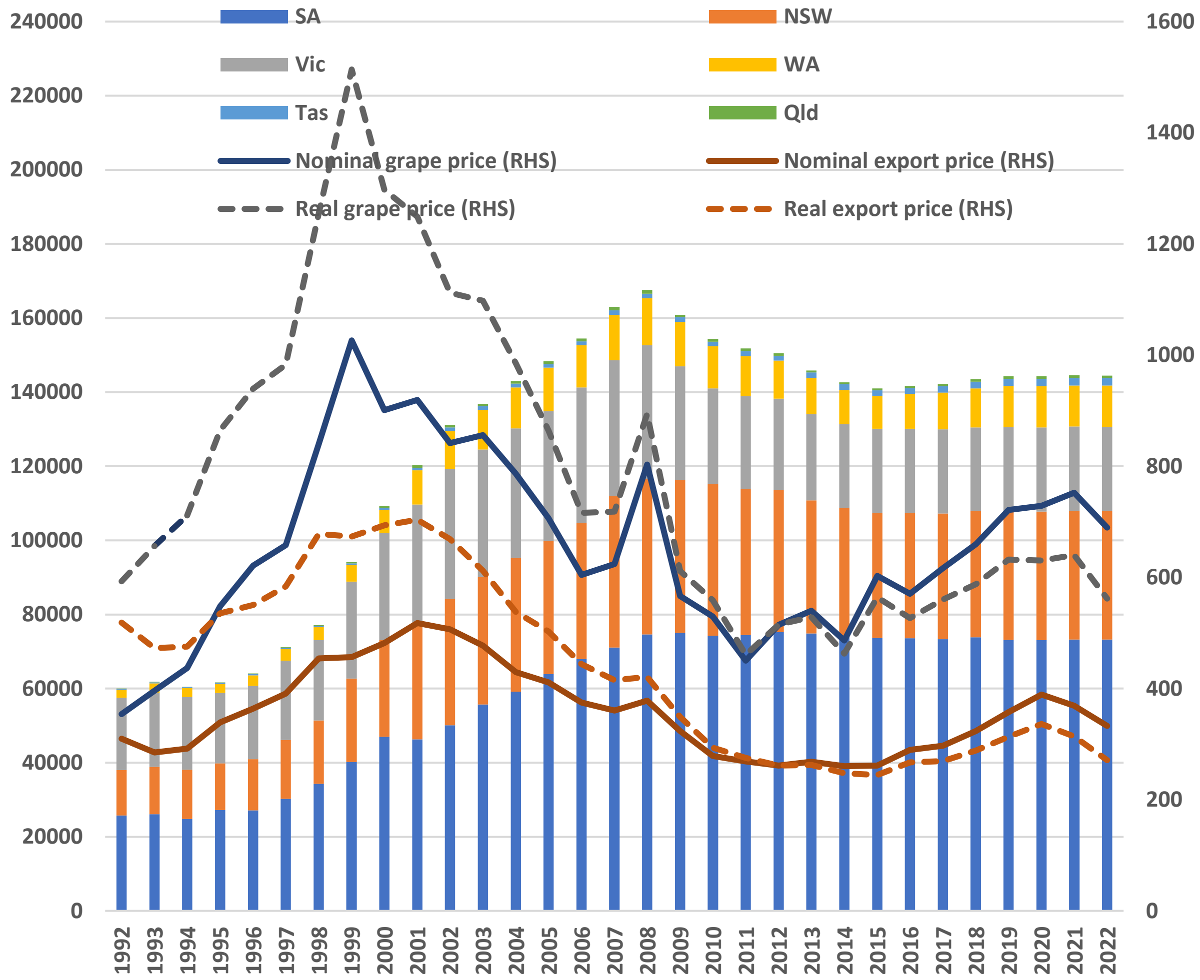

Figure A2.1: Winegrape bearing area by state (left axis in hectares), and prices of winegrapes and of exported wine (right axis in $/tonne and cents/litre), Australia, 1992 to 2022[a] (nominal and real AUD)[b].

Notes: [a]Export prices are for fiscal years beginning 1 July. [b]Real prices are nominal prices deflated by the CPI which is set at 2011-12 = 1.00. Source: Authors' compilation from Anderson and Puga (2022b).

However, wineries struggled to expand export markets fast enough to dispose of that rapidly expanding supply, and export prices began to fall also because of a dramatic appreciation of the AUD over the first decade of this century thanks to rapid growth in mineral sales to China. A belated and modest decline in vine bearing area started after 2008 and continued to 2015 before appearing to plateau as prices started to rise again before abruptly declining (especially for red varieties) when China imposed prohibitive tariffs on Australian wine from late 2020. In short, there is no end in sight yet to the downturn part of the industry's current boom/slump cycle, which has involved the real prices of winegrapes and exported wine falling by more than 60% this century.

Turning to the varietal mix of that national vine area, it too has cycled. Red varieties rose in importance in the 1960s and 1970s before being taken over by whites in the 1980s – and then regaining their dominance in the 1990s and holding on to it since then (Figure A2.2). This mirrors changes since 1990 in the rest of the world, where red's share rose from 46% to 49% by 2000 and to 56% by 2016 (Anderson and Nelgen, 2020b, 2021). If China's obsession with reds is an important part of the reason for this century's swing, one might expect red's share to fall over the 2020s given that, according to OIV (2022), China's wine imports have halved since 2017 – and almost completely stopped from Australia which is why the share of reds in its exports is now dipping.

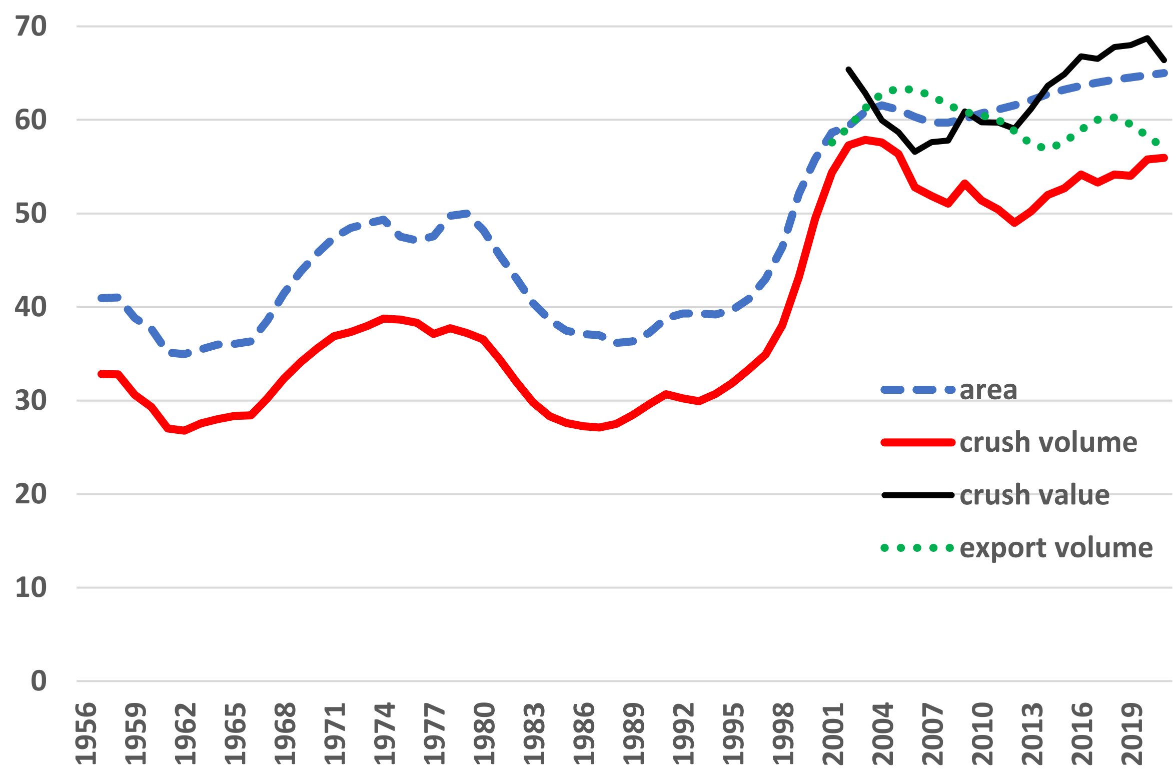

Figure A2.2: Red shares of Australia's vine bearing area, crush volume, export volume, and crush value, 1956 to 2022 (%, 3-year averages around year shown).
Source: Authors' compilation from Anderson and Puga (2022b).

The main varieties are shown in Figure A2.3, which reveals the drift away from the varieties commonly used for fortified wines toward the key varieties that produce premium still and sparkling wines, most of which have their origin in France. Again that change mirrors what is happening in the rest of the world, with key French varieties becoming more popular everywhere (Anderson and Nelgen, 2020a, 2021).

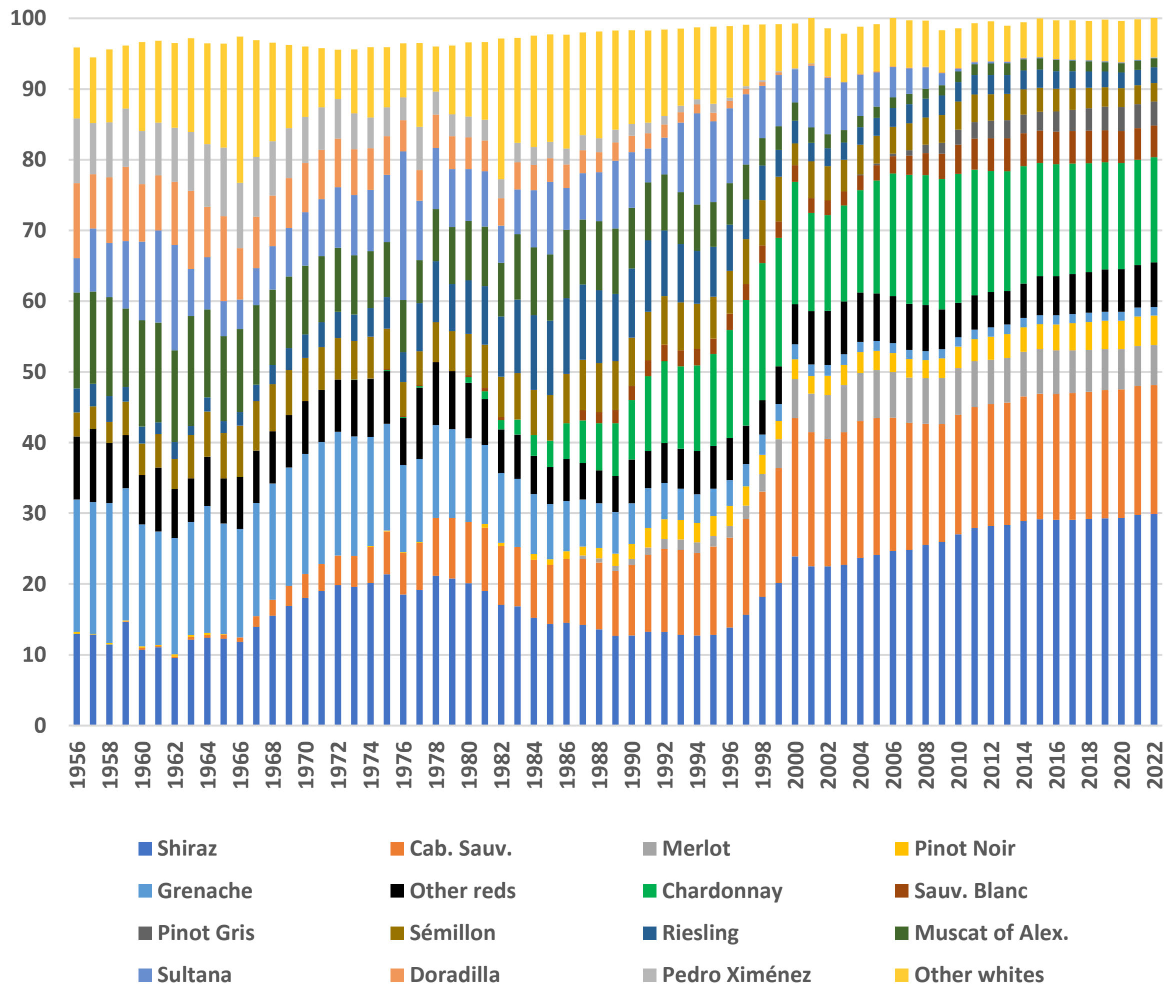

Figure A2.3: Shares of main varieties in the total Australian winegrape bearing area, 1956 to 2022 (%).
Source: Authors' compilation from Anderson and Puga (2022b).

The extent of swing toward French varieties in Australia leading up to the turn of the century is extreme, as shown in Figure A2.4. In the 1950s/early 1960s, the share originating from Spain was more than 40% while the French share was no more than that of Greece at just under 20%, with Turkey next at around 10% (because of Sultana). By the early 1980s the shares of Spanish and French varieties had reversed, and by the turn of the century Spanish shares were less than 4% (because of Grenache's share falling from 20% in the late 1950s to 1% today).

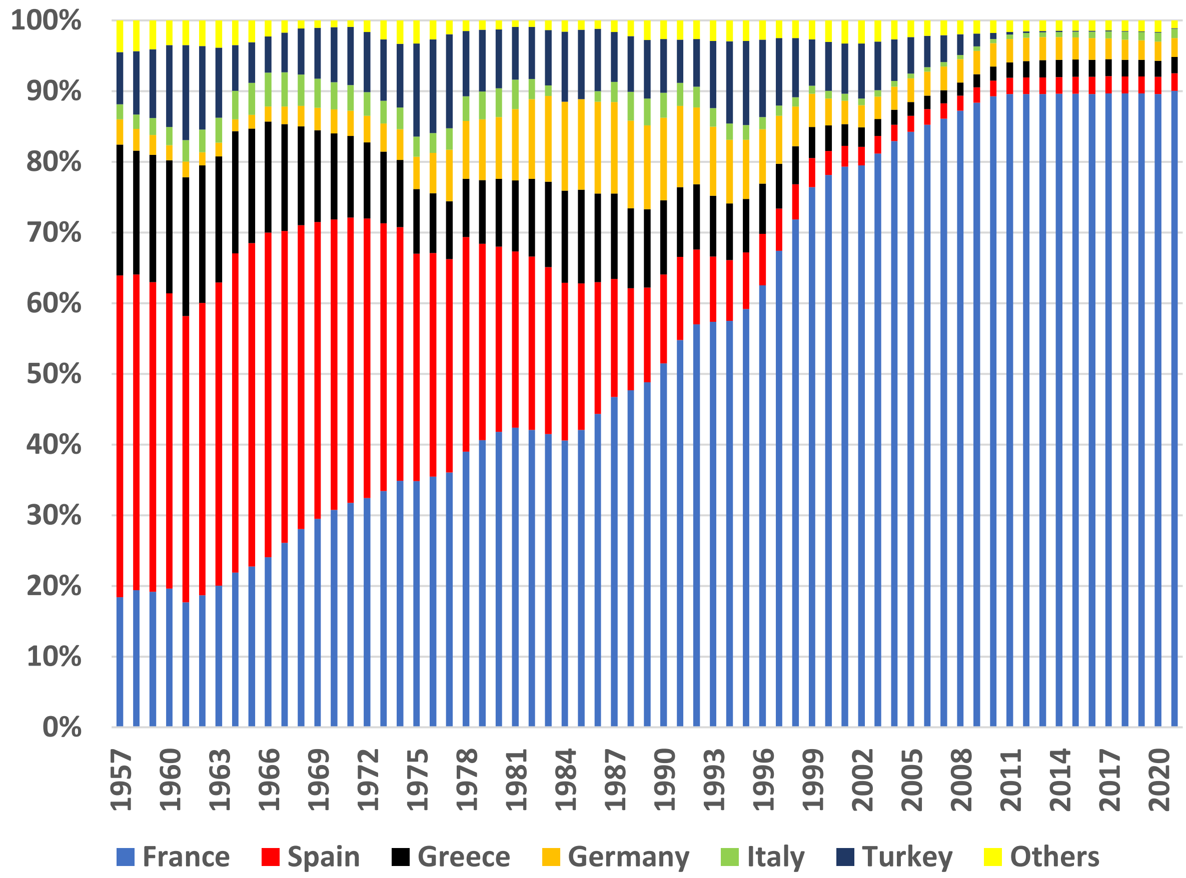

Figure A2.4: Shares of varietal country of origin in Australia's winegrape bearing area, 1956 to 2022 (%, 3-year average around year shown).
Source: Authors' compilation from Anderson and Puga (2022b).

The extent of Australia's convergence on that changing global mix is measured by our varietal similarity index (VSI), which ranges from zero to one: it indicates how close the varietal mix of one region is to another region or to the national or world average mix, based on varietal shares of total bearing area (see definition under 'Further information on the data used in this study'). In 2001 that index for Australia vis-à-vis the world mix was 0.47, but in 2022 it was 0.66.

Associated with that increasing similarity across the world of national winegrape varietal mixes is a greater concentration on fewer varieties in most countries (Puga and Anderson, 2022). In Australia's case, the top ten varieties by area have accounted recently for 87% of the national area, whereas the share of the top ten in 2001 was 83%. True, many vignerons are exploring 'alternative' or 'emerging' varieties (see, e.g., Higgs (2019)), but as yet those listed in Table A2.1 (ones with bearing area between 5 and 1000 hectares and export volumes between 10 and 3600 kl) make up just 3.0% of the nation's vineyard area and 1.5% of its volume of exports, up from 0.9% and 0.3%, respectively, in 2007.

Table A2.1: Australian emerging (and declining) varieties' bearing area of between 5 and 1000 hectares as of 2022, 2007, and 2022, and also an export volume of between 10 and 3600 kl as of 2019-21, 2006-08, and 2019-21.

	Bearing area (ha)		**Export volume (kl)**	
Emerging:	**2007**	**2022**	**2006-08**	**2019-21**
Aglianico		5	0	48
Alicante Henri Bourschet	2	15	2	21
Arneis	1	38	4	16
Barbera	114	118	174	37
Canada Muscat		326	2	1658
Cinsaut		9	3	14
Côt (Malbec)	359	672	694	2390
Dolcetto	15	126	62	128
Durif	412	847	1213	3521
Fiano		380	0	264
Graciano		13	1	27
Grüner Veltliner		20	0	38
Lagrain	1	10	7	28
Montepulciano		96	0	101
Nebbiolo	120	122	31	24
Nero d'Avelo		87	0	290
Prosecco		320	1	550
Rousanne	36	45	40	147
Saperavi		11	0	10
Tempranillo	314	844	335	1074
Touriga National	21	71	32	38
Vermentino		110	1	332
TOTAL of above emerging	**1395**	**4285**	**2602**	**10756**
% of national bearing area or export volume	**0.9%**	**3.0%**	**0.3%**	**1.5%**
	Bearing area (ha)		**Export volume (kl)**	
Declining:	**2007**	**2022**	**2006-08**	**2019-21**
Cabernet Franc	503	313	543	133
Chenin Blanc	666	415	2142	306
Grouchen	91	33	38	9
Marsanne	177	137	241	180
Sangiovese	464	433	1118	576
Tribidrag (Zinfandel)	99	80	34	54
Viognier	1040	692	1941	1707
TOTAL of above declining	**3040**	**2103**	**6057**	**2965**
% of national bearing area or export volume	**1.9%**	**1.5%**	**0.8%**	**0.4%**

Source: Authors' compilation from Anderson and Puga (2022b).

An advantage of us having assembled a full-time series of winegrape bearing area data is that it allows us to estimate winegrape yields per hectare and gross revenue per hectare, since tonnes of winegrapes crushed and their average prices are available by variety and region in the *National Vintage Report* (Wine Australia, 2022b and earlier) and from ABS and Vinehealth. Yields per hectare vary most in Tasmania but on average during 2001-22 were estimated to be lowest in Western Australia at 5 t/ha, compared with 6 in Tasmania, 11 in South Australia, 12 in Victoria, and 14 in New South Wales. Prices over those two decades were highest by far in Tasmania though, at an average of $2650 per tonne over those 22 vintages, compared with just half that in Western Australia, one-quarter that in Victoria and less than one-fifth that in New South Wales. Thus gross revenue per hectare covers a much narrower range on the mainland (between $6340 and $8850) while Tasmania is again an outlier at over $14,000 (Table A2.2). Furthermore, the time series for gross revenue per hectare is trending slightly upward for Tasmania even though its winegrape bearing area has trebled and spread geographically over the island during those two decades. By contrast, gross revenue per hectare trended downwards in all the mainland states in the 2000s, before recovering in the 2010s but turning down again in 2022 (Figure A2.5).

Table A2.2: Average yields (t/ha), prices ($/t) and gross revenue per hectare ($), Australian states, 2001-22 (nominal AUD).

	Yield (t/ha)	**Price ($/t)**	**Gross revenue ($/ha)**
SA	11.2	770	8850
NSW	13.8	470	6340
Vic	12.0	610	7060
WA	4.9	1330	6520
Tas	6.0	2650	14280
AUSTRALIA	**11.3**	**670**	**7710**

Source: Authors' compilation from Anderson and Puga (2022b).

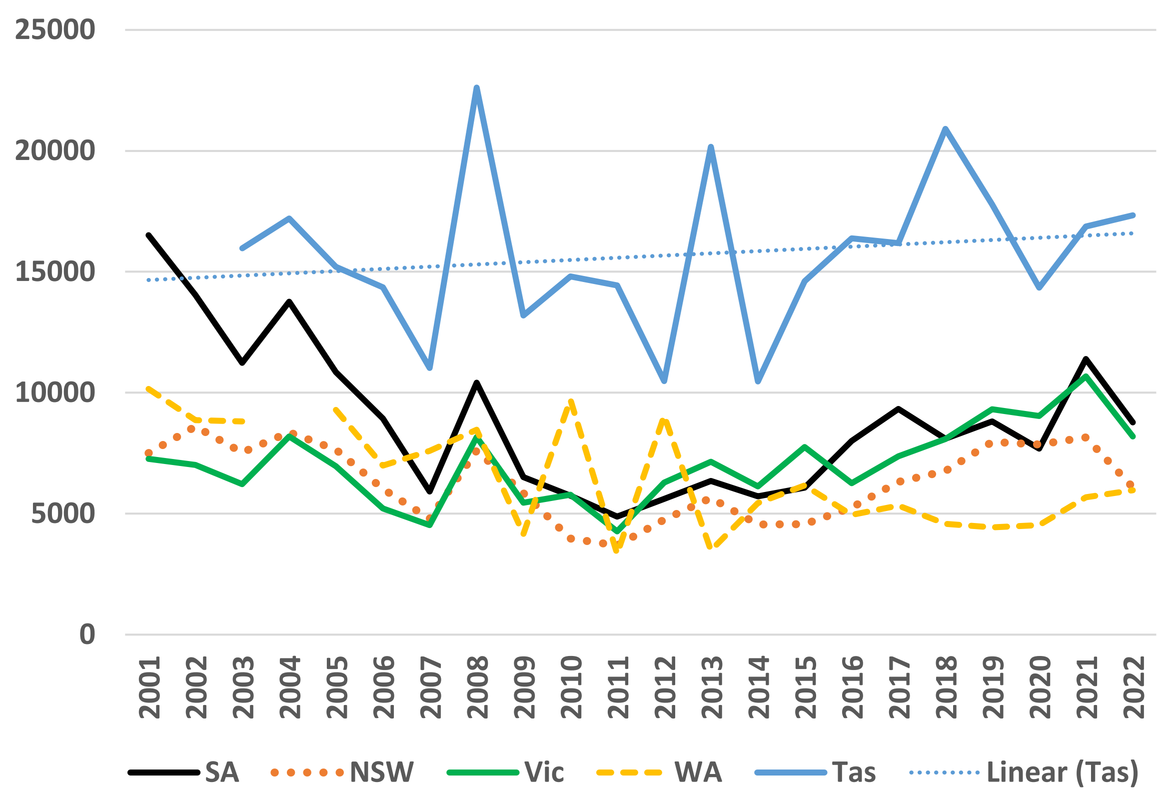

Figure A2.5: Gross revenue per hectare of winegrapes, Australian states, 2001 to 2022 (nominal AUD).
Source: Authors' compilation from Anderson and Puga (2022b).

There is also a large range in the average gross revenue per hectare across varieties. That is true even among the top dozen varieties by bearing area, and even when averaged over 22 years: the range is from $6800 to $10,500 per hectare (Figure A2.6). Since this indicator is the product of the variety's price and its yield per hectare, its ranking by variety is not obvious given that those two variables often have a negative correlation. Nor is there a close ranking between the varietal quality index (VQI, the average price of a particular variety divided by that for all varieties) and the varietal productivity index (VPI, the average gross revenue per hectare of a particular variety divided by that for all varieties), as shown in Table A2.3. While there is a four-fold range in the VQI (from Pinot Noir at 1.8 to Colombard at 0.4), the VPI range is much smaller because yield per hectare and price are negatively correlated.

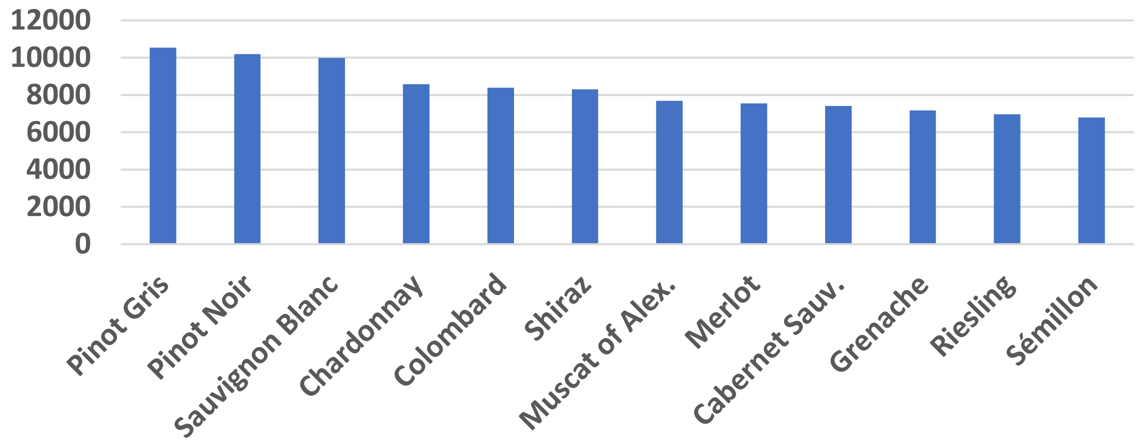

Figure A2.6: Gross revenue per hectare of Australian winegrapes, dozen most-planted varieties, average for 2001-22 (nominal AUD).
Source: Authors' compilation from Anderson and Puga (2022b).

Table A2.3: Average yields (t/ha), prices ($/t), and gross revenue per hectare ($) of the dozen most-planted varieties, Australia, 2001-22 (nominal AUD).

Variety	Yield (t/ha)	Price ($/t)	Gross revenue ($/ha)	VQI[a]	VPI[b]
Cabernet Sauvignon	9.2	790	7410	1.18	0.98
Chardonnay	14.7	580	8570	0.84	1.10
Colombard	29.3	290	8390	0.42	1.17
Grenache	8.3	880	7180	1.32	0.96
Merlot	12.4	610	7540	0.89	0.96
Muscat of Alexandria	23.9	330	7690	0.50	1.12
Pinot Gris[c]	14.2	730	10530	1.35	1.45
Pinot Noir	8.5	1190	10200	1.79	1.25
Riesling	7.6	920	6970	1.37	0.88
Sauvignon Blanc	12.6	810	9990	1.20	1.27
Sémillon	13.9	480	6800	0.72	0.90
Shiraz	9.8	830	8310	1.24	1.11
All reds	*9.8*	*790*	*7860*		
All whites	*14.1*	*540*	*7610*		
All varieties	***11.3***	***670***	***7710***	***1.00***	***1.00***

Notes: [a]Varietal quality index (VQI) is the ratio of national average price of each variety to that of all varieties in that vintage. [b]Varietal productivity index (VPI) is the ratio of varietal to national average gross value of production per hectare in that vintage. [c]In calculating the average price and gross revenue per ha of Pinot Gris, the years 2001-05 are ignored as that variety's bearing area and annual production were well under 400 ha and 2500 tonnes. Source: Authors' compilation from Anderson and Puga (2022b).

It is also not easy to guess how average gross revenue per hectare differs between red and white varieties, since the average price of reds has been much higher than that of whites this century while the average yield per hectare has favoured whites (bottom rows of Table

A2.3). The price difference across the two colours holds in most years, yet the gross revenue per hectare has been almost identical each vintage for the two colours during the past two decades – but with a big divergence in 2022 thanks to the current glut of red wine (Figure A2.7).

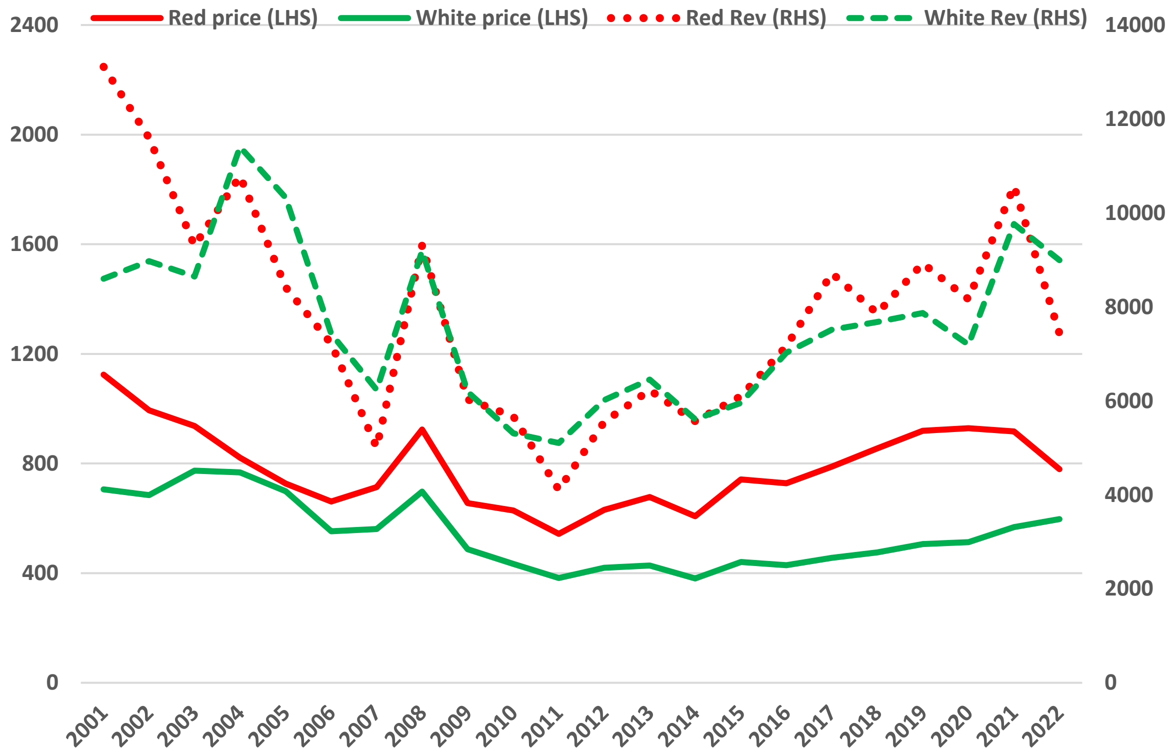

Figure A2.7: Price per tonne (LH axis) and gross revenue per hectare (RH axis) of red and white winegrapes, Australia, 2001 to 2022 (nominal AUD).
Source: Authors' compilation from Anderson and Puga (2022b).

A2.3. Regional data

The regions have been classified based on Jones et al. (2011), according to average growing season temperature (GST), into four groups: Cool (<15ºC), Temperate (from 15º but <17º), Warm (from 17º but <19º), and Hot (≥19º). For present purposes we use the average GST for the period 1989-2019. Over that period, no Australian regions meet the Cool criterion and, apart from Tasmania, the only other regions meeting the Temperate criterion are Coonawarra in SA and the small Victorian regions of Grampians, Henty, Macedon Ranges and Strathbogie Ranges (which together account for less than 10% of the Australian wine industry). However, because their winegrapes are attracting ever-higher prices than warmer regions, their share of the nation's crush *value* has doubled over that period (Figure A2.8).

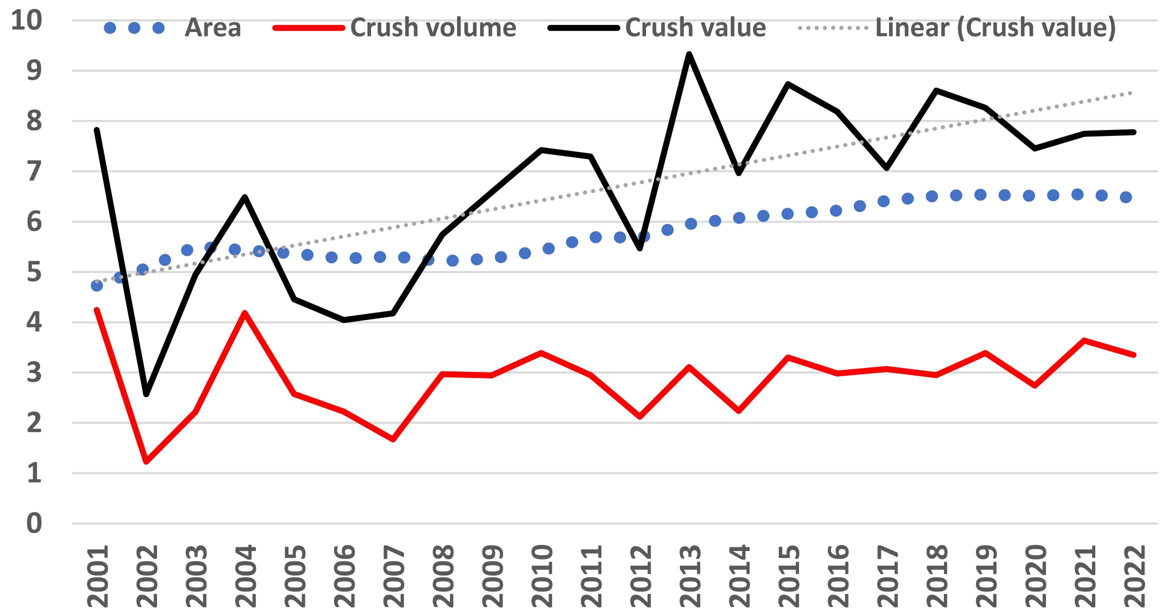

Figure A2.8: Share of Temperate regions[a] in Australia's winegrape area, crush volume, and crush value, 2001 to 2022 (%).

Notes: [a]They are the coolest regions in Australia in terms of average growing season temperature during 1989-2019: Coonawarra, Grampians, Henty, Macedon Ranges, Strathbogie Ranges, and Tasmania. Source: Authors' compilation from Anderson and Puga (2022b).

The gross revenue per hectare range is wider of course at the regional level. While no region except Tasmania has an average above $11,000 over the 2001-22 period, three South Australian regions (two Warm, one Hot) have averages just over $10,000: Adelaide Hills, McLaren Vale, and Wrattonbully. Regions that have among the lowest average gross revenues per hectare also include a mixture of Warm and Hot climates. Of particular note is that average gross revenues per hectare range very widely in the Hot regions, from $9700 in the Riverland, and $8900 in the Murray Darling of NSW, to $7300 in the Murray Darling of Vic, $6000 in the Riverina, and $3900 in the Hunter Valley (Table A2.4). No doubt costs of production per hectare also vary greatly across regions (and across vineyard sizes), but unfortunately there are no comparably comprehensive data available to quantify that.

This heterogeneity across regions in average prices and gross revenues per hectare is reflected in the two indexes reported in Table A2.4, namely the regional quality index and regional productivity index (RQI and RPI). The RQI is the ratio of regional to national average price per tonne of all varieties, while the RPI is the ratio of regional to national average gross value of production per hectare of all varieties. Both have more than a four-fold range, with Tasmania being the highest of each.

Table A2.4: Climate classification, and average yields (t/ha), prices ($/t) and gross revenue per hectare ($) of winegrapes, Australian wine regions, 2001-22 (nominal AUD).

Region	Climate[a]	Yield (t/ha)	Price ($/t)	Gross rev/ha($)	RQI[b]	RPI[c]
Adelaide Hills	Warm	7.3	1461	10777	2.19	1.51
Barossa Valley	Warm	5.9	1532	8674	2.31	1.24
Bendigo	Warm	3.5	1133	4113	1.70	0.51
Canberra District	Warm	3.0	1674	4715	2.54	0.49
Clare Valley	Hot	4.8	1253	6037	1.87	0.82
Coonawarra	Temp.	6.3	1290	8194	1.93	1.13
Cowra	Hot	6.3	742	5099	1.09	0.62
Eden Valley	Warm	4.9	1538	7334	2.31	1.05
Geographe	Hot	4.5	1038	4977	1.54	0.63
Goulburn Valley	Hot	6.9	788	5998	1.29	0.59
Grampians	Temp.	3.7	1418	5363	2.31	0.67
Great Southern	Warm	3.4	1375	5126	2.07	0.66
Heathcote	Warm	4.8	1155	6675	1.82	0.85
Hilltops	Hot	4.3	822	3907	1.54	0.49
Hunter Valley	Hot	3.6	1126	3863	1.69	0.50
Langhorne Creek	Hot	9.0	955	9029	1.41	1.23
Margaret River	Hot	4.9	1429	7371	2.20	1.08
McLaren Vale	Hot	6.7	1509	10034	2.27	1.38
Mornington Peninsula	Warm	3.9	2394	8620	3.67	1.15
Mudgee	Hot	4.5	916	4126	1.33	0.49
Murray Darling/Swan Hill (NSW)	Hot	21.4	434	8905	0.64	1.24
Murray Darling/Swan Hill (Vic)	Hot	17.3	431	7310	0.63	1.02
Orange	Warm	5.2	1103	5819	1.62	0.71
Padthaway	Warm	9.3	996	9366	1.47	1.24
Pyrenees	Warm	1.9	1757	3153	2.84	0.30
Riverina	Hot	14.9	396	5961	0.59	0.84
Riverland	Hot	22.2	427	9689	0.62	1.34
Rutherglen	Hot	5.0	1106	5403	1.68	0.56
Swan District	Hot	7.1	597	6099	1.29	0.60
Tasmania	Temp.	6.0	2647	15717	4.15	2.28

Table A2.4 (cont.): Climate classification, and average yields (t/ha), prices ($/t) and gross revenue per hectare ($) of winegrapes, Australian wine regions, 2001-22 (nominal AUD).

Region	Climate[a]	Yield (t/ha)	Price ($/t)	Gross rev/ha($)	RQI[b]	RPI[c]
Tumbarumba	Warm	4.6	1456	6403	2.39	0.91
Wrattonbully	Warm	8.6	1167	10252	1.73	1.39
Yarra Valley	Warm	4.8	1735	8259	2.63	1.17
All regions		**11.3**	**670**	**70**	**1.00**	**1.00**

Notes: [a]Average growing season temperature for the period 1989-2019 in Temperate (from 15° but <17°C), in Warm (from 17° but <19°), and in Hot (≥19°). [b]Regional quality index (RQI) is the ratio of regional to national average price per tonne of all varieties in that vintage. [c]Regional productivity index (RPI) is the ratio of regional to national average gross value of production per hectare of all varieties in that vintage. Source: Authors' compilation from Anderson and Puga (2022b).

The varietal mixes of most major regions of Australia have converged a lot on the global mix. There are only eight regions whose VSIs vis-à-vis the world has moved by less than one-fifth (left half of Table A2.5). They are Adelaide Hills (0.48 to 0.55), Barossa Valley (0.39 to 0.41) and McLaren Vale (0.45 to 0.47) in South Australia, Grampians (0.35 to 0.37), Mornington Peninsula (0.30 to 0.31) and Yarra Valley (0.44 to 0.46) in Victoria, WA's Swan District (0.37 to 0.40), and Tasmania (0.34 to 0.34).

Table A2.5: Varietal similarity indexes (VSIs), national, state, and regional[a], 2001 and 2022.

	VSI relative to the world			VSI relative to Australia		
	2001	**2022**	**% of 2022 above 2001**	**2001**	**2022**	**% of 2022 above 2001**
AUSTRALIA	0.47	0.66	42	1.00	1.00	0
South Australia	0.46	0.62	34	0.96	0.98	2
New South Wales	0.44	0.66	50	0.97	0.95	-2
Victoria	0.37	0.66	79	0.85	0.96	13
Western Australia	0.50	0.68	35	0.94	0.88	-7
Tasmania	0.34	0.34	0	0.48	0.32	-33
Queensland	0.40	0.58	43	0.94	0.94	1
Adelaide Hills	0.48	0.55	14	0.78	0.63	-19
Barossa Valley	0.39	0.41	6	0.87	0.86	-1
Bendigo	0.33	0.56	70	0.85	0.91	7
Canberra District	0.47	0.61	29	0.90	0.92	3

Table A2.5 (cont.): Varietal similarity indexes (VSIs), national, state, and regional[a], 2001 and 2022.

	VSI relative to the world			VSI relative to Australia		
	2001	**2022**	**% of 2022 above 2001**	**2001**	**2022**	**% of 2022 above 2001**
Clare Valley	0.43	0.52	21	0.90	0.86	-5
Coonawarra	0.43	0.59	36	0.79	0.72	-9
Cowra	0.40	0.56	40	0.83	0.71	-14
Eden Valley	0.33	0.51	52	0.74	0.86	16
Geographe	0.48	0.66	37	0.95	0.86	-9
Goulburn Valley	0.44	0.64	45	0.94	0.96	2
Grampians	0.35	0.37	5	0.92	0.84	-9
Great Southern	0.48	0.62	31	0.94	0.97	2
Hilltops	0.43	0.59	37	0.94	0.93	0
Hunter Valley	0.33	0.44	32	0.76	0.79	4
Langhorne Creek	0.45	0.62	38	0.87	0.94	9
Margaret River	0.49	0.67	35	0.88	0.81	-9
McLaren Vale	0.45	0.47	3	0.94	0.89	-5
Mornington Peninsula	0.30	0.31	4	0.46	0.33	-29
Mudgee	0.44	0.69	58	0.95	0.96	1
Murray Darling/Swan Hill (NSW)	0.37	0.69	87	0.85	0.93	9
Murray Darling/Swan Hill (Vic)	0.26	0.66	156	0.68	0.96	41
Orange	0.45	0.71	58	0.93	0.95	2
Padthaway	0.45	0.65	45	0.90	0.98	9
Pyrenees	0.39	0.61	55	0.89	0.97	9
Riverina	0.41	0.64	56	0.88	0.93	6
Riverland	0.47	0.65	40	0.96	0.97	2
Rutherglen	0.29	0.37	25	0.78	0.74	-5
Swan District	0.37	0.40	7	0.69	0.52	-25
Tasmania	0.34	0.34	0	0.48	0.32	-33
Tumbarumba	0.31	0.39	24	0.51	0.45	-11
Wrattonbully	0.43	0.64	47	0.80	0.85	6
Yarra Valley	0.44	0.46	3	0.69	0.52	-25

Notes: [a]The world's winegrape bearing area's varietal mix refers to 2000 and 2016 (the most recent year available), from Anderson and Nelgen (2020b). See 'Further information on the data used in this study' for the VSI's definition. Source: Authors' compilation from Anderson and Puga (2022b).

To get a clearer idea of the contribution of different varieties to those rising VSIs, it is helpful to generate the varietal intensity index (VII), defined as a variety's share of the bearing area in Australia relative to its share in the world. Shown in Table A2.6 are the top dozen varieties. Apart from Grenache and Pinot Gris, all had VIIs well above one in 2001 but they have declined substantially this century, indicating that their shares in the country's bearing area have grown (or shrunk) less rapidly than in the rest of the world.

Table A2.6: Varietal intensity index[a] of the dozen most-planted varieties in Australia, relative to the world, 2001 and 2021.

Variety	2001	2021
Cabernet Sauvignon	4.2	2.7
Chardonnay	4.9	3.4
Colombard	1.7	1.5
Grenache	0.4	0.4
Merlot	1.3	1.0
Muscat of Alexandria	3.8	1.7
Pinot Gris	0.0	3.2
Pinot Noir	1.9	1.8
Riesling	3.1	1.9
Sauvignon Blanc	1.6	1.6
Sémillon	10.2	6.5
Shiraz	11.3	7.5

Notes: [a]Varietal intensity index (VII) is defined as a variety's share of the bearing area in Australia relative to its share in the global bearing area of winegrapes in the years 2000 and 2016 (the most recent year available), from Anderson and Nelgen (2020b). Source: Authors' compilation from Anderson and Puga (2022b).

The VSIs of regions relative to Australia, by contrast, suggest many smaller regions are differentiating themselves from the large hottest regions along the Murray River. Indeed more than half of the regions listed in Table A2.5 have seen their VSI relative to Australia fall this century, and for four of the cooler regions their VSI relative to Australia has fallen by around one-quarter since 2001 (Adelaide Hills, Mornington Peninsula, Tasmania, and Yarra Valley) while the varietal mix of the big hot irrigated regions has become more similar to the national average according to VSI changes (right half of Table A2.5).

A.2.4. How similar are changes in the varietal mix of exports?

Changes in the shares of the dozen top varieties in vine bearing area, winegrape crush and wine export volumes over the past two decades are shown in Table A2.7. Those dozen varieties account for all but one-ninth of the industry, but their relative importance has changed considerably in that time and most so for volume of exports. Note that for two of these dozen varieties (Chardonnay and Merlot) the export shares have moved in the opposite direction to the area and crush shares, while for Shiraz the area and crush shares have risen a lot while the export share has hardly changed. It remains to be seen whether the recent decline in exports of premium reds (thanks to the high tariffs by China from late 2020) reverses the past two decades' growth in red varietal plantings.

Table A2.7: Shares of the dozen most-planted varieties (and all reds) in Australia's winegrape bearing area, crush and wine export volume, 2001-03 and 2020-22 (%).

	Bearing area		**Crush volume**		**Wine export volume**	
	2001-03	**2020-22**	**2001-03**	**2020-22**	**2001-03**	**2019-21**
Cabernet Sauvignon	18.7	18.3	17.8	15.1	16.8	14.8
Chardonnay	13.7	14.9	17.5	19.8	24.6	22.8
Colombard	1.4	1.0	3.8	3.0	2.8	1.1
Grenache	1.5	1.2	1.6	0.8	1.4	0.4
Merlot	6.1	5.7	6.6	6.1	6.1	6.9
Muscat of Alexandria	2.0	1.3	3.1	3.3	0.8	1.4
Pinot Gris	0.0	3.4	0.0	4.5	0.0	5.7
Pinot Noir	2.7	4.1	1.5	2.5	0.8	1.2
Riesling	2.5	2.2	1.9	1.0	1.0	0.6
Sauvignon Blanc	2.1	4.5	1.7	5.4	1.3	4.2
Sémillon	4.8	2.6	6.3	3.2	6.4	1.0
Shiraz	23.0	29.8	23.4	26.1	27.3	27.6
SUM of ABOVE	**78.5**	**89.0**	**85.2**	**90.6**	**89.4**	**87.7**
Next ten varieties in area in 2020-22	5.1	5.9	6.2	6.6	2.6	3.7
Remaining varieties	16.4	5.2	8.6	2.8	8.0	8.6
TOTAL	**100.0**	**100.0**	**100.0**	**100.0**	**100.0**	**100.0**
% red varieties	***59***	***65***	***57***	***56***	59	58

Source: Authors' compilation from Anderson and Puga (2022b).

A2.5. Final word

The above numbers are but a tiny fraction of the data and indicators compiled by and reported in the approximately 150 tables in Anderson and Puga (2022b). For readers interested in the smaller regions, or the many varieties beyond the top dozen, or the combination of those two (a particular variety in a particular region), the full dataset is freely available in Excel to access at any time at https://economics.adelaide.edu.au/wine-economics/databases#australian-winegrape-vine-area-production-and-price-database-by-region-and-variety-1956-to-2022

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Further information on the data used in this study

Concordance between regions

Since the data for this database come from different sources (listed below), we created a concordance between regions. This concordance uses as its basis the definitions of Australian Geographical Indications (GIs), which are available on the Wine Australia website (https://www.wineaustralia.com/labelling/register-of-protected-gis-and-other-terms/geographical-indications).

Some region names begin with the word 'Other'. These residual regions are often not constant over time (e.g., they may vary across years in their vine area or winegrape production coverage). 'Canberra', listed here as a region of NSW, includes data that are part of the (not included) Canberra ACT region. The Northern Territory is excluded from this database because it is so minor.

Concordance between varieties and their colours

The names of the varieties are based on the prime names as in Anderson and Nelgen (2020b), which are based mostly on Robinson et al. (2012). Just three of Australia's prime varieties in the area data are listed as 'grey', namely Flora, Pinot Gris, and Schönburger. Since they are typically thought of as white wines in Australia, we have classified them as such in this national database. There are three additional minor grey varieties in the wine export data that we classified as white, namely Barbaroux, Perle, and Roter Veltliner.

Years

The years shown refer to fiscal years ending 30 June except for export data, which refer to fiscal years beginning 1 July since almost no wine from a particular vintage is exported before 1 July of that year. Vintage is always in the latter half of the fiscal year, mostly during February-April.

Winegrape bearing area

For the wine regions of South Australia, we used area data from Vinehealth for 2001 to 2022, see Wine Australia (2022a and earlier) and Vinehealth Australia (2014 and earlier). For wine regions in other states, we used winegrape bearing data from Anderson (2015) for 2001-08, 2010, and 2012, which were based on ABS (2015 and earlier), as are our data for 2015.

To estimate the winegrape bearing area by variety for missing years in regions outside South Australia, we first use a five-step methodology to estimate the 2019 areas based on the total vineyard area for 2019 as revealed in a satellite scan by Wine Australia (2019). The first step consists of estimating the bearing area from the total vine area of each non-SA region, which we assumed was lower to the same extent as the bearing to total area for South Australia in that year (0.97). The second step consists of calculating the average yield by variety in each non-SA region, for the 11 years for which there are area, crush and yield data available from ABS (2015 and earlier): 2001-08, 2010, 2012, and 2015. We assume this gives us the 'expected yield' for each variety-by-region combination. The third step consists of estimating the average production by variety for each non-SA region, for the three years 2018, 2019, and 2020, from

Wine Australia (2022b and earlier). We refer to these values as the ‘average production’ for each variety-by-region combination. The fourth step consists of estimating the area by variety and region, for each non-SA region, as: ‘area without any adjustment’ = ‘average production’ / ‘expected yield’. The fifth step consists of adjusting the ‘area without any adjustment’ estimate by multiplying each variety-by-region estimate by a ‘region-specific index’ which is set so that the sum of the area for all varieties in a given region equals the total bearing area in that region as per the 2019 National Vineyard Scan (Wine Australia, 2019) after deflating it as in step 1 above to account for non-bearing areas.

Having so estimated non-SA regional bearing areas by variety for 2019, we then estimated the total area of each region for the years without area data as follows: for 2009, the average of 2008 and 2010; for 2011, the average of 2010 and 2012; for 2013 and 2014, a linear trend from 2012 to 2015; for 2016, 2017 and 2018, a linear trend from 2015 to 2019; and for 2020, 2021 and 2022, we set them equal to 2019 – since the total (including non-bearing) area in SA in 2022 (73226 ha) is very similar to this state's total area in 2019 (73135 ha). Some regions, most of whose names start with the word ‘Other’, are not reported in the 2019 National Vineyard Scan. For those regions, we assumed their area by variety after 2015 is the same as in 2015.

Data for the region Murray Darling – Swan Hill, which spreads across the state border between NSW and Vic (which is the River Murray), are combined for some years. In order to have state-specific area statistics, we divided this region into two: Murray Darling – Swan Hill (NSW) and Murray Darling – Swan Hill (Vic). We assumed that 45% is planted in NSW and 55% in Vic.

The ABS area data for Queensland prior to 2010 included grapes for non-wine purposes. In the subsequent years to 2015 the area was only 32.65% of the 2001-09 average, so we multiplied the Queensland total area by 0.3265 in 2001-09.

For Tasmania, we used Wine Tasmania area data for 2011-21 (personal communication from Wine Tasmania).

In a preliminary article that examined trends just in South Australia (Anderson and Puga, 2022), total winegrape area was used rather than just bearing area.

Winegrape production

For SA regions, we used production data from Vinehealth as published by Wine Australia (2022a and earlier) from 2015 and Vinehealth Australia (2014 and earlier) for previous years. For non-SA regions, the following process applies. First, we used production data from Anderson (2015) for non-SA regions in 2001-08, 2010, and 2012, and ABS (2015) production data for 2015.

For the other years, we relied on production and price data from Wine Australia (Wine Australia, 2022b and earlier) for 2008-22, as follows. Since the 2008-14 data only refer to purchased winegrapes, we generated a regional index for 2015-21 = (production purchased + production own grown) / production purchased. In cases when this index is higher than 10 or when it cannot be calculated, we set it to 10. Then we calculated production as production purchased times that index. As with the area data, Murray Darling – Swan Hill, which spreads across the border between NSW and Vic, appears combined for some years. In order to have state-specific production statistics, we divided this region into two: Murray Darling – Swan Hill (NSW) and Murray Darling – Swan Hill (Vic). We assumed that 45% was produced in NSW and 55% in Vic in those years.

For Qld, we interpolated production for 2009, 2011, and 2013-14 using surrounding year data.

Winegrape prices

Price is a weighted average for the receival prices paid per tonne by wineries to growers. It does not include end-use bonuses or quality adjustments determined post-receival. There is a wide range of different pricing/contractual arrangements, including per hectare pricing, fair market value, achievement of specifications, and adjustments for regional average. Wineries do not supply pricing information for own-grown winegrapes, so they are valued at the same average value as purchased winegrapes in order to determine the total value of winegrapes for each region.

For SA regions, we used price data from Vinehealth as reported by Wine Australia (2022a and earlier) for recent years. For non-SA regions, we used data from Anderson (2015) for 2001-08, 2010, and 2012, and from Wine Australia (2022b and earlier) for 2009, 2011, and 2013-22.

Weighted averages

Across the database, the variables are weighted averages when appropriate. For example, when applicable, yield per ha and revenue per ha are area-weighted averages, and price is a production-weighted average.

Underestimation of winegrape gross revenues

For calculating regional, state, and national gross revenues, we used only those region-by-variety combinations for which there are data on both production and price. There are some region-by-variety combinations for which there are data only for production or price that are not included in the calculation. As a result, some regional, state, and national revenues are underestimated.

Wine sales and inventory volumes

Sourced from Wine Australia (2022c and earlier).

Wine export volumes

The volume of exports of each variety is compiled by Wine Australia and made available at https://marketexplorer.wineaustralia.com/export-dashboard

Varietal similarity index (VSI)

We use the varietal similarity index (VSI) for analysing similarities in the mix of winegrape varieties between two regions. This index was first introduced by Anderson (2010) and it is also known as the regional similarity index. The VSI for regions i and j takes the form:

$$VSI_{ij} = \frac{\sum_{v=1}^{V} f_{i,v} f_{j,v}}{\left(\sum_{v=1}^{V} f_{i,v}^2\right)^{1/2} \left(\sum_{v=1}^{V} f_{j,v}^2\right)^{1/2}}. \tag{1}$$

$f_{i,v}$ ($f_{j,v}$) is the area of variety v in region i (j) as a proportion of the total winegrape bearing area in that region.

The VSI ranges between 0 and 1. The closer the index is to 1, the more similar is the mix of varieties between two regions. An index of 0 indicates a completely different mix of winegrape varieties, while an index of 1 means that both regions have exactly the same varieties and the same proportional area for each of those varieties. We also use equation (1) to compute CSIs between regions and countries, between regions and the world as a whole, and between Australia and other countries or the world as a whole. For the VSIs for 2001 and 2019, we used world data for 2000 and 2016, respectively, from Anderson and Nelgen (2020b).

Climatic classifications

Based on TerraClimate's high-resolution (1/24^{o}, 4-km) monthly data, Gregory Jones averaged them over the period 1989-2019. Jones and many others have found that growing season temperature (GST) is the most representative single indicator of climate insofar as it affects viticulture, so that is used to summarize regional climates by classifying regions as either Cool, Temperate, Warm, or Hot. In Australia, no regions were classified as Cool over that period. Anderson and Nelgen (2020) similarly classified all regions of the world but used TerraClimate's data over the longer period 1958-2019, which was cooler than the more-recent period 1989-2019. Remenyi et al. (2020) have since estimated the GST for Australia's wine regions for the two decades to 2060 and found they average 1.4℃ above the average for the two decades to 2017. That suggests the shares of winegrape regions in Australia (as elsewhere in the world) that are Warm and Hot are rising over time as the Temperate area shrinks. Puga et al. (2022) estimate that this could reduce Australian winegrape prices by 12% by mid-century, assuming no adaptation by vignerons.

Reliability of our estimates of bearing area by variety for non-SA regions in 2019

The area by variety is available for South Australian regions, hence allowing us to compare the estimates of area by region and variety outlined above with the actual South Australian data by region and variety as reported by Vinehealth. Table A2.8 reports the mean and standard deviation of the percentage difference between our estimates and the Vinehealth data for 2019, across regions. This is shown for all varieties combined, as well as for the five most-planted varieties. Positive mean values indicate an overestimated mean area while negative values point to an underestimated mean area. The first columns show the unweighted values, and the last two columns show the area-weighted mean and standard deviation.

Table A2.8: Mean and standard deviation (SD) of the percentage difference between our estimates and the Vinehealth data, across SA regions, 2019.

	Unweighted		Area-weighted	
	Mean	**SD**	**Mean**	**SD**
Shiraz	-1.2	8.6	-0.8	6.4
Cabernet Sauvignon	-5.0	15.2	-0.6	14.9
Merlot	0.6	24.4	7.2	19.6
Chardonnay	-3.4	9.3	1.9	7.6
Sauvignon Blanc	4.4	36.5	14.6	23.5
All varieties	3.4	53.7	0.3	20.0

While the mean area across all varieties is overestimated by 3.4% across regions in SA, the area-weighted mean area is overestimated by just 0.3%. Similarly, the standard deviation across all varieties in SA is quite high at 54%, but the area-weighted standard deviation is much lower at 20%. This suggests that our estimates of area by variety may be most reliable in the largest regions. The standard deviations are also lower for the top five varieties by area (except for the area-weighted standard deviation of Sauvignon Blanc), indicating that our estimates are most reliable for the most-planted varieties.

Another way of testing the reliability of our estimates involves using the VSI. Table A2.9 below shows the VSI between each region using our area estimates for 2019 and the same region using the area data from Vinehealth. The last row of this table shows all the SA regions combined. The average VSI across regions in SA is 0.99, and 1.00 for the state as a whole.

These values are close to perfect alignment, providing confidence in our estimates for non-SA regions.

Table A2.9: Varietal similarity index (VSI) between each region using our area estimates and the same region using the area data from Vinehealth, 2019.

Region	VSI
Adelaide Hills	1.00
Adelaide Plains	0.98
Barossa Valley	1.00
Clare Valley	0.99
Coonawarra	1.00
Eden Valley	1.00
Langhorne Creek	1.00
McLaren Vale	1.00
Padthaway	1.00
Riverland	1.00
Wrattonbully	0.98
All South Australia	1.00

List of tables available in Anderson and Puga (2022b)

This article draws on the data available in Anderson and Puga (2022b). Table A2.10 lists all the tables available in that database, which are freely available at https://economics.adelaide.edu.au/wine-economics/databases#australian-winegrape-vine-area-production-and-price-database-by-region-and-variety-1956-to-2022

Table A2.10: List of tables available in Anderson and Puga (2022b).

Part	Table	Sheet name
Title, index, notes, and concordance	1	Title
	2	INDEX
	3	Notes
	4	Regional concordances
	5	Map of Geographical Indications
Historic viticulture data	6	Area by V from 1956 (ha)
	7	Production by V from 1956 (t)
	8	Yield by V from 1956 (t per ha)
	9	Varietal area from 1956 (%)
	10	V production from 1956 (%)
	11	Area by colour from 1956 (%)
	12	Production by C from 1956 (%)
	13	Area by origin from 1956 (%)
	14	Production by O from 1956 (%)

Table A2.10 (cont.): List of tables available in Anderson and Puga (2022b).

Part	Table	Sheet name
Historic data on wine sales and inventories	15	Wine sales from 1968
	16	Wine inventories from 1990
	17	Wine export volume by V
	18	Wine export volume by V (%)
Historic state-level data	19	Historic state winegrape data
	20	Wine exports by S
Viticulture data	21	Area (ha)
	22	Production (t)
	23	Yield (t per ha)
	24	Price (AUD per t)
	25	Revenue (1000 AUD)
	26	Revenue per ha (AUD)
	27	Area by V (ha)
	28	Production by V (t)
	29	Yield by V (t per ha)
	30	Price by V (AUD per t)
	31	Revenue by V (1000 AUD)
	32	Revenue per ha by V (AUD)
	33	Varietal area (%)
	34	Varietal production (%)
	35	Varietal revenue (%)
	36	Area by colour (%)
	37	Production by colour (%)
	38	Revenue by colour (%)
	39	Area by origin (%)
	40	Production by origin (%)
	41	Varietal Quality Index
	42	Varietal Productivity Index
	43	2001 area VIIs - world
	44	2011 area VIIs - world
	45	2021 area VIIs - world
Viticulture state-level data	46	Area by S (ha)
	47	Production by S (t)
	48	Yield by S (t per ha)
	49	Price by S (AUD per t)
	50	Revenue by S (1000 AUD)
	51	Revenue per ha by S (AUD)
	52	Area by S and V (ha)
	53	Production by S and V (t)
	54	Yield by S and V (t per ha)
	55	Price by S and V (AUD per t)
	56	Revenue by S and V (1000 AUD)

Table A2.10 (cont.): List of tables available in Anderson and Puga (2022b).

Part	Table	Sheet name
Viticulture state-level data	57	Revenue per ha by S and V (AUD)
	58	Area by S (%)
	59	Production by S (%)
	60	Revenue by S (%)
	61	Varietal area by S (%)
	62	Varietal production by S (%)
	63	Varietal revenue by S (%)
	64	Area by S and colour (%)
	65	Production by S and colour (%)
	66	Revenue by S and colour (%)
	67	Area by S and origin (%)
	68	Production by S and origin (%)
	69	State Quality Index
	70	State Productivity Index
	71	2001 state area VIIs - nation
	72	2015 state area VIIs - nation
	73	2021 state area VIIs - nation
	74	2001 S production VIIs - nation
	75	2015 S production VIIs - nation
	76	2021 S production VIIs - nation
	77	2001 S area VIIs - world
	78	2011 S area VIIs - world
	79	2021 S area VIIs - world
Viticulture regional-level data	80	Area by R (ha)
	81	Production by R (t)
	82	Yield by R (t per ha)
	83	Price by R (AUD per t)
	84	Revenue by R (1000 AUD)
	85	Revenue per ha by R (AUD)
	86	Area by R and V (ha)
	87	Production by R and V (t)
	88	Yield by R and V (t per ha)
	89	Price by R and V (AUD per t)
	90	Revenue by R and V (1000 AUD)
	91	Revenue per ha by R and V (AUD)
	92	RVCA
	93	Area by R (%)
	94	Production by R (%)
	95	Revenue by R (%)
	96	Varietal area by R (%)
	97	Varietal production by R (%)
	98	Varietal revenue by R (%)

Table A2.10 (cont.): List of tables available in Anderson and Puga (2022b).

Part	Table	Sheet name
Viticulture regional-level data	99	Area by R and colour (%)
	100	Production by R and colour (%)
	101	Revenue by R and colour (%)
	102	Area by R and origin (%)
	103	Production by R and origin (%)
	104	Regional Quality Index
	105	Regional Productivity Index
	106	2001 area VIIs - nation
	107	2015 area VIIs - nation
	108	2021 area VIIs - nation
	109	2001 production VIIs - nation
	110	2015 production VIIs - nation
	111	2021 production VIIs - nation
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	123	Area by C (%)
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	137	Area by climate (%)
	138	Production by climate (%)
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Table A2.10 (cont.): List of tables available in Anderson and Puga (2022b).

Part	Table	Sheet name
Climate and other area-related data	140	Area by climate and V (%)
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List of varieties	148	Varieties by prime name
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Name of co-author	Kym Anderson		
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Co-author contributions

By signing the Statement of authorship, each author certifies that:

I. the candidate's stated contribution to the publication is accurate (as detailed above);
II. permission is granted for the candidate in include the publication in the thesis; and
III. the sum of all co-author contributions is equal to 100% less the candidate's stated contribution.

Name of co-author	Alfinura Sharafeyeva		
Contribution to the paper	Prepare data for analysis and performed econometric estimations. Contributed to the study conception and design, and to the interpretation and discussion of the results. Edited drafts/versions of the paper and helped responding reviewers' questions.		
Signature		Date 6.06.2023	

Name of co-author	Kym Anderson		
Contribution to the paper	Contributed to the study conception and design, and to the interpretation and discussion of the results. Edited drafts/versions of the paper and helped responding reviewers' questions.		
Signature		Date	

Statement of authorship

Title of paper	Explaining bilateral patterns of global wine trade, 1962-2019
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Principal author

Name of principal author (candidate)	German Puga		
Contribution to the paper	Led the study conception and design (including the econometric models), reviewed the literature, prepared part of the datasets for analysis, and interpreted the results. Wrote drafts/versions of the paper. Presented the paper at a conference to get feedback. Led the review/publication process.		
Overall percentage	70%		
Certification	This paper reports on original research I conducted during the period of my Higher Degree by Research candidature and is not subject to any obligations or contractual agreements with a third party that would constrain its inclusion in this thesis. I am the primary author of this paper.		
Signature		Date	

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Name of co-author	Alfinura Sharafeyeva		
Contribution to the paper	Prepare data for analysis and performed econometric estimations. Contributed to the study conception and design, and to the interpretation and discussion of the results. Edited drafts/versions of the paper and helped responding reviewers' questions.		
Signature		Date	

Name of co-author	Kym Anderson		
Contribution to the paper	Contributed to the study conception and design, and to the interpretation and discussion of the results. Edited drafts/versions of the paper and helped responding reviewers' questions.		
Signature		Date	10/07/2023

Statement of authorship

Title of paper	The impact of the European grapevine moth on grape production: Implications for eradication programs
Publication status	Published
Publication details	Puga, G., Umberger, W., & Gennari, A. (2020). The Impact of the European Grapevine Moth on Grape Production: Implications for Eradication Programs. *Journal of Wine Economics*, *15*(4), 394-402. https://doi:10.1017/jwe.2020.34

Principal author

Name of principal author (candidate)	German Puga		
Contribution to the paper	Led the study conception and design, reviewed the literature, cleaned the data and prepared the dataset for analysis, performed econometric estimations, and interpreted the results. Wrote drafts/versions of the paper. Led the review/publication process.		
Overall percentage	80%		
Certification	This paper reports on original research I conducted during the period of my Higher Degree by Research candidature and is not subject to any obligations or contractual agreements with a third party that would constrain its inclusion in this thesis. I am the primary author of this paper.		
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Name of co-author	Wendy Umberger		
Contribution to the paper	Contributed to the study conception and design, and to the interpretation and discussion of the results. Edited drafts/versions of the paper and helped responding reviewers' questions.		
Signature		Date 06/06/2023	

Name of co-author	Alejandro Gennari		
Contribution to the paper	Contributed to the study conception and design, and to the interpretation and discussion of the results. Edited drafts/versions of the paper.		
Signature		Date	

Statement of authorship

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Principal author

Name of principal author (candidate)	German Puga		
Contribution to the paper	Led the study conception and design, reviewed the literature, cleaned the data and prepared the dataset for analysis, performed econometric estimations, and interpreted the results. Wrote drafts/versions of the paper. Led the review/publication process.		
Overall percentage	80%		
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Name of co-author	Wendy Umberger		
Contribution to the paper	Contributed to the study conception and design, and to the interpretation and discussion of the results. Edited drafts/versions of the paper and helped responding reviewers' questions.		
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Name of co-author	Alejandro Gennari		
Contribution to the paper	Contributed to the study conception and design, and to the interpretation and discussion of the results. Edited drafts/versions of the paper.		
Signature		Date June 21st 2023.	

Statement of authorship

Title of paper	Climate change and the evolving mix of grape varieties in Australia's wine regions
Publication status	Published as conference proceeding
Publication details	Puga, G., Anderson, K., Jones, G., & Smart, R. (2022). Climate change and the evolving mix of grape varieties in Australia's wine regions. *IVES Conference Series Terclim 2022*. https://newives.kinsta.cloud/13153/

Principal author

Name of principal author (candidate)	German Puga		
Contribution to the paper	Contributed to the study conception and design, prepared the data, performed statistical analyses, and interpreted the results. Wrote parts of drafts/versions of the paper. Presented the paper at a conference to get feedback.		
Overall percentage	40%		
Certification	This paper reports on original research I conducted during the period of my Higher Degree by Research candidature and is not subject to any obligations or contractual agreements with a third party that would constrain its inclusion in this thesis. I am the primary author of this paper.		
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Name of co-author	Kym Anderson		
Contribution to the paper	Contributed to the study conception and design, and to the interpretation and discussion of the results. Wrote parts of drafts/versions of the paper.		
Signature		Date	10/07/2023

Name of co-author	Gregory Jones		
Contribution to the paper	Contributed to the study conception and design, and to the interpretation and discussion of the results. Wrote parts of drafts/versions of the paper.		
Signature		Date	

Name of co-author	Richard Smart		
Contribution to the paper	Contributed to the study conception and design, and to the interpretation and discussion of the results. Wrote parts of drafts/versions of the paper.		
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Name of co-author	Kym Anderson		
Contribution to the paper	Contributed to the study conception and design, and to the interpretation and discussion of the results. Wrote parts of drafts/versions of the paper.		
Signature		Date	

Name of co-author	Gregory Jones		
Contribution to the paper	Contributed to the study conception and design, and to the interpretation and discussion of the results. Wrote parts of drafts/versions of the paper.		
Signature		Date June 8, 2023	

Name of co-author	Richard Smart		
Contribution to the paper	Contributed to the study conception and design, and to the interpretation and discussion of the results. Wrote parts of drafts/versions of the paper.		
Signature		Date	

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Name of co-author	Kym Anderson		
Contribution to the paper	Contributed to the study conception and design, and to the interpretation and discussion of the results. Wrote parts of drafts/versions of the paper.		
Signature		Date	

Name of co-author	Gregory Jones		
Contribution to the paper	Contributed to the study conception and design, and to the interpretation and discussion of the results. Wrote parts of drafts/versions of the paper.		
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Name of co-author	Richard Smart		
Contribution to the paper	Contributed to the study conception and design, and to the interpretation and discussion of the results. Wrote parts of drafts/versions of the paper.		
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Title of paper	Two decades of grape variety trends in Australia's wine regions
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Co-author

Name of co-author (candidate)	German Puga		
Contribution to the paper	Prepared the data used in the analyses. Wrote parts of drafts/versions of the paper.		
Overall percentage	20%, but a much larger share of the database in which this appendix draws. The index of that database is available at the end of this appendix.		
Certification	This paper reports on original research I conducted during the period of my Higher Degree by Research candidature and is not subject to any obligations or contractual agreements with a third party that would constrain its inclusion in this thesis. I am NOT the primary author of this paper.		
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Name of co-author	Kym Anderson		
Contribution to the paper	Contributed to the study conception and design, and to the interpretation and discussion of the results. Wrote drafts/versions of the paper.		
Signature		Date	10/072023