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# Assessing the impact of weather variables on the quality ratings of nine wine indexes across four French wine regions: Bordeaux, Burgundy, Rhône and Loire

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19/07/2024

Guilhem Vanden Berghe Naomi Bouton

# Foreword

We would like to express our gratitude to all the people who contributed to the writing of this master's thesis. This milestone in our academic journey would not have been possible without them.

Firstly, we heartfully thank our research supervisor, Professor Leonardo Iania, for his availability, assistance and insightful advice. His guidance, coupled with his expertise and knowledge, enabled us to research and write the best thesis possible.

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Lastly, we would like to thank each other for the hard work, continuous support and smooth collaboration that have defined our journey through this thesis. This partnership has been pivotal for the thesis and an invaluable learning experience.

## Abstract

This research aims to analyse the relationships between climatic conditions and the quality of wines produced in France's most prestigious viticultural regions. Specifically, this study examines wine vintages from 1970 to 2019 across nine Appellation d'Origine Contrôlée (AOC) indices from four French wine regions: Bordeaux (St. Julien/Pauillac/St. Estephe, Pomerol, St. Emilion, Sauternes/Barsac), Burgundy (Côte de Nuits, Côte de Beaune, Burgundy White), Rhône (Côte Rôtie/Hermitage) and Loire (White). This study seeks both to investigate the different impacts of weather variables on the quality of French wines and to explore the similarities and differences among wine regions in aspects such as colour and grape variety. To fulfil this purpose, the research uses four types of regression models (linear, quadratic, semi-log linear and semi-log quadratic) for each of the nine AOC indexes, using quality ratings data from Robert Parker Wine Advocate and weather data from the National Oceanic and Atmospheric Administration National Centers for Environmental Information (NOAA NCEI). The explanatory variables in the regression models include mean temperature, temperature difference measures, precipitation, number of freezing days, the North Atlantic Oscillation (NAO) index and a trend component for non-weather-related improvements. The main findings of this research show that weather variables significantly impact French wine quality. Mean temperature, precipitation and the number of frost days show a significant presence in explaining the wine quality. In contrast, temperature differences and the North Atlantic Oscillation Index show a more limited impact. On a regional level, Bordeaux and Rhône share certain similarities: a strong sensitivity to frost and precipitation extremes, with an explanatory power based solely on weather variables. On the contrary, Burgundy and Loire include the trend variable, yet the explanatory level of this variable remains limited. White wines, particularly those from Loire and Burgundy, show less sensitivity to extreme weather conditions than red wines. These results highlight the crucial role of climate conditions on French Viticulture. It is therefore pivotal to have a better understanding of both the influence of these climate factors and the future impacts that climate change will have on these wine-growing regions, enabling winemakers to learn, pivot and adapt.

## Acronyms

AOC = Appellation d'Origine Contrôlée

NAO = North Atlantic Oscillation

NOAA NCEI = National Oceanic and Atmospheric Administration National Centers for Environmental Information

SOI = Southern Oscillation Index

PDO = Protected Designation of Origin

CV = Coefficient of variation

SD = standard deviation

$s$ = Grape Seasons

$W$ = Winter season (November to February)

$EG$ = Early Growing season (March to April)

$G$ = Growing season (May to August)

$H$ = Harvest season (September to October)

$TAVG_s$ = Average monthly temperature for season $s$

$Diff_s$ = Average monthly temperature difference for season $s$ (monthly maximum temperature – monthly minimum temperature, averaged over season $s$)

$DT32_s$ = Average monthly number of days with minimum temperature below 0 degrees Celsius (32°F) for season $s$

$PRCP_s$ = Average monthly total precipitation for season $s$

$NAO_s$ = Average monthly NAO index for season $s$

VIF = variance inflation factor

Adj. $R$-squared = adjusted $R$-squared

# Table of contents

## List of figures



## List of tables

# 1. Introduction

France, a country well known for its vineyard regions, is currently the world's leading wine producer (Le Figaro, 2023). The country is composed of 17 wine-growing regions and achieved a total production of 45.7 million hectoliters of wine in 2022 (Le Figaro, 2023; Statista, 2023). As for the rest of the world, wine enthusiasts rate French wines across a spectrum from disastrous to superb (Ramirez, 2008). Various factors, such as production methods and vines' health, play a part in determining the quality of these wines. However, according to viticultural research, weather stands out as one of the determining factors influencing wine quality today (Ramirez, 2008). Throughout its life cycle, the grape is influenced by the weather conditions in which it grows, affecting the quality of the resulting wine (Ramirez, 2008).

Simultaneously, climate change and its consequences have taken on a great deal of importance in recent years (Ashenfelter, 2010). The impact of climate change on agriculture, and particularly on viticulture, has become obvious, making its impact on quality a subject of great interest (Jones, White, Cooper & Storchmann, 2005). As a result, regions where the weather is currently favourable, such as various French regions, may not remain suitable in the future. New regions, impacted by climate change, could emerge, resulting in economic winners and losers among producers (Ollat, Touzard & van Leeuwen, 2016).

The focus of this study is to analyse the relationship between various climatic variables and the specific quality rating assigned to certain French wines. More specifically, this paper analyses this relationship for wines of vintage between 1970 and 2019 for nine AOC (Appellation d' Origine Controlée) indexes from different French wine regions: Bordeaux (St. Julien/Pauillac/St. Estephe, Pomerol, St. Emilion, Sauternes/Barsac), Burgundy (Côte de Nuits, Côte de Beaune, Burgundy (White)), Rhône (Côte Rôtie/Hermitage), and Loire (Loire (White)) (See Figure 1 - Appendix 1). Therefore, this study seeks to answer the following research question: "How do weather variables impact the quality ratings of nine different wine indexes (AOCs) in France from Bordeaux, Burgundy, Rhône and Loire wine regions for vintage from 1970 to 2019?". The aim is to understand how different weather variables affect the quality of these French wines and to look at potential similarities and differences between wine regions according to characteristics such as colour and grape variety.

Investigating the question of the impact of weather on wine quality will both confirm knowledge and provide new insights into this increasingly urgent issue. These insights can help producers to better understand grape production and potentially adapt practices to produce high-quality wine in an environmentally and economically sustainable way (Ollat, Touzard & van Leeuwen, 2016). Given the potential impacts of future climate change, the cultural and economic importance of viticulture in France makes this topic a growing social issue (Jones & al., 2005; Ollat, Touzard & van Leeuwen, 2016).

Although some papers already examine the weather-quality relationship for France, either they base their investigation on other quality benchmarks, such as price and other rating index or their investigation only focuses on the Bordeaux wine region (Ashenfelter, 2010; Baciocco, Davis & Jones, 2014; Jones & al., 2005; Wood, Gascoigne, Gambetta, Jeffers & Clouson, 2023). In addition, examining the weather-quality relationship for various French wine regions over the period 1970-2019 extends several previous studies on French wines that stopped before 2010 (Ashenfelter, 2010; Baciocco, Davis & Jones, 2014; Jones & al., 2005; Tsai & Lin, 2020). Moreover, unlike some studies that only include a limited number of weather variables, such as average temperature and the level of precipitation, this study incorporates more diverse climatic factors (Ashenfelter, 2010; Jones & al., 2005). Additionally, as France's climate is less stable than other wine-producing countries and regions such as Chile or California, its analysis adds an extra layer of interest. As such, various papers show that regions and countries with more divergent climates tend to have stronger explanatory power, i.e the ability of the independent variables to explain the dependent variable, leading to more significant and nuanced conclusions (Ashenfelter, 2010; Charlin & Cifuentes, 2023; Cifuentes & Charlin, 2022; Oczkowski, 2016; Ramirez, 2008).

This study is based on a quantitative research approach including data collection, regression models and statistical analysis. This paper focuses on a cross-regional and comparative analysis using different regressions for each AOC wine. Wine quality indexes were collected from the Robert Parker Wine Advocate website. Weather data, including mean, minimum and maximum temperature measures, precipitation, number of freezing days and the North Atlantic Oscillation (NAO) index, were obtained from a US governmental website: the National Oceanic and Atmospheric Administration National Centers for Environmental Information (NOAA NCEI). A trend component was added to account for non-weather-related improvements. Five different regression models were tested for each AOC.

The main findings of this research show that weather variables significantly impact French wine quality. The signs of previously studied variables confirm the formulated hypotheses. Less studied variables, such as temperature difference and the NAO also show an impact:

negative/positive for temperature difference depending on the season while the NAO has a negative effect, although limited. When looking at the regional comparison, Bordeaux and Rhône show similarities: a strong sensitivity to frost and precipitation extremes with an explanatory power based solely on weather variables. On the contrary, the Burgundy and Loire wine regions both include the trend variable. Moreover, red wines under study show more sensitivity to extreme weather variables than white wines. Finally, the complementary analysis highlights the future suitability of the Burgundy wine region for the Côte de Nuits and Côte de Beaune AOCs in the short and medium term.

The research is organised into six different chapters. The paper starts with a review of the existing theoretical and empirical literature as well as a presentation of the tested hypotheses. Chapter three presents the detailed methodology followed by the statistical findings outlined in chapter four.  Then, the study discusses the potential limitations and implications of the study (Chapter 5), ending with a general conclusion.

# 2. Literature review

This literature review begins with a theoretical framework by presenting an overview of the existing studies. It then describes the optimal weather conditions for grapevines and the link to climate change. Afterwards, the main analytical techniques used in the previous papers are presented, along with their findings. Finally, the hypotheses of the study are formulated based on previous sections.

## 2.1 Review of existing literature and theoretical framework

Many studies have analysed the impact of weather on wine quality for different vintages and in different regions. Most of these studies have concluded that the quality of wine, which depends on the quality of the grape, is affected by variations in weather (Ashenfelter, 2010; Charlin & Cifuentes, 2023; Cifuentes & Charlin, 2022; Hayez, 2023; Jones & al., 2005; Oczkowski, 2016; Ramirez, 2008). Many of these studies are based on the idea of the vintage effect: a high-quality wine or a low-quality wine depends on how the grape has been affected by the climatic conditions of the year in question (Ollat, Touzard & van Leeuwen, 2016). However, in certain regions, the weather can be subject to considerable fluctuations (Ashenfelter, 2010). These studies therefore analyse the impact of climatic variables such as temperature and rainfall on different vintages of wines from diverse regions.

Regarding the northern hemisphere, one of the first studies investigates the weather-quality and weather-price relationship for Cabernet Sauvignon from California's Napa Valley from 1970 to 2004 (Ramirez, 2008). The paper tests various models and concludes that weather does have an impact on quality and price, but this impact is stronger for the weather-price relationship (Ramirez, 2008). In 2023, a thesis completed the previous analysis of Californian wines by looking at the impact of weather on the quality of wines from the counties of Sonoma and Napa Valley for four different grape varieties and over a more recent period: from 1978 to 2018 (Hayez, 2023). This paper, which is the first research to include the Southern Oscillation Index (SOI) as a weather variable, found that weather does play a role in wine quality, yet to a limited extent (Hayez, 2023). Concerning Italian wines, Corsi and Ashenfelter looked in 2019 at how various measures of quality based on different expert opinions were determined by regional climatic conditions. Using data from 1970 to 1997, they concluded that weather variables play a role in determining wine quality (Corsi & Ashenfelter, 2019).

In the southern hemisphere, Oczkowski (2016) examined how the weather conditions affect the quality and, subsequently, the price of eight types of Australian premium wine for the vintage

2014. The study highlights that temperature and rainfall play crucial roles in determining wine quality, especially when explaining quality variation between different regions (Oczkowski, 2016). Recently, Cifuentes and Charlin (2022) have given more attention to the southern hemisphere by adding to the literature a paper on Chile's Cabernet Sauvignon and encompassing data up to a recent period: 1982-2019. In 2023, these same authors extended their analysis exploring the weather-quality relationship, this time focusing on Argentinian Malbec wines over a period from 1995 to 2020 (Charlin & Cifuentes, 2023). Both recent studies found that climate, particularly temperature, does have an impact on wine quality, although the impact is relatively modest. It has been shown that in regions with a more stable climate, such as California, Chile or Argentina, the weather does have an effect, although it is less pronounced than in regions with a climate of greater instability, such as Europe (Charlin & Cifuentes, 2023; Cifuentes & Charlin, 2022; Ramirez, 2008).

It is also worth mentioning that various other scientific articles also study the relationship between wine quality and climatic conditions, either using quantitative methods other than regressions or adopting a more theoretical point of view. Nonetheless, these documents can provide valuable insights into the subject matter (Ashenfelter & Storchmann, 2016; Cook & Wolkovich, 2016; Haeger & Storchmann, 2006; Leeuwen & Darriet, 2016; Mira de Orduña, 2010; Ollat, Touzard & van Leeuwen, 2016).

### 2.1.1 France

Ashenfelter was one of the first researchers to take an interest in the weather-quality relationship, notably in his research on Bordeaux wines in 1995, which he republished in 2010. In this paper, Ashenfelter analyses the influence of the weather during the growing season (April to September) on the quality of Bordeaux wines. The author chooses to represent the wine quality variable by the wine price, analysing the weather-quality relationship through the weather-price relationship (Ashenfelter, 2010). Based on market prices from 1990 to 1991 for six Bordeaux châteaux with vintages ranging from 1960 to 1969, Ashenfelter concluded that weather is indeed a key determinant of wine quality (Ashenfelter, 2010). The author found a high $R$-squared of 80%, which is often mentioned in other studies. Using price as a quality index allowed him to achieve a higher $R$-squared than most studies based directly on quality indexes, as it is determined by the supply-demand interaction (Cifuentes & Charlin, 2022). This difference in explanatory power is also confirmed by, Oczkowski (2016) and Ramirez (2008), who both increased their $R$-squared by 20-50% using prices.

In another study considering French wines, conducted by Jones et al. in 2005, the impact of temperature on wine quality across different regions of the world, such as Europe and America, is investigated. The research uses regression data covering the 1950 to 1999 period and bases the wine's quality on Sotheby’s vintage ratings. Afterwards, the author proposes a predictive model for potential future temperature changes from 2000 onwards. For France, the wine regions analysed are Bordeaux, Burgundy (Côte d’Or and Bojelais), Rhône, Alsace, Loire and Champagne. The analysis of the different regressions concludes that growing season temperature (April to October in the Northern Hemisphere and October to April in the Southern Hemisphere) significantly impacts the wine quality for most US and European regions. Specifically, temperature is significant for all regions of France except Burgundy-Côte d'Or (Jones & al., 2005).

In 2014, Baciocco, Davis and Jones also conducted a study on the differentiation of different climatic variables on a consensus rating of Bordeaux wines. Using data from 1961 to 2009, the authors carried out various statistical analyses, separating red wines from sweet wines (Baciocco, Davis & Jones, 2014). The study concludes that most weather variables are consistent for Bordeaux wines, with some variables having a greater impact on white or red wines depending on the grape life cycle season (Baciocco, Davis & Jones, 2014).

A few years later, Tsai and Lin (2020) analysed the viticulture conditions of French wines from 1970 to 2010 using the LASSO regression method. They took into account more diverse climatic factors compared to other studies, such as water balance, atmosphere, the North Atlantic Oscillation Index (NAO), etc. The authors concluded that the climate-wine quality relationship could indeed be established based on the various climatic factors used (Tsai & Lin, 2020).

Finally, the link between weather variables and quality scores of Bordeaux wines has been studied again in a recent study using data from 1950 to 2020 (Wood & al., 2023). Based on different sources of quality data, the paper concludes that weather variables are determining factors in the quality of Bordeaux wines by comparing the regional and local impact (Wood & al., 2023).

## 2.2 Climate and viticulture

### 2.2.1 Grapevine life cycle and optimal climate conditions

Wine production depends on the grapevine life cycle, spanning from winter dormancy to grape harvest (Apallas, 2016; Ashenfelter & Storchmann, 2016). In the various papers, authors generally divide the life cycle of the grapevine into four distinct seasons, depending on whether the vineyard is located in the southern or northern hemisphere (Oczkowski, 2016). Concerning the northern hemisphere, from November to February, vines enter a dormant state due to the winter conditions, helping to synchronise the future growing period (Ashenfelter & Storchmann, 2016; Jones & al., 2005). The growing season, which runs from March to August, is characterised by distinct stages including bud break, followed by bloom, and finally resulting in berry growth and coloration (Ashenfelter, 2010; Ashenfelter & Storchmann, 2016; Cifuentes & Charlin, 2022; Hayez, 2023; Ramirez, 2008). Many studies divide this growing season into two or three sub-seasons to allow greater flexibility in the impact of weather variables. These studies refer to the early-growing and growing seasons (Cifuentes & Charlin, 2022; Hayez, 2023; Ramirez, 2008). Finally, in September and October, the grape begins to ripen, indicative of the harvest season (Apallas, 2016; Ashenfelter, 2010; Ashenfelter & Storchmann, 2016; Cifuentes & Charlin, 2022; Hayez, 2023; Ramirez, 2008).

At each stage of the grapevine's life cycle, various weather variables can exert a distinct impact on the development of the berries, altering their size, sugar content, acidity, and colour, with consequences for the quality of the wine produced (Ashenfelter & Storchmann, 2016). For example, excessive rain or drought in the wrong seasons can have a significant impact on the final quality of the product (Ashenfelter & Storchmann, 2016). As a result, certain optimal climatic conditions have emerged from the studies, depending on the stage of the grapevine's life cycle. For instance, wine quality is favoured by high temperatures during the growing seasons contributing to optimal levels of sugar, acid and flavour while cold temperatures during the winter season mitigate the risk of vine damage (Ashenfelter, 2010; Baciocco, Davis & Jones, 2014; Charlin & Cifuentes, 2023; Cifuentes & Charlin, 2022; Cook & Wolkovich, 2016; Corsi & Ashenfelter, 2019; Hayez, 2023; Jones & al., 2005; Ramirez, 2008; Wood & al., 2023). However, researchers have shown that the notion "the warmer the better" during the growing season is not always true. As such, high temperatures are beneficial only up to a certain threshold, after which they can have a deleterious effect on wine grapes and create unbalanced wines (Ashenfelter, 2010; Ashenfelter & Storchmann, 2016; Charlin & Cifuentes, 2023;

Cifuentes & Charlin, 2022; Hayez, 2023; Jones & al., 2005; Leeuwen & Darriet, 2016; Mira de Orduña, 2010; Oczkowski, 2016; Ramirez, 2008). In addition, some studies and theories show that frost negatively affects grapevines, by reducing the number of developing shoots and damaging them (Ashenfelter & Storchmann, 2016). Ashenfelter and Storchmann (2016) as well as Leeuwen and Darriet (2016) highlight this negative impact during spring whereas Cifuentes and Charlin (2022) in their study on Chilean wines, also found a significant negative impact during winter. Concerning rainfall, wet winter and wet early growing seasons have been shown to have a positive impact on quality (Ashenfelter, 2010; Cifuentes & Charlin, 2022; Cook & Wolkovich, 2016; Corsi & Ashenfelter, 2019; Ollat, Touzard & van Leeuwen, 2016; Ramirez, 2008; Wood & al., 2023). Although adequate rainfall is crucial to vine health, rain during the late growing and harvest seasons can prove detrimental to the vines by diluting the concentration of berries (Ashenfelter, 2010; Ashenfelter & Storchmann, 2016; Baciocco, Davis & Jones, 2014; Charlin & Cifuentes, 2023; Cook & Wolkovich, 2016; Corsi & Ashenfelter, 2019; Oczkowski, 2016; Ramirez, 2008). As with the intuition on temperature, a too high precipitation level can become detrimental to the grape (Ramirez, 2008).

While the authors share these optimal conditions, it is important to note that the impact of weather variables may still vary slightly depending on certain factors. First, due to climate variability affecting their weather threshold, the impacts may vary between regions (Ashenfelter & Storchmann, 2016; Leeuwen & Darriet, 2016). In addition, white and red wines may not react in the same way to climatic conditions, given their distinct skin-derived components, such as pigment and tannin (Gladstones, 1992, as cited in Ashenfelter & Storchmann, 2016). As red wines depend more on these components and because the berry skin is the most sensitive part of the fruit, red wines may show more sensitivity to extreme weather conditions (Gladstones, 1992, as cited in Ashenfelter & Storchmann, 2016). Moreover, grape varieties with their different growth and ripening patterns may require different climatic conditions, leading to different responses to weather factors (Oczkowski, 2016).

Some weather factors appear less frequently in studies and theory. As a result, there is no clear consensus on the optimal conditions linked to these factors. For example, this is the case for the temperature difference, which recurs in some studies but with different impacts. In her study of Californian wines, Hayez (2023) found that the temperature difference had a significant positive impact for most varieties, while Oczkowski (2016) in his study of Australian wines concluded that the impact during the growing season, when it was significant, was negative. Cook and Wolkovich (2016) found a significant positive impact during the harvest season.

#### 2.2.1.1 North Atlantic Oscillation (NAO) index

Another component that comes up in very few studies is the North Atlantic Oscillation (NAO) index. This index describes the fluctuations in the difference in atmospheric pressure at sea level in the North Atlantic region, more specifically between the Icelandic Low and the Azores High (Met Office, 2024). Since the NAO is linked to changes in the intensity and location of the North Atlantic jet stream and storms, as well as changes in the usual patterns of heat and moisture movement, it can create anomalies in temperatures and precipitation in several regions, including Europe (NOAA NCEI, 2024). The impact of the NAO is mainly studied during the winter and early growing months, spanning from December to March. However, it may also exhibit long-term patterns that impact the months following the winter season (Lindsey & Dahlman, 2009; Rafferty, 2011).

The NAO index is characterised by positive and negative phases, which have opposite effects on the climate of the areas affected (See Figure 2 – Appendix 2). When the NAO is in a positive phase, high pressure over the Azores and low pressure over Iceland can be observed. During a negative phase of the NAO, the same pressure patterns can be seen in the same places, although described as weak (Rafferty, 2011). During the winter season, when the NAO is in a positive phase, there is a high chance of above-normal temperatures and precipitation in northern Europe, while southern Europe will experience a drop in storms and below-normal precipitation (Lindsey & Dahlman, 2009; Met Office, 2024; NOAA NCEI, 2023; Rafferty, 2011). On the contrary, when the NAO index is in a negative mode, this brings below-normal temperature and precipitation in northern Europe and above-normal precipitation and storms in the south. In summary, a positive NAO tends to make northern Europe warmer and wetter and southern Europe drier, while a negative index will make northern Europe colder and drier and southern Europe wetter (Met Office, 2024).

Some studies have demonstrated that the NAO index does impact the quality of wines in certain European regions. In 2012, three authors analysing the relationship between climate and wine quality in the north-west region of Spain showed that the NAO had a significant positive impact during the bloom stage, i.e. between June - July (Lorenzo, Taboada, & Ramos, 2012). In 2020, Tsai and Lin in their study on certain French regions, observed that the NAO had a significant impact on wine quality. They found a negative impact in November and May and a positive impact in June and July for the Champagne region. The following year, a study about the impact of climate change on the quality of Slovakian wines also demonstrated the significance of the

NAO index, with a positive coefficient in March and April and a negative one in May and June (Jeřábek, Tvrzník, Málek & al., 2021).

### 2.2.2 Climate change and viticultural regions

Nowadays, the evidence of climate change and its impact on Earth is undeniable. As such, human activity, through greenhouse gas emissions, has an impact on the Earth's energy balance and hence on its climate (IPCC, 2023; Jones & al., 2022). The first direct impact of this activity is global warming, which creates widespread changes in biodiversity, oceans, sea levels, etc. (IPCC, 2023). According to the NASA Earth Observatory (2024), the temperature has risen by at least 1.1°C since 1880. In France, the increase in temperature has reached 1.7°C over the last decade and is forecast to continue rising (Ministère de la transition écologique et de la cohesion des territoires, 2022). Various scenarios show projected temperature rises in France over the next few years, reaching 2°C in 2030, 2.7°C in 2050 and 4°C in 2100 (Fraccaro, 2024; Ministère de la transition écologique, 2022).

Climate change has a direct impact on agriculture, and therefore viticulture, by causing extreme weather events such as droughts, heat waves and heavy rainfall (IPCC, 2023; Jones & al., 2005). As explained above, berries, like any other fruit, are directly affected by the weather and climate around them (Jones & al., 2005). As a result of global warming and its impact on crop production, there is a risk that grapes may no longer enjoy the optimal conditions they once did. As climate change is not uniform geographically or varietally, each wine-growing region and grape variety will be affected differently (Jones & al., 2005). Some regions may therefore no longer be suitable for optimal grape production (Hannah & al., 2013; Jones & al., 2005). In some regions, warming is likely to exceed the optimum temperature threshold, while in others the increase might bring them closer to the optimum. (Jones & al., 2005). This could lead to a northward shift in production areas, creating winners and losers (Ashenfelter & Storchmann, 2016). Several studies show that the suitability of regions such as the Mediterranean wine regions (southern Europe) will decline sharply, while regions further north in Europe could become more favourable in the future (Hannah & al., 2013; Jones & al., 2022; Santos & al. 2020).

However, many studies mention adaptation strategies to limit the impact of climate change on grapes, such as replanting, optimised irrigation, adapted plant material and the use of new varieties (Hannah & al., 2013; Leeuwen & Darriet, 2016). Compared with other regions, Europe, and France in particular, is limited when it comes to these adaptation strategies

(Ashenfelter & Storchmann, 2016). Several European regions have introduced strict regulations on the quality of the wine produced (Santos & al., 2020). In France, there is the notion of terroir, which refers to a limited geographical area from which wine production draws its particularities through a certain number of factors such as the soil, the know-how put in place over centuries and the climate present in the geographical area (Greenpeace, 2019; INAO, 2024). This concept of terroir is the foundation of the "Appellation d' Origine Controlée" (AOC) concept, used in this study. The AOC designation displays that a product comes from a particular terroir which confers special characteristics (INAO, 2024). The AOC meets the criteria of the PDO (Protected Designation of Origin), a European sign that protects the name of a product (INAO, 2024). Climate change and certain adaptation strategies would therefore cause these wines to lose their unique characteristics and their specificity built up over centuries (Greenpeace, 2019). Successfully adapting to climate change without compromising French wines' distinctive qualities and aromatic complexity might be challenging (Greenpeace, 2019).

## 2.3 Technique deployed

This section of the literature review shall investigate the methodology as well as the findings of selected relevant previous research briefly presented above.

As discussed previously, many studies have tackled the issue of climate conditions over wine quality in different wine regions in the world. A review of existing literature reveals a diversity of data sources employed to define wine quality. Expert quality ratings, as seen in previous studies, are often used as a valid proxy for quality. As such, while some previous studies have relied on either using Wine Spectator or Robert Parker as renowned reviews to determine wine quality over time or more specific wine expert sources, other studies find a consensus between multiple published quality ratings to avoid biases in their analysis (Baciocco, Davis & Jones, 2014; Cifuentes & Charlin, 2022; Cook & Wolkovich, 2016; Corsi & Ashenfelter, 2019; Hayez, 2023; Oczkowski, 2016; Ramirez, 2008; Tsai & Lin, 2020; Wood & al., 2023). Regarding climatic impacts on wine quality, there is a consensus in the literature about the use of weather data. Temperature and precipitation emerge as the most frequently analysed climate factors due to their well-known impact on vine growth and grape quality. In addition to these, a trend variable is usually used to account for non-weather-related improvements in quality over time. Furthermore, some studies incorporate unique weather-related variables such as cloudiness, frost days, SOI, NAO, drought, the difference between maximum and minimum temperature or even winery-specific variables depending on their respective dataset (Charlin & Cifuentes, 2023; Cifuentes & Charlin, 2022; Cook & Wolkovich, 2016; Hayez, 2023; Oczkowski, 2016; Tsai & Lin, 2020). Regarding the methodology, many researchers construct multivariate linear and/or quadratic regressions and argue onwards the results of their model (Charlin & Cifuentes, 2023; Cifuentes & Charlin, 2022; Corsi & Ashenfelter, 2019; Hayez, 2023; Jones & al., 2005; Oczkowski, 2016; Ramirez, 2008; Wood et al., 2023).

As such, Jones et al. (2005), examine the relationship between climate factors and wine quality across various global wine-producing regions from 1950 to 1999 with Sotheby's vintage ratings. The research uses averaged weather data for growing (from April to October in the Northern Hemisphere and from October to April in the Southern Hemisphere) and dormant season (from November to March in the Northern Hemisphere and from May to September in the Southern Hemisphere) to build 27 time series for each season. Assuming initially a linear relationship between growing season temperatures and wine quality, the paper builds a first model:

***Equation 1***

$$R_{i,t} = \alpha_{0,i} + \alpha_1 \cdot temp_{i,t} + \beta_1 \cdot trend_i + \varepsilon_{i,t} \tag{1}$$

In this first model, $R_{i,t}$ represents the rating of wine vintage and $temp_{i,t}$ signifies the mean temperature during the growing season for vintage $t$ in region $i$. To account for non-climatic quality improvements over time, a trend variable is incorporated.

As a temperature threshold exists beyond which higher temperatures may not correspond to improved quality ratings, a quadratic term $temp_{i,t}^2$ is included in the model.

***Equation 2***

$$R_{i,t} = \alpha_{0,i} + \alpha_1 \cdot temp_{i,t} + \alpha_2 \cdot temp_{i,t}^2 + \beta_1 \cdot trend_i + \varepsilon_{i,t} \tag{2}$$

Jones et al. (2005) uses also this quadratic form to compute, through the first derivative, an estimated optimum of the growing season temperature for the wines under study and their region. This is mostly done to grasp whether certain regions already exceeded their optimum in terms of temperature or not. In addition, it allows the research to identify the future impacts of global warming on specific regions.

***Complementary analysis***

$$\frac{\partial R}{\partial temp} = \alpha_1 + 2\alpha_2 \cdot temp = 0$$

$$\equiv temp_{opt} = \frac{-\alpha_1}{2\alpha_2}$$

The study concludes that the temperature during the growing season from 1950 to 1999 increases the vintage quality ratings. The linear model (Equation 1) showed that variations in growing season temperatures significantly impacted vintage ratings in 16 out of 30 studied regions. The quadratic model (Equation 2) enhanced the linear model by incorporating potential non-linear impacts. This model showed a significant improvement, with many French regions possibly being near their ideal climatic conditions. The quadratic terms increase the $R$-squared for French regions by 5%. Overall, the regressions in the French sub-regions showcased adjusted $R$-squared ranging from 10% to 44% for the linear models and from 25% to 50% for the quadratic models. In contrast, for many non-French wine regions, the relationship between growing season temperatures and wine quality was less straightforward. Several new world regions, such as parts of the U.S., showed no significant or even a slight negative relationship between temperature and wine ratings. Conversely, emerging wine regions like Australia, Chile, and South Africa saw increased wine ratings that did not appear directly linked to climatic conditions.

A second interesting study, conducted by Ramirez (2008) which investigates further a potential non-linear relationship between quality and climate factors, utilises a longitudinal dataset of Cabernet Sauvignon wines from Napa Valley rated by Wine Spectator between 1970 and 2004. This paper separates the six-month growing and harvest temperature data into three two-month distinct periods: early growing (April – May), growing season (June – July), and harvest season (August – September) to allow the temperature effects to be non-linear. Similarly, it splits the precipitation data into four averaged distinct periods: winter precipitation period (January - February), early growing season precipitation period (April -May); late growing precipitation (June - July) and harvest precipitation period (August - September).

After designing similar models to equations 2 and 3 and building on the methodologies of Jones et al. (2005), this paper, states that wine ratings can be expressed as a potentially non-linear function of climatic factors, such as a log-log transformation or a quadratic equation.

***Equation 3***

$$R_t = f(\text{trend,temperature,precipitation}) \qquad (3)$$

Inspired by the work of Ashenfelter (2008) and Ashmore and Lalonde (1995), this study examines firstly the impact of introducing quadratic terms for precipitation and temperature on the predictive accuracy of the ratings. Additionally, the research confronts the issue of multicollinearity often present in quadratic models and introduces a log-linear regression. This means that the function logarithmic was applied to both the dependent and independent variables.

The paper finds similar conclusions from the linear and log-linear regressions, indicating that temperature and precipitation influence ratings. However, the overall explanatory power of the regression models was somewhat limited with respectively 29.12% and 28.19% of adjusted $R$-squared for the linear and log-linear regressions. Lastly, even though the quadratic regression showcases a higher adjusted $R$-squared (30.68%), the author argues that due to the multicollinearity introduced by the quadratic variables, the paper cannot draw additional insights from the coefficient values.

Among other studies worth mentioning is the paper written by Charlin and Cifuentes (2023) which examines the relationship between the Malbec wine from Argentina and its weather. As such, the paper separates the year into four distinct wine seasons: the winter season "W" (November - February), the early-growing season "G1" (March-April), the growing season "G2" (May-August), and the harvest season "H" (September-October).

The study carries three different multivariate regressions with Wine Spectator ratings and uses diverse weather-related variables: the average of the minimum and maximum daily temperature (Tmax & Tmin), the most extreme values of the season (Max(Tmax) and Min(Tmin)), the humidity, the cloudiness (Cloud) and the number of days with a temperature above 32°C. Nevertheless, this model does not incorporate a trend variable, arguing about the potential presence of multicollinearity.

The first model, in equation 4, finds its relevance by using the same approach as Ashenfelter (2008).

***Equation 4***

$$R_i = \alpha_0 + \beta_1(Rain_{G1})_i + \gamma_1(Rain_{G2})_i + + \beta_2(Temp_{G1})_i + \gamma_2(Temp_{G2})_i + \varepsilon_i \tag{4}$$

Secondly, the second model, shown in equation 4, is considered the most important framework of the study by incorporating more weather-related variables. It aligns closely with the methodologies previously adopted by Ramirez (2008) and Oczkowski (2016).

***Equation 5***

$$R_i = \alpha_0 + \alpha_1(Tmax_W)_i + \alpha_2(Cloud_W)_i + \beta_1(max(Tmax_{G1}))_i + \beta_2(Cloud_{G1})_i + \gamma_1(Temp_{G2})_i + \gamma_2(Temp_{G2})_i^{\,2} + \gamma_3(max(Tmax_{G2}))_i + \gamma_4(Cloud_{G2})_i + \delta_1\left(TempH_i\right)^2 + \delta_2(min(Tmin_H))_i + \delta_3(Cloud_H)_i + \varepsilon_i \tag{5}$$

Lastly, the third and final model presented uses the same variables as model 4, with the addition of an index to differentiate between wineries. As discussed before, even though most weather-related variables of the three models tested are statistically significant at a level of 1%, the models crafted showcase low explanatory rates with respectively 3.2%, 7.3%, and 24.9% for models 1, 2 and 3. This is due to the stability of the weather in that region which does not mean that weather conditions are irrelevant but rather that a stable climate demonstrates fewer variations in climate conditions with impacts less important on the wine quality.

The last research which takes a similar approach is the analysis of Hayez in 2023 on the impact of climate variables on the quality ratings of four Californian wine varieties. The paper uses Robert Parker wine ratings as a proxy for the quality of wines and utilises weather data coming from the NOAA National Centers for Environmental Information which are split into the following wine seasons: the winter season (November to February), the early-growing season (March to April), the growing season (May to August) and the harvest season (September to October). The paper builds different models, yet the following one is the most relevant:

***Equation 6***

$$Z_{i,t} = \beta_0 + \beta_1 AT_{G,i} + \beta_2 AT_{G,i}^2 + \beta_3 AT_{E,i} + \beta_4 Prec_{h,i} + \beta_5 Prec_{w,i} + SOI + trend_i \tag{6}$$

In this model, $Z_{i,t}$ represents the transformed rating of wine vintage *t* for variety *i* (as explained later in this research), $AT_{G,i}$ $and$ $AT_{G,i}^2$ is the mean temperature and the mean temperature squared during the growing season for the variety $i$. The variable $AT_{E,i}$ represents the average temperature during the early growing season. $Prec_{h,i}$ $and$ $Prec_{w,i}$ are the precipitations during the harvest and winter season respectively. The SOI variable is the Southern Oscillation Index, and the trend is the non-weather-related variable.

The result of this study shows that the wines from the specific region under study do not depend much on weather-related variables. Despite adj. $R$-squared going from 45% to 60% and most variables significant in most seasonal models, the study emphasises that the trend variables account for much of the results for certain wines, especially varieties such as the Pinot Noir and the Chardonnay. The former regressions without the trend variable lose 45% and 46% in explainability respectively. This means that the weather-related variables do not explain as much of the variability in the wine qualities as in other regions of the world, mainly due to the stability of the weather in that region.

## 2.4 Hypotheses

Based on the optimal conditions drawn from the literature review (section 2.2.1), eight different hypotheses were formulated for this research:

**H1**: High average temperature during the growing season (May to August) will positively impact the quality of French wine.

*Warm summers provide optimal levels of sugar, acidity and flavour.*

**H2**: Lower average temperature during the winter (November to February) season will positively impact the quality of French wine.

*Cold winters mitigate the risk of vine damage.*

**H3**: The quadratic average temperature during the growing season will negatively impact the quality of French wine.

*After a certain threshold, temperatures can have a deleterious effect on the vines and create unbalanced wines.*

**H4**: A high level of rainfall during the winter and early growing (March to April) season will positively impact the quality of French wine.

*Enough rain during the winter and early growing season is crucial to the health and development of the vines.*

**H5**: A high level of rainfall during the growing and harvest season (September to October) will negatively impact the quality of French wine.

*Rain during the growing and harvest seasons can damage vines by diluting the concentration of berries.*

**H6**: The quadratic average precipitation will negatively impact the quality of French wine.

*After a certain threshold, precipitation can have a deleterious effect on the vines and create unbalanced wines.*

**H7**: The number of days with a minimum temperature below 0 degrees will negatively impact wine quality.

*Frost can considerably reduce developing shoots and damage them, whatever the season.*

**H8**: The North Atlantic oscillation index will impact the quality of French wine.

*The NAO can impact the quality of wines, but finding a clear consensus on the direction of its impact seems difficult (see detailed explanation in section 2.2.1.1).*

# 3. Methodology

## 3.1 Research objective

This paper analyses and examines the relationships between climatic conditions and the quality of wines produced in France's most prestigious viticultural regions. The study focuses on nine AOC indexes in the Bordeaux (St. Julien/Pauillac/St. Estephe, Pomerol, St. Emilion, Sauternes/Barsac), Burgundy (Côte de Nuits, Côte de Beaune, Burgundy (White)), Rhône (Côte Rôtie/Hermitage), and Loire (Loire (White)) wine regions from 1970 to 2019 (See Figure 1 – Appendix 1). It seeks to explain how various weather variables affect the quality of these French wines and to look at the potential similarities and differences between wine regions according to characteristics such as colour and grape variety. This study addresses the following research question: "How do weather variables impact the quality ratings of nine different wine indexes (AOCs) in France from Bordeaux, Burgundy, Rhône and Loire wine regions for vintage from 1970 to 2019?".

The research is based on quantitative methodology including hypotheses, data collection, regression models, the use of Rstudio as a modelling tool, and the analysis of statistical results. This paper will focus on a cross-regional and comparative analysis using different regressions for each AOC index.

## 3.2 Data collection

This study is based on three types of data: wine quality as the dependent variable, and weather and trend variables as the independent variables. The wine quality is defined by quality indexes provided by Robert Parker Wine Advocate for different wine sub-regions of France, covering the period from 1970 to 2019. The weather variables are obtained from four meteorological stations, including general components such as temperature (minimum, maximum, mean, freezing days) and precipitation, as well as the Nort Atlantic Oscillation Index. These were downloaded from November 1969 to November 2019, reorganised into wine seasonal variables and aligned with the quality rating of the corresponding vintage. Following the established literature, the weather variables are divided into four distinct seasons: the winter season (from November of year *t*-1 to February), the early growing season (from March to April), the growing season (from May to August) and the harvest season (from September to October). In addition, a trend variable has been added to consider weather-independent improvements in quality, represented by a scale from 1 to 50.

### 3.2.1 Robert Parker Wine Advocate

Historically, studies have predominantly utilised either pricing or expert ratings as indicators of quality (Ashenfelter, 2010; Cifuentes & Charlin, 2022). Even though price is a valid indicator in economic theory to determine consumer preferences and perceived quality, this research will focus on the use of expert quality ratings as done in certain prior research (Charlin & Cifuentes, 2022; Jones et al., 2005; Oczkowski, 2016; Ramirez, 2008). Specifically, in this study, Robert Parker's ratings are used as an indicative measure for assessing the quality of wines. Several previous authors, like Corsi and Ashenfelter (2019), also base their studies on the Robert Parker quality ratings. Robert Parker is known as one of the world's greatest wine tasters and wine critics, with its rating system being the standard for wine quality criteria. In the late 1970s, he began publishing commentaries and anecdotes on wines, leading to the publication of his first quarterly wine magazine, “The Wine Advocate”. Robert Parker founded this independent magazine intending to share unbiased opinions on wines from around the globe. Over the years, the magazine has stood out for its objectivity and quality (Vinatis, 2024). Subsequently, the Robert Parker Wine Advocate website was launched, bringing together the various wine-related publications (Robert Parker Wine Advocate, 2023).

Robert Parker Wine Advocate offers a wine rating system that evaluates the quality of wines on a scale of 50 to 100. Robert Parker himself or other experts from his reviewer team assign scores to the wines, denoted by the characteristic "RP" at the beginning of the score. A higher score indicates better overall quality at the time the wine was tasted. Each year, Robert Parker and his rating experts provide comprehensive wine quality averages for significant wine regions around the world in the "Vintage Charts" (Robert Parker Wine Advocate, 2023). These wine quality indexes represent averages of all the quality ratings given to the corresponding AOC in the regions studied for a specific year. As such, this research will use nine published rating indexes from 1970 to 2019 for the following AOC wines: St. Julien/Pauillac/St. Estephe, Pomerol, St. Emilion, Sauternes/Barsac, Côte de Nuits, Côte de Beaune, Burgundy (White), Côte Rôtie/Hermitage, Loire (White). Each quality index varies in its computation and is based on different quantities and types of wines (colour and grape variety) each year (Table 1). While each AOC contains 50 observations (one quality index per year), these are calculated and based on thousands of wine tastings. The detailed wine composition, as well as the Robert Parker scale, are described in Appendix 3.

Table 1: Wine Regions and Wine types

| Wine Region | AOC | Color | Grape Variety |
|---|---|---|---|
| Bordeaux | St. Emilion | Red | Blend |
| Bordeaux | St. Julien/Paulliac/St. Estephe | Red | Blend |
| Bordeaux | Pomerol | Red | Blend |
| Bordeaux | Sauternes/Barsac | White | Blend |
| Burgundy | Côte de Beaune | Red | Pinot Noir |
| Burgundy | Côte de Nuits | Red | Pinot Noir |
| Burgundy | All over | White | Chardonnay |
| Rhône | Côte Rôtie/Hermitage | Mix | Blend |
| Loire | All over | White | Chardonnay/Chenin Blanc |

*Source: Table prepared by the authors*

The collection of these data was done manually as Robert Parker's website does not have any automated or integrated user-friendly export function. Given that the ratings are reported with both a score and maturity letter, an Excel file was used to store the data and split the wine indexes into two main components: the rating ranging from 50-100 and the maturity letter. Since the maturity of wines is not the focus of this research, they were stored but not used further in the analysis. Finally, the data for each of the nine AOCs was stored in different Excel files with 50 rows representing the wine indexes from 1970 to 2019.

### 3.2.2 Climate data

To analyse the impact of climatic variables on the quality of French wines, the weather variables in this study were collected from the National Oceanic and Atmospheric Administration National Centers for Environmental Information (NOAA NCEI), as done previously by Hayez (2023) and Tsai and Lin (2020). The NOAA NCEI is an environmental information agency providing a variety of products, services, and data on the environment in the US and around the world. It provides access to a variety of data ranging from ocean chemistry data and meteorological station records to space weather data (NOAA National Centers for Environmental Information, 2023). NOAA NCEI (2023) data aims to support organisations across all sectors to perform economically and environmentally safely in this fast-changing world. This agency is an official organisation of the U.S. government, ensuring the reliability of its data (NOAA National Centers for Environmental Information, 2023).

In the Data Search tab, the NOAA NCEI provides a dataset of monthly meteorological elements for different regions and countries, including France: the 'Global Summary of the Month'. In addition, under the climate monitoring tab, the environmental information agency also offers information and data on the North Atlantic Oscillation (NAO) index. For this study, raw data from the Merignac, Dijon, Lyon and Tour weather stations, as well as data from the monthly

NAO index, have been downloaded for each month from November 1969 to November 2019. After converting this data into Excel format and incorporating the monthly NAO index as a weather variable for each weather station, the dataset for each station comprised 601 lines representing each month over the 50 years considered.

To align the weather variables with the quality ratings for the vintage in question and to take account of the different stages in the life cycle of the grape, the data have been restructured. The quality of the grape, which directly determines the quality of the wine, depends on weather conditions throughout its life cycle, i.e. from November of the previous year to the end of October when the grapes are harvested. Furthermore, previous studies have shown that the optimum climatic conditions differ according to the stage of the grape life cycle. Therefore, based on the aggregate literature, monthly climate variable data for each of the meteorological stations were aggregated into four distinct seasonal periods: the winter season *W* (November to February), the early-growing season *EG* (March to April), the growing season *G* (May to August) and the harvest season *H* (September to October). For each vintage *v* corresponding to a quality rating, an average of each weather variable was calculated for every stage of the grape lifecycle. These seasonal averages of the weather variables represent the independent variables in this research. It is important to note that for a quality rating of vintage *v*, the average calculated for the winter season includes the months of November and December of year *t*-1.

Then, each viticultural region was assigned to the nearest meteorological station: the four different quality indexes for the Bordeaux wine region were assigned to the Merignac station, the three indexes for the Burgundy wine region were assigned to the Dijon station, the index for the Rhône wine region was assigned to the Lyon station and finally, the index for the Loire wine region was assigned to the Tour station (See Figure 1 - Appendix 1). Considering different stations within France allows the research to highlight the potential variability of the climate between these four French regions, whose climates can differ significantly. France is often divided into four distinct climate areas based on temperature and precipitation: oceanic (Bordeaux and Loire), continental (Burgundy and Rhône), and Mediterranean and mountain climates (France, 2024). However, within a region, the different AOC indexes, which represent different wine sub-regions, are linked to the same weather station. Local weather within the same region is so similar that going into such detail contributes minimally to the study (Lecocq & Visser, 2006).

#### 3.2.2.1 Average temperature, total precipitation, difference temperature, number of days with a minimum temperature below 0 °C (32°F).

In the Global Summary of the Month dataset, five elements were downloaded to derive four distinct weather variables for each season. Firstly, like most authors who have carried out studies on the subject, the average monthly temperature, expressed in degrees, and the total monthly rainfall, expressed in mm, have been collected. These two components, which appear in almost all the studies, are factors on which the optimal conditions for grapes have been confirmed by most authors and on which it is easy to draw hypotheses (H1 to H6). The minimum and maximum monthly temperatures, expressed in degrees, as well as the number of days per month with a minimum temperature below 32°F or 0 °C were also gathered. Then, the difference between the maximum and minimum temperature has been computed to have a variable monthly temperature difference. Adding components other than just temperature and precipitation seemed to be an interesting way of adding explanatory powers to the models. Although fewer authors have mentioned frost, as the literature shows, some studies and theories have drawn conclusions that allow a hypothesis to be formulated (H7). As for the difference between maximum and minimum temperature, as shown in the literature there seems to be no consensus as to the impact of this component.

#### 3.2.2.2 North Atlantic Oscillation (NAO) index

In addition to the four weather variables presented above, the study also includes the North Atlantic Oscillation index (NAO). Given its potential impact on climatic variables and hence on wine quality, it seemed worthwhile to add this index to the weather variables. The North Atlantic Oscillation index is often calculated monthly, based on a statistical analysis comparing the NAO model with the monthly anomalies (NOAA NCEI, 2023). As with the Global Summary of the Month, the NAO index is then calculated for each season of the grapevine lifecycle. Calculating the NAO on the same basis as the grape's lifecycle enables this study to grasp the potential variability of its impact, offering a more detailed and nuanced perspective.

As the North Atlantic Oscillation index affects both temperature and precipitation, its impact on wine quality seems uncertain. For instance, based on the aggregate literature review, during the dormant season of the grapevine life cycle, lower temperatures and more precipitation are favourable for grape quality. However, the NAO index, whether positive or negative, can potentially impact one of these climatic variables in a direction opposite to its optimal state (See Figure 2 - Appendix 2). Moreover, given France's geographical position between southern and northern Europe, it is quite complex to formulate a precise hypothesis regarding the impact of the NAO index on wine quality for these wine regions (H8).

### 3.2.3 Trend variable

The study also included a trend variable as an independent variable to account for non-weather-related improvements in quality over time, a method used by several authors. This trend variable reflects the idea that wine ratings have increased over time due to technological improvements resulting from the accumulation of experience and knowledge (Charlin & Cifuentes, 2023; Jones & al., 2005; Ramirez, 2008). As detailed by Jones et al. (2005), the trend starts with a value of 1 in 1970 and increases by one unit each year, reaching a value of 50 by 2019.

## 3.3 Data description

The final dataset consists of nine different Excel files for each quality index, each containing 50 rows (years studied) and 22 columns representing the study's variables. For each year, the dataset includes a quality index as well as the independent variables: the trend and the five weather variables for each of the four seasons.

### 3.3.1 Summary statistics

The summary statistics of all variables used in this research (quality ratings and climate variables) are given in Table 2 and Appendix 4. As such, they include the mean, standard deviation (SD), coefficient of variation (CV), minimum value (Min) and maximum value (Max) of each variable.

Regarding quality ratings, it is striking to see that the wine sub-regions of Bordeaux show both high consistency in quality scores and relatively low coefficients of variation. As such, the AOC St. Julien/Paulliac/St. Estephe has the highest quality ratings mean, amounting to 88.61, with the second lowest coefficient of variation in the quality ratings dataset (0.07). Moreover, the AOCs Sauternes/Barsac, St. Emilion, and Pomerol also show a highly consistent quality rating means at least exceeding 86 for the three of them, yet with slightly higher coefficients of variation (< 0.1). Regarding the Burgundy wine region, the quality rating means are often slightly lower than those of the Bordeaux sub-regions. The AOCs Côte de Beaune and Côte de Nuits highlight the lowest quality averages, with 85.07 and 85.46, respectively, with higher coefficients of variation (0.10 and 0.13, respectively). The AOC Burgundy White showcases interestingly a very similar pattern to the wines in the Loire wine region, with quality averages respectively amounting to 86.91 and 86.19 and with coefficients of variation lower than 0.09. Lastly, the wines from the Rhône wine region under study (Côte Rôtie/Hermitage) have a high mean among the wines (87.78), with a coefficient of variation of 0.09.

Table 2: Summary Statistics Quality Ratings

| Wine Region | AOC | Mean | Median | Min | Max | SD | CV |
|---|---|---|---|---|---|---|---|
| Bordeaux | St. Emilion | 87.11 | 88.00 | 59.00 | 99.00 | 7.76 | 0.09 |
| Bordeaux | St. Julien/Paulliac/St. Estephe | 88.61 | 88.00 | 72.00 | 99.00 | 6.46 | 0.07 |
| Bordeaux | Pomerol | 88.65 | 89.00 | 58.00 | 98.00 | 7.60 | 0.09 |
| Bordeaux | Sauternes/Barsac | 86.48 | 88.00 | 68.00 | 98.00 | 7.99 | 0.09 |
| Burgundy | Côte de Beaune | 85.07 | 87.00 | 51.00 | 96.00 | 8.57 | 0.10 |
| Burgundy | Côte de Nuits | 85.46 | 88.00 | 51.00 | 98.00 | 10.69 | 0.13 |
| Burgundy | All over | 86.91 | 88.00 | 65.00 | 97.00 | 6.79 | 0.08 |
| Rhône | Côte Rotie/Hermitage | 87.78 | 89.00 | 58.00 | 98.00 | 7.69 | 0.09 |
| Loire | All over | 86.19 | 86.50 | 68.00 | 96.00 | 6.05 | 0.07 |

*Source: Table prepared by the authors*

Concerning the temperature variables, it is evident that Bordeaux showcases the higher average temperatures for each wine season on average with 7.77°C in winter, 11.05°C in early growing, 19.28°C in growing and 16.55°C in harvest season (Appendix 4). The Bordeaux wine region also showcases the lowest coefficient of variation during the winter (0.15) and early growing (0.11) seasons, which means that its temperatures are relatively more stable during these periods than the other regions under study. Following Bordeaux, the wine regions Loire and Rhône are considerably similar in terms of mean temperature, yet Loire is only warmer in the winter (5.76°C) and Rhône is slightly hotter during the early growing (9.56°C), growing seasons (19.19°C) and Harvest seasons (15.10°C). Regarding their coefficient of variations, they are in most cases higher than the Bordeaux wine region, especially in the winter season with 0.19 and 0.26 for Loire and Rhône respectively. Lastly, the Burgundy wine region is the coldest area in terms of mean temperatures over the years, except during the growing season where Loire is colder than Burgundy with 17.65°C and 18.11°C respectively. Its weather varies a lot during the winter season as its variation coefficient is the highest of them all (0.30), yet more stable during the other seasons, especially in the growing and harvest seasons, where it is comparable to the Bordeaux wine region. Overall, the winter season is where one can observe the most temperature variation, followed by the early growing season, the harvest season, and the growing season.

The variable that tackles the difference between the highest and lowest temperature is very similar from one wine to another each season. These numbers always increase in value from the winter season to the growing season before decreasing slightly at the harvest. Its variation is rather low each season, regardless of the wine region.

When it comes to precipitation, the Bordeaux wine region is where it rains the most during the winter with an average of 92.68 mm. All three other wine regions have similar precipitation amounting to around 60 mm of rain during this period. The early growing season is still marked by Bordeaux with the most rain, followed by the Rhône wine and the two other wine regions with similar amounts of rain. On the contrary, during the growing season, the Burgundy and Rhône wine regions have the highest amount of rain with 67.94 mm and 76.36 mm respectively. It is followed by Bordeaux(60.87mm) and Loire (51.21mm). Lastly, during the harvest, Rhône is still the location with the most rain and Loire the least rain. However, Bordeaux has the second most rain compared to Burgundy. In terms of variability, all wine regions have similar coefficients of variation over all seasons. This coefficient increases heavily from the winter season to the early growing season and from the growing season to the Harvest season, which means that the early growing and Harvest seasons are the most variable seasons in terms of rainfall.

Furthermore, the NAO variable is the same in every wine region as it impacts equally each area. Interestingly, its value is positive during winter and early growing and negative during the two other seasons with a very positive coefficient of variation during the first two seasons and highly negative the following ones. Lastly, the variable encompassing the freezing days acknowledges that it freezes more overall in the Burgundy wine region, followed by Loire, Rhône, and Bordeaux, yet it shows more variability in the Bordeaux wine region and least variability in the Burgundy wine region during all seasons.

### 3.3.2 Temperature and quality evolution

The evolution of the quality indexes and the temperature variables over the 50 years concerned was analysed. For each quality index and temperature variable from each meteorological station, the trend of its evolution was plotted and its evolution over the 50 years was calculated using regression coefficients (Appendix 5). This analysis allows for the examination of trends, delivering insights into these components' trajectories.

Regarding temperature, the average annual temperature has risen from 1.58 degrees to 2.74 degrees over the 50 years, depending on the weather station (Table 4). Burgundy and the Loire have experienced the smallest increase, with a rise of 1.58 and 1.99 degrees respectively. On the other hand, Bordeaux and the Rhône are the wine regions with the largest increases, experiencing a rise of 2.42 and 2.74 degrees respectively over the 50 years. Looking at the change in temperatures by season, the greatest increase in temperature occurs in the early growing season, with a rise of up to 3.65 degrees, whereas the lowest change occurs during the winter period, with a rise of no more than 1.78 degrees over the 50 years.

Table 4: Average Temperature Growth from 1970 to 2019

| **Wine Region** | **$TAVG_W$** | **$TAVG_{EG}$** | **$TAVG_G$** | **$TAVG_H$** | **$TAVG_{Yearly}$** |
|---|---|---|---|---|---|
| Bordeaux | 1.54 | 3.21 | 2.86 | 2.52 | 2.42 |
| Burgundy | 1.22 | 1.10 | 1.73 | 1.61 | 1.58 |
| Rhône | 1.78 | 3.65 | 3.28 | 2.71 | 2.74 |
| Loire | 1.36 | 2.50 | 2.38 | 2.01 | 1.99 |

*Source: Table prepared by the authors*

Of the nine quality indices, those for Côte de Beaune and Côte de Nuits, both representing red Burgundy wines, show the most significant increase, with a rise of 19.62 and 24.87 quality points respectively over the 50 years (Table 5). The quality index for St. Emilion, Sauternes/Barsac and Burgundy white has increased each by about 13 to 14 quality points over this period. In contrast, the quality index for St. Julien/Paulliac/St. Estephe, Pomerol, Côte Rôtie/Hermitage and the Loire showed the lowest change in quality, ranging from 9.75 points for Pomerol to 12.05 points for the Loire. Analysing these results at a regional level, Burgundy stands out with the best quality evolution over the period concerned. The other three wine regions, Bordeaux, the Rhône and Loire, show similar quality evolution with an average increase of 11 to 12 quality points over the 50-year period.

Table 5: Quality Mean Growth from 1970 to 2019

| **Wine Region** | **AOC** | **Quality Mean Growth** |
|---|---|---|
| Bordeaux | St. Emilion | 13.33 |
| Bordeaux | St. Julien/Paulliac/St. Estephe | 10.31 |
| Bordeaux | Pomerol | 9.75 |
| Bordeaux | Sauternes/Barsac | 13.14 |
| Burgundy | Côte de Beaune | 19.62 |
| Burgundy | Côte de Nuits | 24.87 |
| Burgundy | All over | 13.88 |
| Rhône | Côte Rôtie/Hermitage | 11.18 |
| Loire | All over | 12.05 |

*Source: Table prepared by the authors*

## 3.4 Statistical models

### 3.4.1 Model type

Several regressions have been carried out for each AOC wine and its quality index. As a reminder, the regressions are conducted on each quality index separately. This approach allows the research to highlight the differences in impacts among these indexes and the potential variances in the optimal weather threshold for each weather station. For each index, five different models were tested: the linear, quadratic, log-linear, semi-log linear and semi-log quadratic models. Except for the log-linear model, all the weather variables for each season were initially included in each model. Then, each model of each index was refined by choosing the best composition of variables, resulting in the five best models based on the adjusted $R$-squared.

#### 3.4.1.1 Linear and quadratic model

The first model to be conducted is the linear model. It can be seen as the baseline model because of its large use by numerous authors and as it serves as a foundation for all the following models. For example, Jones et al. (2005) and Cifuentes and Charlin (2022) initially employed a linear model, one using only temperature and trend and the other one incorporating other weather variables, as in this study. For this first model, which assumes a linear relationship between the quality index and the weather variables, the following regression was applied:

$$R_v = \beta_0 + \beta_1 TREND_v + \sum_{s=1}^{4}(\beta_{2,s} TAVG_{s,v} + \beta_{3,s} Diff_{s,v} + \beta_{4,s} DT32_{s,v} + \beta_{5,s} PRCP_{s,v} + \beta_{6,s} NAO_{s,v}) + \varepsilon_v \quad (1)$$

The dependent variable $R_v$ represents the quality indexes of vintage $v$ spanning from 1970 to 2019. Each independent variable in the model corresponds to a specific vintage, denoted by the index $v$. The $TREND$ variable represents the wine improvements that are not related to the weather. The regression model is composed of five weather variables: $TAVG$ for the average temperature, $Diff$ for the temperature difference between maximum temperatures and minimum temperatures, $DT32$ for the number of days where the minimum temperature is below 0°C (32°F), $PRCP$ for total precipitation and finally $NAO$ for the North Atlantic Oscillation Index. Each of these variables is associated with a specific season $s$ in the grape's growth cycle: winter (*W*), early growing (*EG*), growing (*G*), and harvest (*H*). For example, the variable $TAVG_{W,v}$ corresponds to the average temperature of the winter season for vintage $v$.

The second model used, which is inspired by the first linear model and very present in the literature review, is the quadratic model. This model builds on the linear model by adding two weather components to the independent variables: $TAVG^2$ and $PRCP^2$. Studies have shown that adding these quadratic variables can increase the adjusted $R$-squared of the model, and therefore its explanatory power. As with the weather variables in the linear model, the quadratic variables are associated with each season $s$ for each vintage $v$. The quadratic model applied is:

$$R_v = \beta_0 + \beta_1 TREND_v + \sum_{s=1}^{4}(\beta_{2,s} TAVG_{s,v} + \beta_{3,s} Diff_{s,v} + \beta_{4,s} DT32_{s,v} + \beta_{5,s} PRCP_{s,v} + \beta_{6,s} NAO_{s,v} + \beta_{7,s} TAVG_{s,v}^2 + \beta_{8,s} PRCP_{s,v}^2) + \varepsilon_v \qquad (2)$$

Several authors have also applied this quadratic model to capture the potential non-linear relationship between quality ratings and both temperature and precipitation. Temperature can have a positive effect on wine quality, but only up to a certain threshold. A too-high temperature can be detrimental to the grape and overripen it, producing unbalanced wines (Jones & al., 2005; Oczkowski, 2016; Ramirez, 2008). The same reasoning applies to rainfall.

### 3.4.1.2 Log-linear model

The third model which investigates non-linear effects is the log-linear model. This model is based directly on the linear model but applies a logarithmic transformation to all the variables in the model. As presented in the literature review, Ramirez (2008) applies this log-linear model. The quadratic model, which emphasises the non-linear relationship between the dependent variable and the independent variables, can potentially lead to problems of multicollinearity. Although several sources stress that this multicollinearity due to a variable and its quadratic term do not pose a problem, the author tried to represent this non-linear relationship with another type of model. The application of this logarithmic transformation occurs directly in modifications to variables of the linear model. Since the $DT32$ variables can take values of 0, a value of 1 was added to all of them to facilitate the transformation. In addition, since the $NAO$ includes many negative values, it was excluded from this model. The following regression for the log-linear model was therefore applied:

$$log\,(R_v) = \beta_0 + \beta_1 log\,(TREND_v) + \sum_{s=1}^{4}(\beta_{2,s} log\,(TAVG_{s,v}) + \beta_{3,s} \log\,(Diff_{s,v}) + \beta_{4,s} \log\,(DT32_{s,v}) + \beta_{5,s} \log\,(PRCP_{s,v})) + \varepsilon_v \qquad (3)$$

After analysing the results, it was decided not to present this model in the statistical results. Except for one AOC index, the log-linear model showed a lower adjusted $R$-squared compared to the four other models tested in this study. In some cases, this decrease is even quite significant, with up to a 20% reduction in explanatory power. Furthermore, as the results do not differ materially from those of the linear model, the model does not provide any additional insights. Finally, the exclusion of the NAO variable further reduces the interest in this model.

**3.4.1.3 Semi-log linear and semi-log quadratic model**

Following the initial three models, this paper investigates the semi-log linear and semi-log quadratic models. This merely means that the quality ratings are transformed before performing the regressions. The main reason behind this transformation is that the quality ratings are bounded between 50 and 100, and linear regressions can have a dependent variable of any value, which means that it could go under 50 or over 100. As such, one way to deal with that potential issue is to transform the explanatory variable to bound it between 0 and 1. This transformation is crucial as it enhances the model's reliability and validity.

To do so, the quality ratings were subtracted by 50 and divided by 50 ($R_v{}'$). This allows the quality ratings to be bounded between 0 and 1. It is important to note that the quality ratings which were equal to 50 were added one unit to ensure that the transformation would not cause any errors. As such, a probabilistic regression (logistic) would therefore be more suitable for this type of explanatory variable as it gives the probability of an event happening. However, the literature shows that by applying a function $ln\left(\frac{R_v{}'}{1-R_v{}'}\right)$ (equation 4c) to the former transformation, a multiple linear regression can be used to estimate the dependent variables (Kantar, 2021; Hayez, 2023).

$$P(X)_i = Y_i = \frac{1}{1 + e^{-(\beta_0 + \beta_1 X_{1,i} + \cdots + \beta_n X_{n,i})}} \tag{4a}$$

$$\frac{Y_i}{1 - Y_i} = exp\left(\beta_0 + \beta_1 X_{1,i} + \cdots + \beta_n X_{n,i}\right) \tag{4b}$$

$$ln\left(\frac{Y_i}{1 - Y_i}\right) = \beta_0 + \beta_1 X_{1,i} + \cdots + \beta_n X_{n,i} \tag{4c}$$

(Hayez, 2023; Kanade, 2022; Kantar, 2021)

Therefore, this last transformation was applied to the quality ratings bounded between 0 and 1. According to previous research, the ratings after such transformation maintain similar patterns and proportional statistics so that it suggests that the transformation does not alter the proportional relationships within the quality ratings (Hayez, 2023). The regression of the semi-log linear and semi-log quadratic models are therefore used:

$$ln(\frac{R_{v'}}{1 - R_{v'}}) = \beta_0 + \beta_1 TREND_v + \sum_{s=1}^{4}(\beta_{2,s} TAVG_{s,v} + \beta_{3,s} Diff_{s,v} + \beta_{4,s} DT32_{s,v} + \beta_{5,s} PRCP_{s,v} + \beta_{6,s} NAO_{s,v}) + \varepsilon_v \tag{5}$$

$$ln(\frac{R_{v'}}{1 - R_{v'}}) = \beta_0 + \beta_1 TREND_v + \sum_{s=1}^{4}(\beta_{2,s} TAVG_{s,v} + \beta_{3,s} Diff_{s,v} + \beta_{4,s} \mathrm{DT32}_{s,v} + \beta_{5,s} PRCP_{s,v} + \beta_{6,s} NAO_{s,v} + \beta_{7,s} TAVG_{s,v}^2 + \beta_{8,s} PRCP_{s,v}^2) + \varepsilon_v \tag{6}$$

Even though these models are very similar to the linear and quadratic, it is important to present them in the findings as they are likely to improve the significance of variables as well as the adjusted $R$-squared of certain regressions. Lastly, they can be used as predictors and deal with the limitation of unbounded linear regressions.

### 3.4.2 Best model

For each type of model and each AOC index, the best model was found by evaluating all variable combinations to find the composition fitting best the data. To do so, the first step in building each of these best models was to analyse the correlation between the variables, using Pearson's correlation coefficient. The correlation represents the strength of the relationship between two variables (Siegel, 2012). If the correlation coefficients are too high, i.e. too close to -1 or 1, including these over-correlated variables in the model can lead to incorrect interpretations (Tsai & Lin, 2020). As Oczkowski (2016) and Charlin and Cifuentes (2023) did in their research, over-correlated variables were removed from the models. Based on a correlation threshold of 0.85, it was observed that the variables $TAVG_W$ and $DT32_W$ were highly correlated across the different data sets (Appendix 6). Considering the best model results, the variable $DT32_W$ was retained based on the adj. $R$-squared. The winter average temperature, as well as its quadratic form, are therefore not included in any of the models.

The second step was to test the multicollinearity of the models with all the variables. Strong multicollinearity occurs when two variables are highly similar, which can affect the model's coefficients (Siegel, 2012). If the two variables are too identical, the model lacks sufficient information to identify which one truly explains the impact on the dependent variable (Siegel, 2012). The consequences can then be an inflation of the standard errors and a reduction in statistical power, decreasing the detection of significant links between variables (Kyriazos & Poga, 2023; Siegel, 2012). To measure this multicollinearity, the variance inflation factor (VIF) was computed for each of the models. This factor measures the extent to which multicollinearity increases the variance of the regression coefficients (Kyriazos & Poga, 2023). Theory often refers to a VIF threshold of 5 or 10 to detect strong multicollinearity (Kyriazos & Poga, 2023; Jong Hae, 2019; James, Witten, Hastie & Tibshirani, 2013). James et al. (2013), speak of moderate multicollinearity between 5 and 10, while a value above 10 is said to be unacceptable. In this study, an intermediate threshold of 8 was used to detect strong multicollinearity while allowing some flexibility in the selection of variables to construct the best model.

Several variables were subsequently removed. The $DT32_G$ variable, mainly composed of zero values, was removed directly for all the AOC indexes. For the Côte Rôtie/Hermitage AOC, the variable $TAVG_{EG}$ was eliminated from all models because of its multicollinearity with the variable $DT32_{EG}$. For the Loire wine region, the variable $Diff_{EG}$ was excluded from all models. When two variables showed a high VIF value due to their similarity, the variable leading to the highest adj. $R$-squared was retained. Concerning the trend variable, Charlin and Cifuentes (2023) mention that the variable can present problems of multicollinearity, requiring careful consideration. The trend variable only showed high multicollinearity in the Côte Rôtie/Hermitage models, leading to its removal from these models. Regarding the quadratic models, the quadratic variables exhibit very high multicollinearity due to the presence of their linear terms in the models. However, several sources claim that strong multicollinearity emerging from a variable and its quadratic term can be safely ignored (Allison, 2012; Corporate Finance Institute; 2024; Frost, 2024).

As the models contained many variables, it was necessary to find the model fitting best the data for each index. There are several possible methods for selecting models, among others, the highest $R$-squared, adjusted $R$-squared, or the lowest AIC are the most common methods. The adjusted $R$-squared method was chosen because it balances model fit with the number of variables, penalising unnecessary complexity. As such, using the best subset selection of variables based on the adjusted $R$-squared allows for reliable identification of the best model. This balances goodness-of-fit with model simplicity and it also avoids overfitting and ensures better generalisation to new data (James & al., 2013). In practice, this involved using the "regsubsets" function in Rstudio to identify the best variables for each model. Each AOC thus had five best regressions with different adjusted $R$-squared values and variables, amounting to a total of 45 regressions. However, as explained above, the results of the log-linear model were not taken into account for various reasons. The results are based on the four other model types so 36 regressions.

### 3.4.3 Regression model assumptions

For each of the 36 regressions, the different assumptions on which linear or quadratic regression models are based have been tested to be aware of the potential limitations and biases in the results. Each of these hypotheses was evaluated based on the results of statistical tests confirmed by graphical analysis. Firstly, the linearity assumption implies that the relationship between the dependent variable and the coefficients of the independent variables is linear (Greene, 2011). This hypothesis was tested by looking at the distribution of the residuals of the model, using the Reset test as well as the residuals vs fitted graph values (Tiplica, 2022). Secondly, the assumption of homoscedasticity, which reflects the idea that the variance of the model is constant, was tested using the Breusch-Pagan test (Greene, 2011; Tiplica, 2022). The third assumption is the independence of residuals. This assumption was verified by the Durbin-Watson test (Tiplica, 2022). Finally, the hypothesis that the residuals are normally distributed has been tested through diverse methods including the quantile-quantile plot, the histogram of the residuals and tests such as the Lilliefors test, the Anderson-Darling test, the Shapiro-Wilk test, etc. (Tiplica, 2022).

The hypotheses results are shown in Appendix 8, based on decisions derived from tests and graphs, with a threshold p-value of 5% used. As can be seen, linearity is a problem for the first linear model for half of the AOCs regressions as well as for the quadratic model. Following the semi-logarithmic transformation, linearity improves and is only a problem for two AOC indexes in the semi-log linear and semi-log quadratic models. As for the other hypotheses, they are generally verified, with a few exceptions. It is mainly the Sauternes/Barsac and Pomerol AOCs that pose problems of homoscedasticity and normality in certain models. In the quadratic model, homoscedasticity is not verified for Côte de Nuits and Loire. In the semi-log quadratic model, the homoscedasticity is not verified for St. Julien/Pauillac/St. Estephe and the normality of the residuals for Côte de Beaune. The limitations associated with the non-validation of certain hypotheses will be discussed in more detail later.

# 4. Statistical results

This section of the study, separated into two main parts, presents the results of the regression models. Firstly, through a cross-analysis, the results of the four types of models for the nine AOCs, totalling 36 best model regressions, are presented to draw general insights and compare them with existing literature. The second part examines afterwards the differences and similarities between the wines from the four wine regions: Bordeaux (St. Julien/Paulliac/St. Estephe, St. Emilion, Sauternes/Barsac, and Pomerol), Burgundy (Côte de Nuits, Côte de Beaune, and Burgundy White), Loire (Loire White) and Rhône (Côte Rôtie/Hermitage). As a reminder, the four regression types used are the linear model, the semi-log linear model, the quadratic model, and the semi-log quadratic model. Presenting the cross-tabulated results of these four best models ensures the robustness of the findings and provides an overview of the overall results. In addition, as the two semi-log models improve the assumptions of the regression models, it allows the study to see whether the results of the models are consistent and whether one model, specifically, stands out.

## 4.1 Part I: Comparison of model types and variable coefficients

Across the four types of models and the nine indexes, the signs of the coefficients of each of the variables included in the best models are fairly identical and follow the optimal conditions presented in the literature review. Furthermore, for each AOC, the results of the four different best models are relatively similar, especially between the two linear models and the two quadratic models respectively. These similarities within the 36 regressions allow the study to draw general results regarding the significant variables at a level of at least 10%. In this first part, these conclusions will be compared with the hypotheses. The detailed results of each of the four best models for each AOC are presented in Appendix 7 and summarised in Tables 7 and 8.

### 4.1.1 Model types

Firstly, comparing generally the four model types, the variables included in the best models for each of the AOC, as well as the number of them that are significant, are relatively identical. The two linear model types include on average the same number of significant variables. The semi-log quadratic model generally includes the same number of variables as the quadratic model, but it often identifies one additional significant variable. There is only one significant variable of difference, or no difference at all in the number of significant variables, between the linear and the quadratic models. This small difference between the number of variables in the linear and quadratic best models is explained by the inclusion of the quadratic terms. Some coefficients of linear variables in the linear models are found under a quadratic form in the quadratic models. Regarding the significance level of variables, the semi-log models generally exhibit a slightly higher significance level than the two models without transformation.

Based on the adjusted *R*-squared for the linear models, five out of nine quality indexes (St. Emilion, St. Julien/Pauillac/St. Estephe, Sauternes/Barsac, Côte de Beaune and Côte Rôtie/Hermitage) have a better linear model without the transformation and the other four (Pomerol, Côte de Nuits, Burgundy White and Loire) have a better linear model with the semi-log transformation. On average, the difference in adj. *R*-squared between the linear and semi-log linear models is 0.7% but can be as high as 6.2% as in the Sauternes/Barsac AOC. The adj. *R*-squared of the linear regressions are between 42.2% and 66.3% while those of the semi-log linear regressions are between 40.2% and 64.5% (Table 6).

Concerning the quadratic models, six of the nine quality indexes (St. Emilion, St. Julien/Pauillac/St. Estephe, Sauternes/Barsac, Côte de Beaune, Côte de Nuits and Côte Rôtie/Hermitage) have a higher adj. *R*-squared in the basic quadratic model, while three of the nine (Pomerol, Burgundy White and Loire) have a higher adj. *R*-squared in the semi-log quadratic model. On average, the difference in adj. *R*-squared between the quadratic and semi-log quadratic models is about 1.9%. The quadratic regressions without transformation have an adjusted *R*-squared of between 43.1% and 73.1%, while the adj. *R*-squared of the semi-log quadratic regressions is between 41% and 67.3% (Table 6).

For most AOCs, if the linear model with the highest adjusted *R*-squared is the one without the logarithmic transformation, the quadratic model with the highest adj. *R*-squared will also be the one without the logarithmic transformation. Between the best linear and quadratic models, whether with or without the logarithmic transformation, it is important to note that the adj. *R*-squared always increases, except in the Burgundy wine region for the white wines. The increase between linear and quadratic models is 2.9% on average for the models without transformation and 1.7% for the semi-log models. As noted in the literature, the addition of quadratic variables can improve the predictive quality of the model relatively, i.e. its level of explanatory power. For instance, Ramirez (2008) found a 1% improvement between the linear quadratic model and Jones et al. (2005) found an average improvement of 5% for the French regions analysed. This explanatory power improvement underlines AOCs' sensitivity to extreme weather conditions.

Table 6: Adjusted $R$-squared from all regressions

| Wine Region | AOC | Linear | Quadratic | Semi-log Linear | Semi-log Quadratic |
|---|---|---|---|---|---|
| Bordeaux | St. Emilion | 55.9% | 56.8% | 52.5% | 54.2% |
| Bordeaux | St. Julien/Paulliac/St. Estephe | 47.8% | 48.9% | 40.2% | 41.0% |
| Bordeaux | Pomerol | 49.2% | 51.0% | 55.3% | 56.9% |
| Bordeaux | Sauternes/Barsac | 54.0% | 60.5% | 47.8% | 51.6% |
| Burgundy | Côte de Beaune | 54.4% | 58.6% | 50.5% | 52.6% |
| Burgundy | Côte de Nuits | 62.8% | 66.3% | 63.3% | 65.8% |
| Burgundy | All over | 51.6% | 52.2% | 55.4% | 55.4% |
| Rhône | Côte Rôtie/Hermitage | 66.3% | 73.1% | 64.5% | 67.3% |
| Loire | All over | 42.2% | 43.1% | 48.5% | 48.7% |

*Source: Table prepared by the authors*

Therefore, using the model with the highest adjusted $R$-squared among the four model types for each AOC, which in most cases is the basic quadratic model, the adj. $R$-squared ranges between 48.7% and 73.1%. The weather variables and the trend explain, on average, 58.3% of the variance of the French wine quality. Compared to the literature review, these results are at the upper end of the range. As such, most studies found $R$-squared or adj. $R$-squared ranging from 4% to 59%. For example, Hayez (2023) found an adjusted $R$-squared ranging from 36% to 59%, Jones et al. (2005) found an average $R$-squared for the French regions of 41% and Ramirez (2008) found an $R$-squared of 31%.

It is important to point out that the trend, which is the only non-weather-related variable, also plays a role in the percentage of adjusted $R$-squared of certain AOCs. However, by calculating the adj. $R$-squared without the trend of the AOC concerned, these only decrease by 1% to a maximum of 10% depending on the model type (Appendix 9). Most of the explanatory power is therefore due to the weather variables. Moreover, some indexes such as Côte Rôtie/Hermitage or Sauternes/Barsac achieve higher adj. $R$-squared percentages than other AOC indexes even though the trend is not included in their best models.

In conclusion, the adjusted $R$-squared of the regressions highlights an irrefutable impact of the weather variables on the quality of French wines. Based on the variables and the adj. $R$-squared, the four types of models can be seen as equivalent, each with its advantages and disadvantages. Therefore, it is complicated to assert a real superiority of one model or another. However, it can be confirmed that the addition of quadratic variables improves in general the explicability of the models, which underlines their importance.

### 4.1.2 Linear variables

One of the variables most frequently included in the 36 best models is the $TREND$ variable, which accounts for non-weather-related improvements. As seen in Appendix 7 and Table 7, among the nine quality indexes, $TREND$ is significantly included on average in five regressions (St. Julien/Pauillac/St. Estephe, the three Burgundy indexes and the Loire) for each of the four types of models. In all four model types, the $TREND$ coefficient has a positive sign with a level of significance usually ranging from 5% to 0.1%. The positive sign of the trend coefficients is coherent and aligns with existing literature. Since the trend represents the improvement of knowledge and technologies, it is expected to have a positive impact on wine quality. This is also the result found by Hayez (2023) and Jones et al. (2005) in their studies which implies that whenever the trend coefficient is significant, its impact on wine quality is positive.

The variable which is most used in previous research and whose impact has been well-proven is temperature. In this study, the temperature variables are present in several best models for the growing and early growing seasons. Temperature is most prevalent during the growing season for the four types of models. $TAVG_G$ is significant for four quality indexes out of nine in three model types and for two quality indexes in the quadratic model. When the $TAVG_G$ variable is significant, its sign is always positive (Table 7). The positive impact of temperature on wine quality in the growing season confirms hypothesis H1 and is in line with previous studies. Some discrepancies can be observed in the indexes where the variable is significant, as well as in their level of significance across the four types of models. In the linear model, $TAVG_G$ is significant at a level of 5% and 0.1% for the four Bordeaux indexes. The semi-log linear model includes the variable for three of the Bordeaux indexes as well as for Burgundy White, at a minimum significance level of 10%. The quadratic model includes $TAVG_G$ significant at 10% for Sauternes/Barsac and 5% for Côte de Beaune. Finally, the St. Emilion index and the three Burgundy indexes include the variable at a significance level of at least 10% for their semi-log quadratic model.

Concerning $TAVG_{EG}$ variable, when significant, the sign of its coefficients is negative for most quality indexes (Table 7). In this study, $TAVG_{EG}$ has mainly a negative impact on the quality of French wines. Looking at the optimal climate conditions for wine quality, the temperature in the early-growing season does not seem to have a clear consensus in most previous research. However, some research on the quality of Californian and Italian wines found a positive and mostly significant impact on early growing season temperature, contrary to the findings of this study (Corsi & Ashenfelter, 2019; Hayez, 2023; Ramirez, 2008). This difference in sign can be potentially explained by the difference in the location of the wines or by the differences in the monthly separation of the seasons. For instance, Ramirez (2008) presents the early-growing season as April and May, whereas this study describes it as March and April. $TAVG_{EG}$ is included for St. Julien/Pauillac/St. Estephe, Pomerol and Côte de Nuits indexes at significance levels ranging from 10% to 1% for both types of linear models. For the quadratic model, the Pomerol and Côte de Nuits indexes also include the variable at a significance level of 10% and 1% respectively. No $TAVG_{EG}$ variable is included among the nine indexes for the semi-log quadratic model. Concerning the Côte de Nuits index, the sign of its coefficient changes from negative to positive between the linear and quadratic models. These last two characteristics will be argued later in the analysis by the introduction of the quadratic variables.

A second component that recurs in many studies is precipitation. Contrary to Hayez (2023), which found that precipitation had a smaller impact on wine quality than temperature. The findings in this study suggest that precipitation is as significant as temperature, particularly during the growing and harvest seasons. As such, for each of the four models, precipitation appears in five to seven out of nine quality indexes, in at least one of the four seasons.

Concerning precipitation in the winter and early growing seasons, the coefficients of the variables that are significant always have a positive sign (Table 7). As presented in hypothesis H4, $PRCP_W$ and $PRCP_{EG}$ have a positive impact on the quality of French wines. $PRCP_W$ only returns in the best quadratic model of the Côte Rôtie/Hermitage index at a level of 5%. As for $PRCP_{EG}$, the variable is significant on average at 5% for the St. Emilion and Pomerol indexes, for all four model types.

Regarding precipitation in the growing and harvest seasons, most of the significant coefficients for each index have a negative sign, which aligns with the theory (Table 7). Following the literature and hypothesis H5, precipitation in the growing and harvest seasons tends to negatively impact French wine quality. Looking at $PRCP_G$ , the number of significant coefficients among the nine indexes varied between the four types of models. Most of the variables' coefficients are significant at the 5% level. For the linear model type, the Côte Rôtie/Hermitage and St. Julien/Pauillac/St. Estephe indexes include the variable in their best models. For the quadratic model, $PRCP_G$ is significant for St. Emilion, St. Julien/Pauillac/St. Estephe and Côte de Beaune. In the two semi-log model types, four indexes include the variable $PRCP_G$ : St. Emilion, St. Julien/Pauillac/St. Estephe, Côte Rôtie/Hermitage and Côte de Nuits for the semi-log linear and St. Emilion, St. Julien/Pauillac/St. Estephe, Côte de Beaune and Côte de Nuits for the semi-log quadratic model. The Burgundy White index also has a significant $PRCP_G$ variable for three out of the four best models. However, this one exhibits a positive coefficient, which is counterintuitive.

Regarding $PRCP_H$, the variable is significant in four to five indexes out of nine for the two linear models and in one index for the two quadratic models. This difference between the linear and quadratic models is explained by the insertion of the quadratic variables and will be discussed later in the analysis. In the two linear models, $PRCP_H$ coefficients are significant at an average level of 5% for the St. Emilion, Pomerol, Sauternes/Barsac and Burgundy White indexes. The Côte Rôtie/Hermitage index also has the $PRCP_H$ variable significant at 10% in its best linear model without transformation. For the two quadratic models, the Burgundy White index includes $PRCP_H$ at a significance level of 0.1%.

Another component used in the best models is $DT32$. In this study, this component was found to be quite significant in the 36 different regressions, particularly during the winter season. The signs of the significant coefficients of the $DT32$ variable are mostly negative whatever the season (Table 7). This negative sign is aligned with hypothesis H7 and previous studies, which state that the number of days with a minimum temperature below zero degrees damages grape quality, whatever the season.

The $DT32_W$ variable is usually included at a significance level of 5% in the four best models of the St. Emilion, Pomerol, Sauternes/Barsac and Côte Rôtie/Hermitage indexes. The St. Julien/Pauillac/St. Estephe index also includes the variable at a significant level of 10% in its quadratic best model. For the Burgundy White index, $DT32_W$ is also significant in the four types of best models. However, the variable exhibits a positive coefficient, which is counter-intuitive given the theory and the hypothesis.

Concerning $DT32_{EG}$ variable, the Sauternes/Barsac index also has a counterintuitive coefficient sign in all four types of models. For the two types of linear models, $DT32_{EG}$ is usually included at a significance level of 5%, with a negative coefficient for the Côte de Nuits and Côte Rôtie/Hermitage indexes. As for the quadratic models, the Côte Rôtie/Hermitage index also includes $DT32_{EG}$ at a level of 1% while the St. Julien/Pauillac/St. Estephe index includes it at a level of significance of 10% in the semi-log quadratic model.

Regarding $DT32_H$, the variable is included at a 5% level for the Loire and Burgundy White indexes in all four model types as well as at a 10% level in the best linear model of the Côte de Nuits index.

Table 7: Linear Seasonal Variables Impact on Wine Summary

| Variable | Model Types | AOC and Significance Levels | Impact | Hypothesis |
|---|---|---|---|---|
| *TREND* | All types | Côte de Nuits and Côte de Beaune (0.1%), Loire (1%), Burgundy White (5%), St. Julien/Pauillac/St. Estephe (5%) | Positive | None |
| $TAVG_{G}$ | All types | Bordeaux (all four indexes) (5% - 0.1%), Burgundy (all three indexes) (10%-5%) | Positive | H1 |
| $TAVG_{EG}$ | Most types | St. Julien/Pauillac/St. Estephe and Pomerol (10%-5%), Côte de Nuits (1%) | Negative | None |
| $PRCP_{W}$ | Quadratic | Côte Rôtie/Hermitage (5%) | Positive | H4 |
| $PRCP_{EG}$ | All types | St. Emilion and Pomerol (10%-1%) | Positive | H4 |
| $PRCP_{G}$ | All types | Côte Rôtie/Hermitage (0.1%), St. Julien/Pauillac/St. Estephe and St. Emion (5%), Côte de Beaune and Côte de Nuits (10%-1%) | Negative | H5 |
| $PRCP_{H}$ | All types | St. Emilion, Pomerol and Sauternes/Barsac (10%-1%), Burgundy White (0.1%), Côte Rôtie/Hermitage (10%) | Negative | H5 |
| $DT32_{W}$ | All types | Bordeaux (all four indexes) (10%-0.1%), Côte Rôtie/Hermitage (1%-10%) | Negative | H7 |
| $DT32_{EG}$ | All types | Côte de Nuits (10%-5%), Côte Rôtie/Hermitage (1%), St. Julien/Pauillac/St. Estephe (10%) | Negative | H7 |
| $DT32_{H}$ | All types | Loire (5%), Burgundy White (10%-5%), Côte de Nuits (10%) | Negative | H7 |

*Source: Table prepared by the authors*

The temperature difference is another variable less present in the literature, but which recurs moderately in this study. No hypothesis was made beforehand for this variable as no clear consensus was drawn from the theory. $Diff$ recurs throughout three of the four seasons, with a strong presence in the harvest season. In winter, the impact of $Diff_{W}$ on wine quality is split between positive and negative (Table 8). The variable returns for the Pomerol and Loire indexes in all four types of models exhibit a positive coefficient at an average significance level of 5%. On the other hand, the Côte Rôtie/Hermitage index includes the variable in its four best models with a negative coefficient always with a significance level below 5%. The Côte de Nuits index also shows a negative coefficient for its two best quadratic models at least a significant level of 10% while the Côte de Beaune index includes the variable in its best semi-log linear model at the same significance level. Regarding Pomerol, Côte Rôtie/Hermitage, and Loire, $Diff_{W}$ is correlated quite strongly and negatively with $PRCP_{W}$ (Appendix 6). However, theory and findings have shown that rain positively impacts quality during the winter season. The positive sign of the $Diff_{W}$ variable seems therefore counterintuitive. Hayez (2023) also found a positive and counterintuitive impact of the temperature difference during winter. For the two Burgundy red wine indexes, $Diff_{W}$ is positively correlated with $TAVG_{W}$ (Appendix 6). Therefore, the negative impact of the $Diff_{W}$ variable makes sense, as it is well-known that high winter temperature negatively affects wine quality.

Looking at the $Diff_{EG}$ findings, the two or three significant coefficients among the nine indexes in each model type exhibit a positive sign (Table 8). In the linear and quadratic models, $Diff_{EG}$ is at least significant at 10% for St. Emilion and Côte de Nuits. Côte de Nuits also includes $Diff_{EG}$ in both semi-log models at a significance level of 1%. The St. Julien/Pauillac/St. Estephe index also comprises the variable at a 5% level for the two semi-log models while the St. Emilion index includes it at a 10% level for the semi-log quadratic model. For the three indexes concerned, their $Diff_{EG}$ variable is strongly negatively correlated with the season's rainfall (Appendix 6). However, rainfall during the early-growing season positively impacts wine quality, as demonstrated by theory and findings. The positive sign of the $Diff_{EG}$ variable is therefore counterintuitive. Hayez (2023) also found a significant positive impact on one of its models. However, the correlation with other variables makes sense in the case of this study.

Finally, concerning the harvest season, the coefficients of the temperature difference variable for four indexes across all model types are consistently positive (Table 8). The St. Julien/Pauillac/St. Estephe, Côte de Beaune, Côte de Nuits and Côte Rôtie/Hermitage indexes all include $Diff_H$ at fairly variable levels of significance, depending on the model. Looking at the correlation of $Diff_H$ with other variables, this one is strongly negatively correlated to precipitation for the three wine regions concerned (Appendix 6). The positive sign of $Diff_H$ is therefore logical, as it is well-known that rain negatively affects wine quality during the harvest season. Furthermore, this result is confirmed by Cook and Wolkovich (2016) in their analysis of the Diurnal Temperature Range.

The last component to appear in the best models is the $NAO$ (North Atlantic Oscillation Index). Compared to the other variables, the $NAO$ seems to have a smaller impact on the quality of the wines, as it is only significant for an average of one index out of nine for each season and by model type. Looking at the H8 hypothesis, $NAO$ seems to have an impact on the quality of French wines, yet quite limited. When significant the variable exhibits a negative impact whatever the season (Table 8).

Concerning $NAO_W$, the variable is included by the Côte Rôtie/Hermitage index at a significance level of 5% in three of the four model types (linear, semi-log linear and semi-log quadratic). Regarding the early-growing season, the $NAO$ variable is only included by the Côte de Nuits index at the 10% level for its linear model. As presented in the methodology, the North Atlantic Oscillation Index primarily impacts the winter season and extends to the start of the early-growing season. In this case, the negative effect of $NAO_W$ and $NAO_{EG}$ on French wine quality can be due to higher temperature average. Indeed, both variables are positively correlated with the average seasonal temperatures (Appendix 6). Furthermore, as shown in the summary statistics, the $NAO_W$ and $NAO_{EG}$ have been predominantly in a positive phase on average over the fifty years (Appendix 4). However, a positive phase of the $NAO$ is associated with higher temperatures in northern Europe, which, according to theory and results, negatively affects wine quality. In this case, the negative sign of the coefficients seems logical, considering that France is impacted like the northern part of Europe rather than the southern part. This finding is supported by the study of Tsai and Lin (2020), who also found a negative impact during winter for the Champagne region.

Concerning $NAO_G$, the variable recurs for the Pomerol index across all four model types as well as in the best linear regression of Côte de Nuits. $NAO_H$ is significant in both semi-log models for the Loire index. However, it is difficult to conclude from these results. There is a minimal theoretical understanding of the impact of the North Atlantic Oscillation index outside the winter season. Moreover, $NAO_G$ is mainly correlated with weather variables of other seasons (Appendix 6). As for $NAO_H$, it is negatively correlated with seasonal rainfall, which is counterintuitive given its negative impact during harvest season. Finally, studies using $NAO$ in the growing/harvest season have consistently found an opposite impact between the winter and growing season, which is not observed in this study (Jeřábek, Tvrzník, Málek & al., 2021; Tsai & Lin, 2020).

Table 8: Linear Seasonal Variables Impact on Wine Quality Summary - continued

| Variable | Model Types | Significance Levels | Impact | Hypothesis |
|---|---|---|---|---|
| $Diff_W$ | All types | Pomerol and Loire (5%), Côte Rôtie/Hermitage (5%-1%), Côte de Nuits and Côte de Beaune (10%-1%) | Mixed | None |
| $Diff_{EG}$ | All types | St. Emilion (10%), Côte de Nuits (1%-0.1%), St. Julien/Pauillac/St. Estephe (5%) | Positive | None |
| $Diff_H$ | All types | St. Julien/Pauillac/St. Estephe (5%-1%), Côte de Beaune and Côte de Nuits (1%-0.1%), Côte Rôtie/Hermitage (10%-1%) | Positive | None |
| $NAO_W$ | Most types | Côte Rôtie/Hermitage (5%) | Negative | H8 |
| $NAO_{EG}$ | Linear | Côte de Nuits (10%) | Negative | H8 |
| $NAO_G$ | All types | Pomerol (1%-0.1%), Côte de Nuits (10%) | Negative | H8 |
| $NAO_H$ | Semi-log | Loire (10%) | Negative | H8 |

*Source: Table prepared by the authors*

Finally, some linear variables are significantly absent from the various regressions. $TAVG_H$ appears for two coefficients across the 36 regressions, but these are not significant. Similarly, $Diff_G$ is found to have three coefficients, all of which are not significant. The lack of significant impact of these variables on the quality of French wines may be due to the presence of other variables with similar significance. For instance, for $TAVG_H$, the variable $Diff_H$ plays a crucial role in the different regressions. Similarly for the variable $Diff_G$, $TAVG_G$ shows notable importance. As a reminder, $TAVG_W$ and $DT32_G$ were removed from the models as explained in the methodology.

### 4.1.3 Quadratic variables

The first quadratic component that holds notable importance in the various regressions is temperature. $TAVG_{EG}^2$ and $TAVG_G^2$ each appear significantly in one index for the quadratic model and in two to three indexes for the semi-log quadratic model. All coefficients of the $TAVG_{EG}^2$ and $TAVG_G^2$ variables have a negative sign, which is in line with the theory and with hypothesis H3 (Appendix 7 & Table 9). The H3 hypothesis is aimed at the growing season but the same reasoning applies to $TAVG_{EG}$: extreme temperature negatively impacts the quality of French wines. Good illustrations of this hypothesis are the indexes of Côte de Beaune and Côte de Nuits in the semi-log quadratic model as well as in the quadratic model for Côte de Beaune. Their $TAVG_G$ variable is significant and positively affects wine quality, while their $TAVG_G^2$ variable has a significant and negative coefficient. Côte de Nuits shows the same reflection with the variable $TAVG_{EG}$ in the quadratic model. These examples illustrate that temperature can have a positive impact on wine quality, but only up to a certain threshold.

In the semi-log quadratic model, St. Julien/Pauillac/St. Estephe and Pomerol also include the $TAVG_{EG}^2$ variable at a significance level of 5% while Côte de Nuits includes it at a significance level of 1%. These last three coefficients can be explained by the switch between the linear and quadratic models. Indeed, as presented above, $TAVG_{EG}$ has a significant negative impact on these three indexes in the semi-log linear model. When the quadratic variables are inserted into the model, the three coefficients change to the quadratic form of $TAVG_{EG}$, highlighting the sensitivity of these indexes to early growing season's temperature extremes. The lack of significance of both the linear and quadratic forms of $TAVG_{EG}$ in the quadratic model can be explained by the fact that both variables exert a negative impact. The introduction of $TAVG_{EG}^2$ also changed the sign of the $TAVG_{EG}$ coefficient for the Côte de Nuits index between its linear model and its quadratic model. Indeed, the $TAVG_{EG}$ coefficient switches from negative to positive between the linear and quadratic models.

The second quadratic component is precipitation. The impact of precipitation in quadratic form is mainly negative for all seasons (Appendix 7 & Table 9). The negative sign of the squared precipitation variables is in line with hypothesis H6 which states that too much precipitation damages the quality of French wines. This is best illustrated by the Côte Rôtie/Hermitage index in the quadratic model. For this index, $PRCP_W$ has a positive coefficient, but $PRCP_W^2$ negatively affects wine quality. Both variables are significant at the 5% level. This example illustrates that precipitation can have a positive impact on wine quality, but only up to a certain threshold.

Similarly to certain temperature coefficients, most of the significant quadratic precipitation variable coefficients replace the linear form of the variable. Indeed, during the growing and harvest seasons, precipitation negatively impacts wine quality. Therefore, the insertion of the quadratic form of the variables replaces the linear form of the variable for certain indexes. The insertion of $PRCP_H^2$ for the indexes of St Emilion, Pomerol, Sauternes/Barsac, in the two quadratic models replaces the coefficient of the variable $PRCP_H$ of the linear models. The same thing happens for Côte Rôtie/Hermitage for the quadratic model and for the $PRCP_G^2$ variable in the two quadratic models. In the quadratic model, $PRCP_G^2$ is significant for Sauternes/Barsac whereas the linear version is not. The same applies to Côte Rôtie/Hermitage and St. Julien/Pauillac/St. Estephe for $PRCP_H^2$ in the semi-quadratic model and quadratic model respectively. The fact that the quadratic precipitation variables are significant underlines the sensitivity of these indexes to extreme precipitation. All the coefficients of the variables $PRCP_G^2$ and $PRCP_H^2$ have a variable significance ranging from 10% to 0.1%. In each type of quadratic model, two different coefficients of the variable $PRCP_G^2$ are significant between 10% and 5% and exhibit a positive sign, which is counterintuitive. In the quadratic model, these positive coefficients are found in the Côte de Beaune and Burgundy White indexes, while in the semi-log quadratic model, they are found in the Côte de Beaune and St. Emilion indexes. These counter-intuitive signs can be explained by the potential presence of multi-collinearity in the models.

Table 9: Quadratic Seasonal Variables Impact on Wine Quality Summary

| **Variable** | **Model Types** | **AOC and Significance Levels** | **Impact** | **Hypothesis** |
|---|---|---|---|---|
| $TAVG_{EG}^2$ | Quadratic, Semi-log quadratic | Côte de Nuits (1%), St. Julien/Pauillac/St. Estephe and Pomerol (5%) | Negative | H3 |
| $TAVG_G^2$ | Quadratic, Semi-log quadratic | Côte de Beaune (10%-5%), Côte de Nuits (5%) | Negative | H3 |
| $PRCP_W^2$ | Quadratic | Côte Rôtie/Hermitage (5%) | Negative | H6 |
| $PRCP_G^2$ | Quadratic, Semi-log quadratic | Sauternes/Barsac (5%), Côte Rôtie/Hermitage (0.1%) | Negative | H6 |
| $PRCP_H^2$ | Quadratic, Semi-log quadratic | Bordeaux (all four indexes), Côte Rôtie/Hermitage (10%-0.1%) | Negative | H6 |

*Source: Table prepared by the authors*

Some quadratic variables have no significant coefficients among the 36 regressions. $TAVG_H^2$ and $PRCP_{EG}^2$ are never significant, which underlines their lack of impact on wine quality. As a reminder, the $TAVG_W^2$ variable was not included in the models, as was $TAVG_W$.

## 4.2. Part II: Regional analysis

This second section analyses the regional differences through a transversal analysis of the regressions to capture the overall trends in the wine regions (See detailed results in Appendix 7). As discussed earlier, the four types of models for each AOC are relatively similar, facilitating the comparison of AOCs.

### 4.2.1 Bordeaux region

Regarding the different types of models in the Bordeaux wine region, it is interesting to note that the four AOCs exhibit high adjusted $R$-squared values ranging from 40% to 49% for St. Julien/Paulliac/St. Estephe models, from 49% to 57% for Pomerol models, from 53% to 57% for St. Emilion models and from 48% to 61% for Sauternes/Barsac models (Table 6). While three AOCs perform very well in terms of adjusted $R$-squared, the AOC St. Julien/Paulliac/St. Estephe falls below the average and shows the most significant loss in adjusted $R$-squared when applying the semi-log transformation. Compared to existing literature, these results are higher as research with fewer variables had only 39% for St. Emilion/Pomerol and 40% for Sauternes/Barsac (Jones & al., 2005).

Taking a deeper look at what impacts the AOCs Bordeaux, one can easily see that the trend variable matters solely for the St. Julien/Paulliac/St. Estephe index. As such, the trend is only significantly positive for this wine sub-region yet explaining on average only 1% of its explainability (Appendix 9). This means that this AOC is relatively less impacted by weather-related variables, which is also coherent when looking at the adjusted $R$-squared, which is the lowest in this wine region. Moreover, the three other wine sub-regions have a higher adjusted $R$-squared without the trend variable, which means that the quality highly depends on weather conditions.

As such, the AOCs St. Julien/Paulliac/St. Estephe and Pomerol are negatively sensitive to high and extreme temperatures in the early growing season. However, all AOCs in Bordeaux are much positively impacted by temperature in the growing season. In addition, the wines in this French region also depend negatively on the days when the minimum temperature falls below zero in the winter. The AOCs of Bordeaux also rely much on other weather-related variables, particularly precipitations with impacts varying from season to season. As such, precipitations negatively affect the wines during the harvest season except for St. Julien/Paulliac/St. Estephe (only negatively affected by rain in the growing season). The high sensitivity of the three Bordeaux AOCs to harvest season rainfall is underlined by the fact that the quadratic form of the variable recurs significantly in both quadratic models. Moreover, St. Emilion is also positively sensitive to rain in the early growing season and negative in the growing season. Similarly, Pomerol benefits from rain in the early growing season. Furthermore, most AOCs are impacted positively by the difference between the maximum and minimum temperatures: during the winter season for Pomerol, the early growing season for St. Emilion and the early growing and harvest season for St. Julien/Paulliac/St. Estephe. Finally, the impact of NAO is limited and only negative for Pomerol in the growing season.

These results are interesting and showcase similar patterns between one another. What is surprising is the AOC Julien/Paulliac/St. Estephe reacts slightly differently from all other AOCs. Even though this AOC does not have significantly different wines regarding the grape variety in its wine index, this might be explained by how the former is calculated as it takes into account wines from three different wine subregions. It is clear that except for this AOC, red and white wines from Bordeaux react in the same way to weather-related variables. However, the AOC Sauternes/Barsac is less impacted by weather, it has on average less significant variables in all model types. On the contrary, the red wines seem to be more impacted by the weather especially Pomerol and St. Emilion with the most significant variables in most models.

### 4.2.2 Burgundy region

When it comes to the different indexes, it is insightful to mind that the three AOCs exhibit higher adjusted $R$-squared on average than all Bordeaux models, ranging from 51% to 59% for Côte de Beaune models, from 63% to 66% for Côte de Nuits models and from 52% to 55% for Burgundy white models. It is also important to note that Côte de Nuits is the second AOC of all that presents the best-adjusted $R$-squared.

On the contrary to the Bordeaux wine region, the trend variable in the Burgundy wine region is very significant for all AOCs. This means that a part of the explanatory power of these AOCs is due to the presence of the trend. This is confirmed by literature where Pinot Noir (Côte de Beaune and Côte de Nuits) and Chardonnay (Burgundy white) have a trend positively significant for other regions in the world but also for wines in the Burgundy wine region (Hayez, 2023; Jones & al., 2005). In Appendix 9, it can be observed that the adjusted *R*-squared of the three AOCs loses between 3 and 10% when the trend is removed.

The three AOCs from the Burgundy wine region can be regrouped into two categories that exhibit similar patterns in weather sensitivity. Although Côte de Nuits shows more significant weather-related variables overall, this one is fairly similar to Côte de Beaune. In contrast, Burgundy white is distinctly different. As such, Côte de Beaune and Côte de Nuits are similarly dependent on temperature in the growing with positive effects until a certain threshold where they suffer from extreme temperature, as showcased in the quadratic models. This is particularly clear as the regressions for these two AOCs perform best when quadratic variables are included. Côte de Nuits also reacts negatively to extreme temperatures in the early growing season and to temperature differences in the winter season. The wine sub-region is also significantly positively affected by this temperature difference in the early growing season. The two similar Burgundy AOCs are also positively affected by the former variable in the harvest season. Regarding precipitations, Côte de Nuits and Côte de Beaune suffer negatively in the same way in the growing season. On the other hand, the weather sensitivity of Burgundy white is more complex. The AOC is only positively impacted by temperature in the growing season but shows less sensitivity to extreme heat as no quadratic variables are present in the best models. Moreover, the white wines from burgundy are negatively affected during the harvest season by freeze but interestingly positively impacted during the winter season which is the opposite of what has been seen in all other regions. Surprisingly the Burgundy white wines react also completely differently to rain with a positive impact in the growing season. The former impact inverts in the harvest season where rain has a negative impact on this AOC.

In these results, Côte de Beaune and Côte de Nuits are quite similar, which is coherent as they are red wines mostly composed of Pinot Noir. As Haeger and Storchmann (2006) found in their study, Pinot Noir grapes are highly sensitive to extremes of temperature. This is confirmed by the results of this study where Côte de Nuits and Côte de Beaune are more impacted by extreme temperatures. However, the white wines from all over Burgundy are significantly different, showing counterintuitive impacts of the rain during the growing season and freezing days during winter. Overall, the models in the Burgundy region showcase moderately different results from the Bordeaux region, being somewhat less affected by freeze and extreme precipitations.

### 4.2.3 Rhône region

The Rhône wine region, solely composed of Côte Rôtie/Hermitage, is the AOC which showcases the highest adj. $R$-squared in all model types, from 65% to 73%. This surpasses what can be found in existing research, where one example of regression in that region only had 28% of adjusted $R$-squared (Jones & al., 2005).

In that wine region, the regressions do not include the trend variable as it has been withdrawn due to multicollinearity issues. Combined with the highest level of explainability of the regressions, this means that the Rhône wine region is the AOC most impacted by weather-related variables in this research. This also indicates that the grape variety Syrah is vastly impacted by weather conditions as it is the grape type with the most presence in the AOC index (Appendix 3).

Regarding the weather-related variables, one can see that the AOC is not extremely impacted by mean temperature variables. Even though it may seem counterintuitive, these temperature impacts are represented by the difference between maximum and minimum variables which are significant during winter with a negative impact, and during harvest with a positive effect as seen in other regions. This can also be represented by the impact of the freeze on the AOC, which is negatively significant during winter and early growing seasons. What is most striking is the importance of the extreme level of precipitations as this AOC is heavily negatively impacted during the growing and harvest seasons. This wine sub-region is the only AOC which showcases a positive impact of rainfall in winter until a specific threshold where it inverts. Lastly, interestingly, the NAO index during the winter season is also negatively significant in all regressions for this AOC.

These results highlight the resemblance of this AOC with the Bordeaux wine sub-regions except St Julien/Pauilliac/St. Estephe. Like Bordeaux wines, the Rhône wines are highly dependent on weather-related variables such as freeze and extreme level of precipitation.

### 4.2.4 Loire region

The Loire wine region, entirely represented by all white wines in the AOC, has the least significant variables with the lowest average adjusted $R$-squared of the AOCs after St. Julien/Paulliac/St. Estephe. As such, it ranges from 43% to 49%. Only three weather-related variables are significantly important for this AOC: the freezing days during harvest, the NAO during harvest, and the difference between the maximum and minimum temperature during winter. This means that, to some extent, the white wines from the Loire are less impacted by weather except for the difference in temperature in winter and unexpected freezes during harvest. What can partly explain and confirm the lower explainability level of that wine sub-region is the trend variable, which is always significant in all model types. As seen in Appendix 9, the adjusted *R*-squared of the Loire AOC loses between 3% and 8% when the trend variable is removed.

As such, the wines from the Loire region are somewhat similar to the Burgundy white wines: they have less extreme weather sensitivity as showcased with no significative quadratic variables in the quadratic models. In addition, they are also the only wines presenting impacts from freeze during the harvest season but not during the winter season, highlighting that white wines are less affected by harsh conditions during winter. As these two AOCs are both partly composed of Chardonnay, it can be implied that this grape variety is less sensitive to weather. These results coincide with existing research which states that red wines are more affected by extreme temperatures (Gladstones, 1992 cited in Ashenfelter & Storchmann, 2016). This is also confirmed as the three white wine AOCs, Sauternes/Barsac, Burgundy White and Loire, have the fewest significant variables in the two quadratic model types.

## 4.3 Summary of the results

This research, based on four different model types and 36 regressions, demonstrates that weather-related variables in France significantly impact the quality of wine. The crafted models exhibit a high level of explainability and a relatively large number of significant variables in each regression. As such, the adjusted *R*-squared values for linear models range from 42.2% to 66.3%, for semi-log linear models from 40.2% to 64.5%, for quadratic models from 43.1% to 73.1%, and for semi-log quadratic models from 41% to 67.3%. The increase in explainability when adding the quadratic models highlights the significance of investigating non-linear impacts from certain variables such as temperature or precipitation during specific wine seasons. Moreover, the solely non-weather-related variable trend showcased a small impact on the adjusted *R*-squared, ranging from 1% to 10%. This reinforces the relevance of weather conditions' impacts on wine quality in France.

In addition, the similarity in the results of all models performed allows this research to draw numerous insights into the impact of weather on the quality of the nine different AOCs studied and confirm or refute the main hypotheses of this thesis. In this research, several hypotheses are confirmed through the analysis. The hypothesis that temperature during the growing season positively impacts wine quality (H1) is confirmed, with a significant positive impact on wine quality across most models. Similarly, the hypothesis that extreme temperatures, represented by quadratic temperature variables, negatively impact wine quality (H3) is also confirmed. This is evidenced by the several negative quadratic coefficients, indicating that temperatures beyond a certain threshold can detrimentally affect wine quality. The hypothesis that precipitation during the winter and early growing seasons positively impacts wine quality (H4) is slightly supported by the findings. Additionally, the negative impact of precipitation during the growing and harvest seasons on wine quality (H5) is clearly verified. The hypothesis that extreme precipitation, represented by quadratic precipitation variables, negatively impacts wine quality (H6) is also validated, as shown by the negative quadratic coefficients across several models. Finally, the hypothesis that days with minimum temperatures below 0°C negatively impact wine quality whatever the season (H7) is confirmed, with the most significant coefficients showing a negative impact on wine quality.

However, some hypotheses were refuted or not confirmed. The hypothesis that low temperature during winter should positively impact wine quality (H2) cannot be confirmed as the variables are withdrawn from all models due to a high level of correlation with another variable ($DT32_w$). The North Atlantic Oscillation Index (NAO) exhibits a negative impact on wine quality and is significant during different seasons for a few AOCs. These results can imply the general hypothesis that NAO has an impact on the quality of French wines (H8). However, this impact seems relatively small since the number of significant variables in the best models is limited. In addition to these hypotheses, the study reveals new findings for variables without initial hypotheses. High temperatures during the early growing season negatively impact French wine quality. The temperature differences impact wine quality, though the direction is not straightforward for the winter season with positive and negative impacts depending on the AOCs. It is, however, often positively significant during the early growing and harvest seasons.

Our analysis also reveals distinct patterns in how the different wine regions respond to climatic variables. First, the AOCs performing best in the models are Côte Rôtie/Hermitage and Côte de Nuits. In addition, comparing the regions, even though located in different climate areas, most Bordeaux wines share similar responses to climatic conditions with those from the Rhône region, particularly in their reaction to freeze events and extreme precipitation levels. Unlike wines from Burgundy and Loire, those from Bordeaux and Rhône do not incorporate trend variables in their regression models. As this trend variable is not present, their explanatory power relies solely on weather-related variables. This underscores the significant impact of climatic factors on these regions. On the other hand, Burgundy red wines, Côte de Beaune and Côte de Nuits, known for their Pinot Noir vines, are particularly sensitive to temperature extremes.

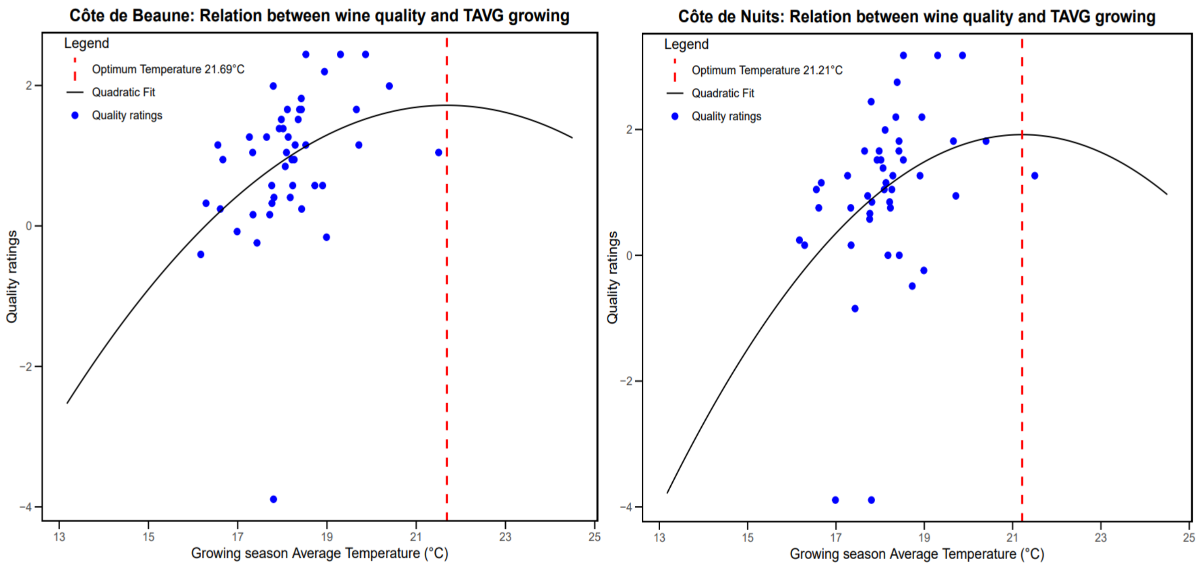
Interestingly, the analysis of white wines from three regions shows a lower number of significant variables in quadratic models. Specifically, Loire (Chardonay, Chenin Blanc) and Burgundy (Chardonay) showcase no quadratic forms in their best models. This indicates that white wines are generally less sensitive to extreme climatic conditions compared to their red counterparts. Finally, the AOCs Sauternes/Barsac and Loire present both counterintuitive coefficients which highlight the fact that these wines could simply react differently from other wines.

## 4.4 Complementary analysis

Given the results of the Côte de Beaune and Côte de Nuits AOCs, an additional analysis has been carried out to find their optimum temperature during the growing season. As these two AOC indexes are the only ones with significant $TAVG_G$ and $TAVG_G^2$ in their semi-log quadratic model, it is interesting to determine the temperature threshold at which the quality of these indexes starts to decrease. As presented in the literature review, climate change has and will continue to affect the suitability of wine regions. Evaluating whether these two indexes of Pinot Noir have already exceeded or not their optimum temperature allows the study to draw conclusions about Burgundy's future suitability for this grape variety. The analysis only looks at temperature components, because, unlike temperature, precipitation trends are much more uncertain (Ashenfelter & Storchmann, 2016; Leeuwen & Darriet, 2016).

As presented in the literature review in Jones et al.'s complementary analysis (2005), the derivative of the semi-log quadratic model was calculated, with temperature variables in growing seasons as variables. As can be seen in Figure 9, an optimum $TAVG_G$ was found for each AOC. Côte de Beaune shows an optimum $TAVG_G$ at 21.69°C while Côte de Nuits's optimum is slightly lower at 21.21°C. In the summary statistics (Appendix 4), Burgundy's average growing season temperature over the fifty years analysed is 18.11°C. For the time being, the average growing season temperature is below the optimum for these two Pinot Noir indexes. The future increase in temperature will therefore favour these two indexes in the years to come. In their 2006 study on Pinot Noir, Haeger and Storchmann also found, based on prices, that the temperature in Burgundy is below the optimum for Pinot Noir in the region. Santos et al. (2020) as well as Hannah et al. (2013) also confirm that Burgundy will remain suitable in the future and that the temperature could have a positive impact on its Pinot Noirs. This contrasts with Bordeaux and the Rhône which could already reach their pivot point by 2050, according to Hannah et al. (2013). The analysis of the quality evolution shows that Côte de Nuits and Côte de Beaune are the two indexes that have experienced the greatest increase in quality over the 50 years analysed (Table 5). This trend is likely to continue in the future.

Figure 9: Relation between wine quality and $TAVG_G$




*Source: Graphs prepared by the authors*

The growing season temperature in Burgundy has increased by 1.73 degrees, over these 50 years (Table 4). Projections presented in the literature review suggest however that this increase will more than double by 2100, posing a long-term threat to Burgundy's suitability for Pinot Noir. Although Burgundy remains suitable in the short to medium term, a continued rise of temperature could at some point exceed the optimums, leading to potential unbalanced ripening (Jones & al., 2022). Furthermore, as presented in the literature, the regulations and specificities surrounding AOCs and their terroir are likely to pose a problem in the future for these regions in the implementation of adaptation strategies (Greenpeace, 2019).

In conclusion, the temperature in Burgundy is currently below the optimum for the Côte de Nuits and Côte de Beaune AOCs. It is therefore likely that these two AOCs will see their quality increase in the short and medium term, as has been the case over the last 50 years. However, when looking at the long term, there will come a time when temperatures reach their threshold, which will affect the suitability of the Burgundy region for these pinot noirs.

# 5. Discussion

As presented above, this study demonstrates that weather variables truly impact the quality of French wines across the nine AOCs studied. Presenting the statistical findings in two main parts allowed grasping insights from two perspectives. Firstly, a cross-analysis of the variables allowed general conclusions about their signs and enabled a comparison with the initial hypotheses. Secondly, a comparison of the AOCs highlighted the specific characteristics of each wine sub-region. Finally, a complementary analysis offered additional insights by linking climate change and the suitability of the Burgundy wine-growing region.

The explanatory power of the models is relatively high compared to the literature, with an average adj. $R$-squared of 58.3% when considering the best model for each AOC. This fairly high result can be explained by the greater climatic variability in France than in other regions of the world. In addition, the fact that the study considers a diverse number of variables and selects the four best models based on the best variable compositions enables a certain level of results. Finally, testing four different models for each AOC enhances the robustness of the findings and contributes to higher adj. $R$-squared.

By conducting a study on various French regions and including data from 1970 to 2019, this research contributes to the understanding of the subject. As such, the optimal weather conditions of the grape, as reflected by the hypotheses, are confirmed for more diverse French wine-growing regions beyond just Bordeaux. Moreover, considering variables up to 2019 ensures that these hypotheses are confirmed over a more recent period, corresponding to the current climate. The research also provides insights into less commonly used variables, such as the temperature difference and the North Atlantic Oscillation Index. Finally, the comparison of AOCs and complementary analysis provides new findings on the specificities of these wine-growing sub-regions.

Furthermore, the impacts of this study are even broader. First of all, the findings of this study allow the winemakers in the different French regions to enhance their understanding of how climate factors influence their wines depending on the types of wines they produce. This knowledge can help them to make more informed decisions regarding their vineyards and the grape varieties best suited for their weather. It will also allow them to plan strategically their schedules all year round and employ some methods to protect their wines from harsh weather conditions. In addition, as discussed earlier, each AOC displays products coming from a specific terroir with special characteristics defined by the PDO (Protected Designation of

Origin). As such, this research could impact AOC policy decisions and adaptation strategies to update the guidelines on certain practices in response to evolving climate conditions.

However, this research contains some limitations. Regarding the reliability and objectivity of wine reviews used in this study, it is essential to consider Robert Parker Wine Advocate's operational and ethical frameworks. As such, the rating website takes strict ethical and operational measures to avoid conflict of interest (Robert Parker Wine Advocate, 2023).

Nevertheless, it is significant to acknowledge that taste is subjective so that it can sometimes limit the objectivity of experts when giving wine ratings. This study understands that the Robert Parker index also presents other specific limitations. The index does not consistently evaluate the same wines annually and it does not review the same number of wines each time. The rating agency should take a more standardised approach using a fixed set of wines reviewed over several years to be more accurate. Moreover, using several renowned critics' ratings could be one potential solution to mitigate the issue of subjectivity. However, some ratings are not given on the same scale depending on the rating agency or do not use the same guidelines when evaluating the wines, which could also be a potential issue.

Moreover, concerning the weather variables, this study uses more climatic variables beyond just average temperature and precipitation. However, the research could have accounted for even more diverse variables to be more precise. For instance, some previous studies use additional parameters such as humidity, sun hours, water balance, and cloudiness (Cifuentes & Charlin, 2022; Tsai & Lin, 2020; Ramirez, 2008). Yet, these variables were not included in this study due to the challenges associated with collecting such data.

Furthermore, this study sets certain thresholds for the variance inflation factor (VIF) of 8 between variables in the methodology section. However, other studies on the topic might employ stricter thresholds such as five (Hayez, 2023). This choice implies a potential presence of multicollinearity issues that might not be fully addressed in the results. This multicollinearity is clear between the variables present in linear and quadratic forms (i.e. temperature and precipitation variables in quadric models). This multicollinearity could explain the presence of a few counterintuitive coefficients in the results. This limitation could be limited by using quadratic variables only for certain seasons or using only linear variables. However, choosing a specific season for quadratic variables could limit the potential of models to understand the overall and season-to-season impacts of the variables on the ratings. Moreover, only using linear forms would not allow the research to account for different impacts upon a certain threshold, which is one of the goals of this study.

This study uses four different types of regression models for robustness of results. However, some of the intrinsic assumptions of regression models are not always respected in every model. In models without the semi-log transformation, some assumptions were not confirmed, yet the signs of the coefficients remained usually consistent. Moreover, even after applying the semi-log transformation which could improve these assumptions, some of them were still not met (Appendix 8). Specifically, linearity issues could imply that the models may not accurately capture the relationship between variables. Also, homoscedasticity issues might indicate that the model's reliability in predictions and confidence intervals may be less accurate and normality troubles could mean that the validity of statistical tests and confidence intervals may not be perfectly precise. Even though these problems must be considered, these regressions are still approximately linear, homoscedastic or normal so that it can be sufficient to draw conclusions from these results.

These limitations can provide potential room for future research and analysis on the topic. As such, the models crafted in this research could be further developed by incorporating additional weather variables. In addition, future studies could compute a consensus of wine ratings to address the subjectivity of taste. Lastly, designing models which resolve the few issues with linearity, homoscedasticity, and normality could also be a potential way to improve the research on the topic.

This study could also trigger the development of new research on different areas of the topic. On the one hand, future studies could draw new predictive models to grasp the impacts of climate change and global warming on wines in France and in other parts of the world. On the other hand, future research should also focus on finding optimums for temperature variables in wine areas to understand which future regions or sub-regions are at risk of losing their wine weather suitability. Finally, these new studies could also broaden the analysis and research further on less known weather-related variables such as NAO or the difference between maximum and minimum temperature. This would contribute to deepening the understanding of their impacts on wine.

# 6. Conclusion

This research analyses the impact of weather variables on the quality of French wines from nine AOCs, part of four well-known wine regions: Bordeaux, Burgundy, Loire and Rhône. Covering vintage from 1970 to 2019, the study aims to understand how weather variables impact French wines' quality and to identify potential similarities and differences between the nine AOCs. Different regressions were conducted for each AOC, employing four different types of models (linear, quadratic, semi-log linear, semi-log quadratic). Each regression was tailored with the best composition of variables, fitting the data for each type of model and each AOC. As a result, the study includes 36 regressions as the four models are applied to each AOC under study.

Based on the analysis of the statistical results, the study concludes that weather variables have a significant impact on the quality of French wines. Indeed, the adjusted *R*-squared (explanatory level) of the different regressions varies between 40% and 73%, with the best model type for each AOC averaging 58.3%. Although some AOCs include the trend in their regressions which is the only non-weather-related variable, it has been demonstrated that the former has a limited impact on the value of the adjusted *R*-squared. Furthermore, the inclusion of quadratic variables increases the adj. *R*-squared, highlighting the sensitivity of French wines to extreme weather conditions.

The first part of the statistical analysis confirmed most of the hypotheses initially formulated and aligned most of the findings with previous studies. Several weather variables, including temperature, precipitation and the number of frost days, showed a significant presence in the 36 regressions. Temperature exhibits a significant positive impact during the growing season. As for precipitation, it has a positive impact in the winter and early growing season and a stronger negative impact during the growing and harvest season. The quadratic form of these two variables, when significant, has mainly a negative coefficient. This confirms that temperature and precipitation can have a positive impact on quality, but only up to a certain threshold. Additionally, the number of frost days comes up significantly quite often with always a negative sign, regardless of the season.

For certain variables for which no initial hypotheses on their potential impact were made, the study provides new insights. Firstly, the early growing season temperature negatively affects the quality of French wines. Concerning the North Atlantic Oscillation index (NAO), as presented in the hypotheses, it has an impact on wine quality although it is limited, occurring only in a few regressions. When significant, the NAO variables show a negative impact whatever the season. Finally, the temperature difference has a mixed impact during the winter season but positively affects quality during the early-growing and harvest seasons.

The second part of the statistical analysis highlighted the disparities between the AOCs, underlining the importance of applying separate regressions to each of them. In terms of explanatory power, the AOCs of Côte de Nuits and Côte Rôtie/Hermitage exhibit the highest adj. $R$-squared values. On a regional level, Bordeaux and Rhône share certain similarities: a strong sensitivity to frost and precipitation extremes, with an explanatory power based solely on weather variables. On the contrary, Burgundy and Loire include the trend in their significant variables. White wines, particularly those from the AOCs Loire and Burgundy white, show less sensitivity to extreme weather conditions than red wines. Finally, the AOCs Côte de Nuits and Côte de Beaune, both pinot noir, exhibit a high sensitivity to temperature extremes. The complementary analysis of these two AOCs revealed that the average temperature over the last fifty years has been below their optimum temperature, indicating the future suitability of the Burgundy region for these two AOCs in the short and medium term.

Unlike Burgundy, other regions of France are at risk of losing their suitability shortly due to climate change. Analysing the impact of weather variables on the quality of French wines provides a better understanding of how these factors influence wine and how future climate change will impact these wine-growing regions. This research contributes therefore to the literature by confirming the impact of weather variables on various French wine-growing regions up to a recent period. The study also offers new insights on weather variables that have been less studied in the past, as well as on potential disparities between AOCs.

In conclusion, this study demonstrates that weather variables have an impact on the quality of French wines. Incorporating the new findings from this study in future research could help confirm and better understand the impact of less-used variables such as NAO, as well as the disparities between wine-growing regions. In addition, the use of predictive models to forecast the future quality of these French wines, as well as calculating more temperature optimums to analyse the future suitability of different French wine-growing regions, could provide valuable information on the wine-growing regions at risk.

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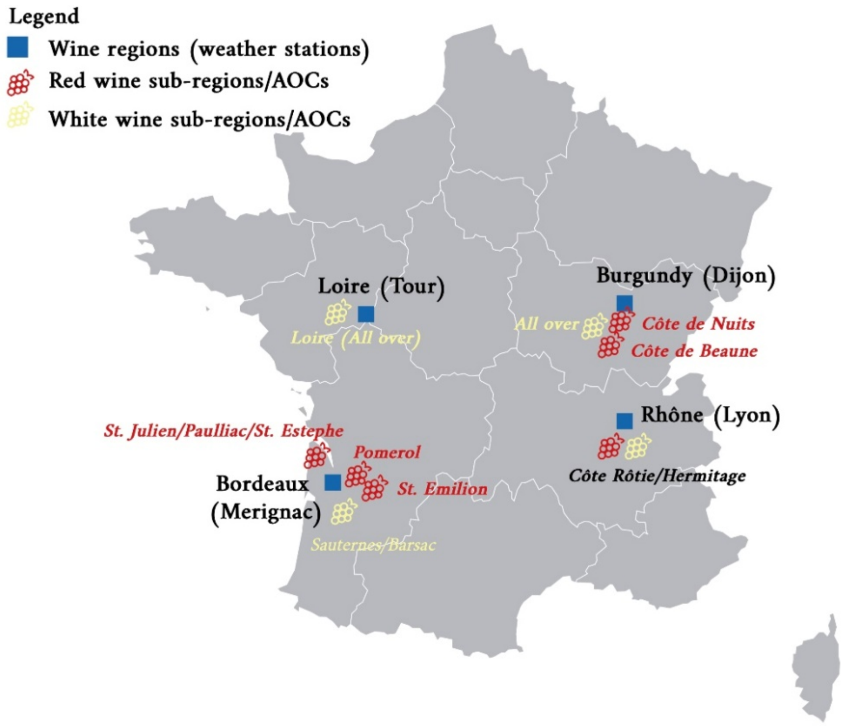
# 8. Appendices

## Appendix 1

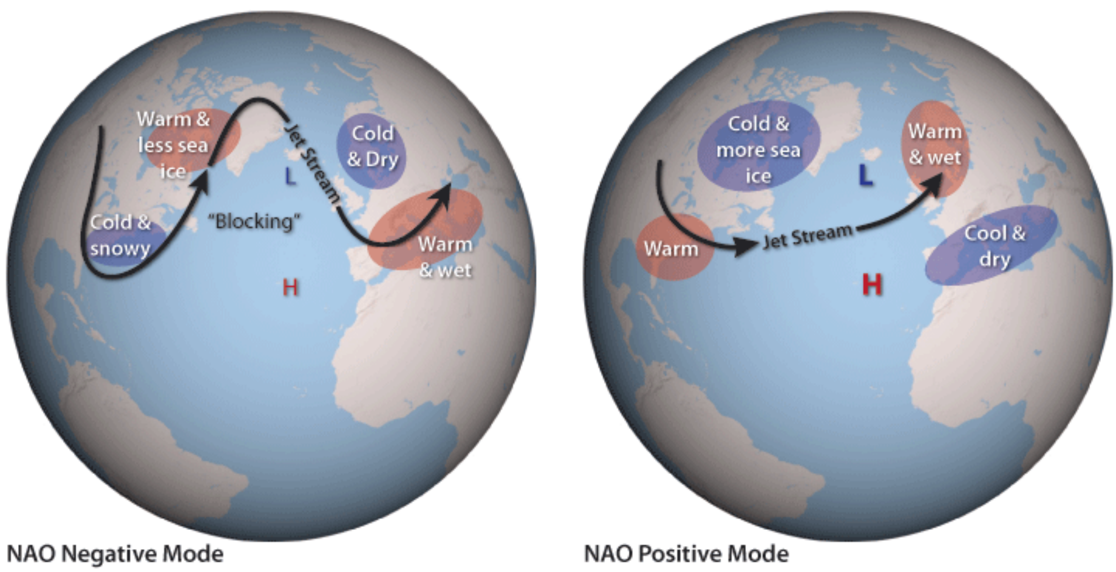
Figure 1: Map of wine regions, AOCs and weather stations.




*Source: Map prepared by the authors*

## Appendix 2

Figure 2: North Atlantic Oscillation map




*Source: NOAA (climate.gov)*

**Appendix 3**

Wine description and Robert Parker scale

In the Bordeaux sub-region of St. Julien/Pauillac/ St. Estephe, the wine indexes are based for Pauillac on 1315 red wines (blend mix of Merlot, Cabernet Sauvignon and Petit Verdot), for St. Estephe on 895 red and 21 white wines (blend of Merlot, Cabernet Sauvignon and Petit Verdot) and St. Julien on 894 red and three white wines (a blend of Cabernet Sauvignon, Merlot and Petit Verdot). In other Bordeaux subregions such as St. Emilion and Pomerol, the wine indexes take into account 4579 red and 59 white wines (Merlot Cabernet Franc and Cabernet Sauvignon) and 2283 red wines (Cabernet and Merlot) respectively. Lastly, the sub-region Sauternes/Barsac incorporates 956 white wines (blend mic of Semillon and Sauvignon Blanc) for Sauternes/Barsac and 314 white wines (blend of Sémillion and Sauvignon Blanc) for Barsac. Similarly, for the wine burgundy region, Côte de Beaune and Côte de Nuits are based on 17961 and 8454 red wines (mostly Pinot Noir) respectively. The Burgundy (white) subregion has 22616 white wines (mainly Chardonnay) for its yearly averages. Moreover, the Rhône's Côte Rôtie/Hermitage sub-region includes 378 red and 376 white wines (primarily Syrah) for Côte Rôtie and 830 red and 519 white wines for Hermitage (a blend of Syrah Marsan and Roussanne). Lastly, the Loire white wine sub-region comprises 59 white wines, predominantly Chenin Blanc and Chardonnay. The indexes for St. Julien/Pauillac/St. Estephe, Pomerol, St. Emilion, Côte de Nuits and Côte de Beaune are all composed of at least 98% red wines and are therefore included as red wine indexes in this analysis. Burgundy (White) and Loire (White) are included as white wine indexes, while Côte Rôtie/Hermitage is included as a mix of the two.

The wine indexes used in this study correlate to the following description:

- **96 - 100**: Wines of extraordinary depth and intricate character.
- **90 - 95**: Outstanding wines with significant complexity and distinction.
- **80 - 89**: Slightly above average to very good wine with varying levels of finesse.
- **70 - 79**: Average wines that are competently produced yet lack notable features.
- **60 - 69**: Below-average wines with clear shortcomings such as too much acidity or tannin, lack of flavour, or off-putting smells or tastes.
- **50 - 59**: Wines that are not acceptable.

## Appendix 4

Table 3: Summary Statistics : Seasonal Weather Variables

| Weather Variables | Mean | Median | Min | Max | SD | CV |
|---|---|---|---|---|---|---|
| ***Winter Season (Nov - Feb)*** | | | | | | |
| **Bordeaux** | | | | | | |
| $TAVG_{\mathrm{W}}$ | 7.77 | 7.57 | 5.63 | 10.36 | 1.13 | 0.15 |
| $PRCP_{\mathrm{W}}$ | 92.68 | 91.25 | 37.25 | 158.25 | 27.08 | 0.29 |
| $DIFF_{\mathrm{W}}$ | 7.53 | 7.46 | 6.62 | 9.57 | 0.56 | 0.07 |
| $NAO_{\mathrm{W}}$ | 0.27 | 0.34 | -1.26 | 1.42 | 0.65 | 2.42 |
| $DT32_{\mathrm{W}}$ | 6.33 | 6.38 | 1.75 | 11.25 | 2.60 | 0.41 |
| **Burgundy** | | | | | | |
| $TAVG_{\mathrm{W}}$ | 3.72 | 3.71 | 1.12 | 6.01 | 1.12 | 0.30 |
| $PRCP_{\mathrm{W}}$ | 59.48 | 57.60 | 28.60 | 101.20 | 15.62 | 0.26 |
| $DIFF_{\mathrm{W}}$ | 6.21 | 6.14 | 4.93 | 7.54 | 0.60 | 0.10 |
| $NAO_{\mathrm{W}}$ | 0.27 | 0.34 | -1.26 | 1.42 | 0.65 | 2.42 |
| $DT32_{\mathrm{W}}$ | 13.10 | 13.00 | 7.50 | 19.50 | 3.16 | 0.24 |
| **Loire** | | | | | | |
| $TAVG_{\mathrm{W}}$ | 5.76 | 5.83 | 2.99 | 8.42 | 1.12 | 0.19 |
| $PRCP_{\mathrm{W}}$ | 63.51 | 62.53 | 29.05 | 101.45 | 17.62 | 0.28 |
| $DIFF_{\mathrm{W}}$ | 5.99 | 5.96 | 4.99 | 6.75 | 0.41 | 0.07 |
| $NAO_{\mathrm{W}}$ | 0.27 | 0.34 | -1.26 | 1.42 | 0.65 | 2.42 |
| $DT32_{\mathrm{W}}$ | 8.38 | 8.25 | 2.75 | 14.50 | 2.67 | 0.32 |
| **Rhône** | | | | | | |
| $TAVG_{\mathrm{W}}$ | 4.80 | 4.78 | 1.80 | 8.09 | 1.24 | 0.26 |
| $PRCP_{\mathrm{W}}$ | 64.80 | 64.41 | 27.10 | 114.48 | 18.58 | 0.29 |
| $DIFF_{\mathrm{W}}$ | 6.34 | 6.28 | 5.54 | 7.95 | 0.56 | 0.09 |
| $NAO_{\mathrm{W}}$ | 0.27 | 0.34 | -1.26 | 1.42 | 0.65 | 2.42 |
| $DT32_{\mathrm{W}}$ | 10.68 | 10.63 | 2.50 | 19.75 | 3.25 | 0.30 |
| ***Early Growing Season (Mar - Apr)*** | | | | | | |
| **Bordeaux** | | | | | | |
| $TAVG_{\mathrm{EG}}$ | 11.05 | 11.14 | 8.00 | 13.73 | 1.27 | 0.11 |
| $PRCP_{\mathrm{EG}}$ | 71.52 | 66.25 | 16.50 | 153.00 | 29.83 | 0.42 |
| $DIFF_{\mathrm{EG}}$ | 9.87 | 9.78 | 7.50 | 12.98 | 1.11 | 0.11 |
| $NAO_{\mathrm{EG}}$ | 0.24 | 0.21 | -1.13 | 1.73 | 0.71 | 2.96 |
| $DT32_{\mathrm{EG}}$ | 2.02 | 1.00 | 0.00 | 8.50 | 2.21 | 1.09 |
| **Burgundy** | | | | | | |
| $TAVG_{\mathrm{EG}}$ | 8.62 | 8.51 | 5.86 | 11.21 | 1.15 | 0.13 |
| $PRCP_{\mathrm{EG}}$ | 52.21 | 46.60 | 12.90 | 119.00 | 25.60 | 0.49 |
| $DIFF_{\mathrm{EG}}$ | 9.86 | 9.73 | 7.50 | 12.59 | 1.30 | 0.13 |
| $NAO_{\mathrm{EG}}$ | 0.24 | 0.21 | -1.13 | 1.73 | 0.71 | 2.96 |
| $DT32_{\mathrm{EG}}$ | 5.29 | 4.75 | 0.50 | 11.50 | 2.75 | 0.52 |
| **Loire** | | | | | | |
| $TAVG_{\mathrm{EG}}$ | 9.18 | 9.09 | 6.55 | 11.80 | 1.14 | 0.12 |
| $PRCP_{\mathrm{EG}}$ | 51.64 | 47.98 | 10.00 | 119.10 | 24.00 | 0.46 |
| $DIFF_{\mathrm{EG}}$ | 9.03 | 8.98 | 7.09 | 11.08 | 1.05 | 0.12 |
| $NAO_{\mathrm{EG}}$ | 0.24 | 0.21 | -1.13 | 1.73 | 0.71 | 2.96 |
| $DT32_{\mathrm{EG}}$ | 3.37 | 2.50 | 0.50 | 11.50 | 2.48 | 0.74 |
| **Rhône** | | | | | | |
| $TAVG_{\mathrm{EG}}$ | 9.56 | 9.60 | 6.65 | 12.19 | 1.41 | 0.15 |
| $PRCP_{\mathrm{EG}}$ | 66.32 | 64.53 | 21.10 | 169.30 | 29.04 | 0.44 |
| $DIFF_{\mathrm{EG}}$ | 9.39 | 9.28 | 7.74 | 11.61 | 0.89 | 0.09 |
| $NAO_{\mathrm{EG}}$ | 0.24 | 0.21 | -1.13 | 1.73 | 0.71 | 2.96 |
| $DT32_{\mathrm{EG}}$ | 3.64 | 3.25 | 0.00 | 10.00 | 2.73 | 0.75 |

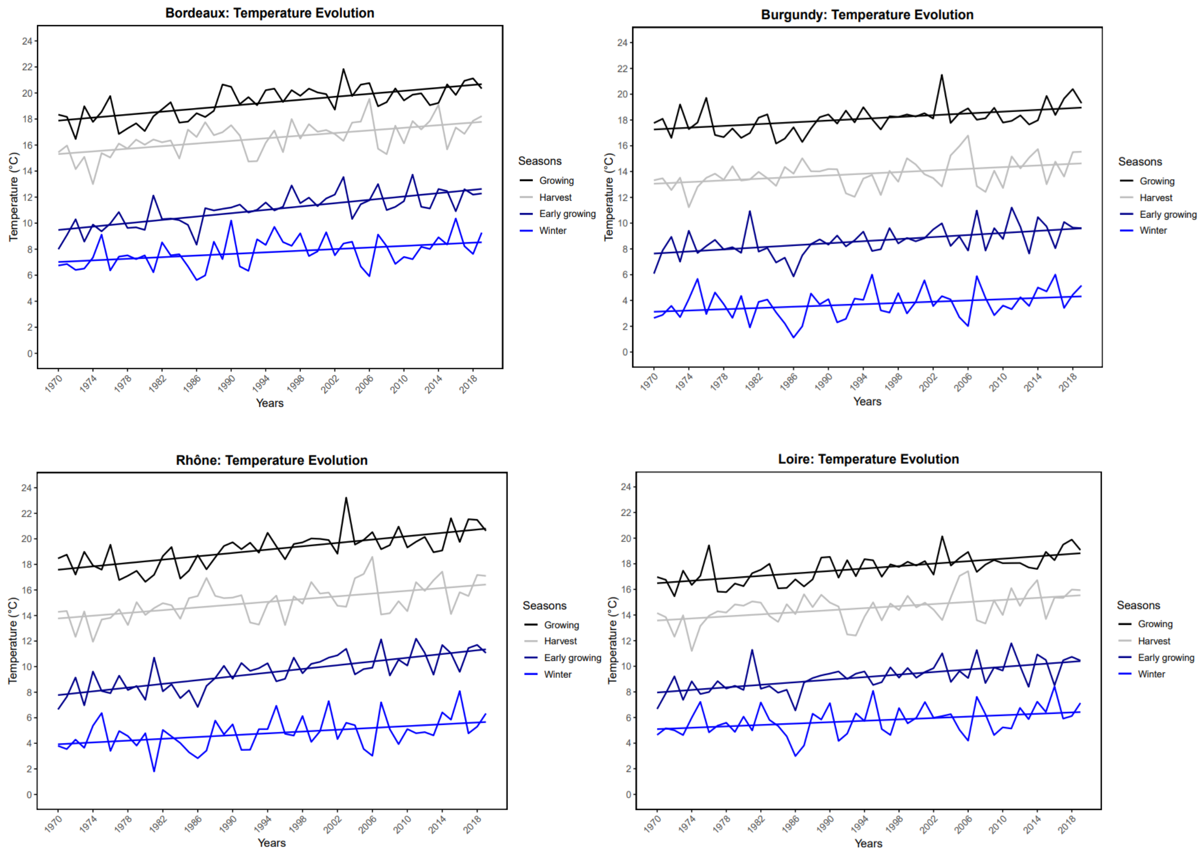
Table 3 – continued from previous page

| Weather Variables | Mean | Median | Min | Max | SD | CV |
|---|---|---|---|---|---|---|
| ***Growing Season (May - Aug)*** | | | | | | |
| **Bordeaux** | | | | | | |
| $TAVG_{\mathrm{G}}$ | 19.28 | 19.30 | 16.46 | 21.84 | 1.20 | 0.06 |
| $PRCP_{\mathrm{G}}$ | 60.87 | 58.25 | 20.50 | 134.00 | 21.13 | 0.35 |
| $DIFF_{\mathrm{G}}$ | 10.84 | 10.76 | 9.15 | 13.19 | 0.77 | 0.07 |
| $NAO_{\mathrm{G}}$ | -0.11 | -0.02 | -1.58 | 1.64 | 0.71 | -6.28 |
| $DT32_{\mathrm{G}}$ | 0.01 | 0.00 | 0.00 | 0.25 | 0.04 | 7.07 |
| **Burgundy** | | | | | | |
| $TAVG_{\mathrm{G}}$ | 18.11 | 18.10 | 16.17 | 21.50 | 1.05 | 0.06 |
| $PRCP_{\mathrm{G}}$ | 67.94 | 70.98 | 32.40 | 117.65 | 18.02 | 0.27 |
| $DIFF_{\mathrm{G}}$ | 11.03 | 10.99 | 9.16 | 12.84 | 0.87 | 0.08 |
| $NAO_{\mathrm{G}}$ | -0.11 | -0.02 | -1.58 | 1.64 | 0.71 | -6.28 |
| $DT32_{\mathrm{G}}$ | 0.02 | 0.00 | 0.00 | 0.25 | 0.06 | 4.00 |
| **Loire** | | | | | | |
| $TAVG_{\mathrm{G}}$ | 17.65 | 17.80 | 15.46 | 20.14 | 1.08 | 0.06 |
| $PRCP_{\mathrm{G}}$ | 51.21 | 50.65 | 19.08 | 96.80 | 16.57 | 0.32 |
| $DIFF_{\mathrm{G}}$ | 10.94 | 10.95 | 9.22 | 13.94 | 0.89 | 0.08 |
| $NAO_{\mathrm{G}}$ | -0.11 | -0.02 | -1.58 | 1.64 | 0.71 | -6.28 |
| $DT32_{\mathrm{G}}$ | 0.02 | 0.00 | 0.00 | 0.25 | 0.06 | 4.00 |
| **Rhône** | | | | | | |
| $TAVG_{\mathrm{G}}$ | 19.19 | 19.34 | 16.64 | 23.23 | 1.37 | 0.07 |
| $PRCP_{\mathrm{G}}$ | 76.36 | 72.31 | 28.88 | 128.13 | 22.50 | 0.29 |
| $DIFF_{\mathrm{G}}$ | 10.76 | 10.72 | 9.13 | 13.10 | 0.74 | 0.07 |
| $NAO_{\mathrm{G}}$ | -0.11 | -0.02 | -1.58 | 1.64 | 0.71 | -6.28 |
| $DT32_{\mathrm{G}}$ | 0.01 | 0.00 | 0.00 | 0.25 | 0.04 | 7.07 |
| ***Harvest Season (Sep - Oct)*** | | | | | | |
| **Bordeaux** | | | | | | |
| $TAVG_{\mathrm{H}}$ | 16.55 | 16.56 | 13.00 | 19.55 | 1.25 | 0.08 |
| $PRCP_{\mathrm{H}}$ | 78.75 | 77.25 | 9.00 | 188.50 | 41.88 | 0.53 |
| $DIFF_{\mathrm{H}}$ | 10.30 | 10.12 | 7.60 | 13.55 | 1.19 | 0.12 |
| $NAO_{\mathrm{H}}$ | -0.16 | -0.14 | -1.93 | 1.30 | 0.74 | -4.50 |
| $DT32_{\mathrm{H}}$ | 0.16 | 0.00 | 0.00 | 1.50 | 0.40 | 2.48 |
| **Burgundy** | | | | | | |
| $TAVG_{\mathrm{H}}$ | 13.84 | 13.77 | 11.23 | 16.79 | 1.11 | 0.08 |
| $PRCP_{\mathrm{H}}$ | 63.85 | 64.85 | 14.25 | 152.15 | 27.74 | 0.43 |
| $DIFF_{\mathrm{H}}$ | 9.50 | 9.50 | 6.82 | 12.50 | 1.22 | 0.13 |
| $NAO_{\mathrm{H}}$ | -0.16 | -0.14 | -1.93 | 1.30 | 0.74 | -4.50 |
| $DT32_{\mathrm{H}}$ | 0.48 | 0.00 | 0.00 | 2.50 | 0.73 | 1.52 |
| **Loire** | | | | | | |
| $TAVG_{\mathrm{H}}$ | 14.55 | 14.64 | 11.20 | 17.42 | 1.20 | 0.08 |
| $PRCP_{\mathrm{H}}$ | 56.53 | 56.75 | 11.15 | 107.05 | 24.42 | 0.43 |
| $DIFF_{\mathrm{H}}$ | 9.58 | 9.53 | 7.28 | 12.51 | 1.17 | 0.12 |
| $NAO_{\mathrm{H}}$ | -0.16 | -0.14 | -1.93 | 1.30 | 0.74 | -4.50 |
| $DT32_{\mathrm{H}}$ | 0.24 | 0.00 | 0.00 | 1.50 | 0.45 | 1.89 |
| **Rhône** | | | | | | |
| $TAVG_{\mathrm{H}}$ | 15.10 | 15.01 | 11.95 | 18.59 | 1.37 | 0.09 |
| $PRCP_{\mathrm{H}}$ | 88.84 | 88.38 | 9.90 | 277.60 | 43.94 | 0.49 |
| $DIFF_{\mathrm{H}}$ | 9.24 | 9.10 | 6.86 | 12.34 | 1.09 | 0.12 |
| $NAO_{\mathrm{H}}$ | -0.16 | -0.14 | -1.93 | 1.30 | 0.74 | -4.50 |
| $DT32_{\mathrm{H}}$ | 0.31 | 0.00 | 0.00 | 2.00 | 0.53 | 1.72 |

*Source: Table prepared by the authors*

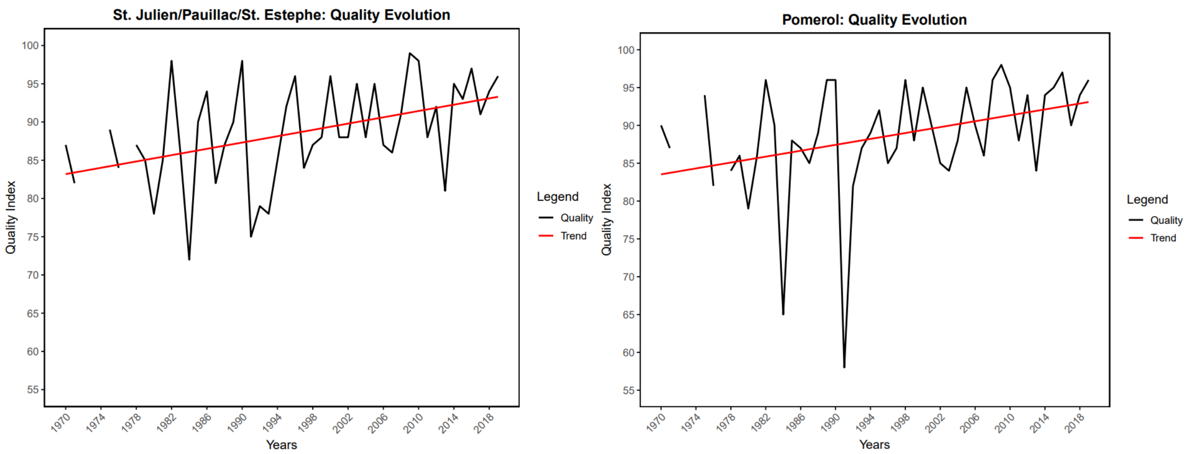
# Appendix 5

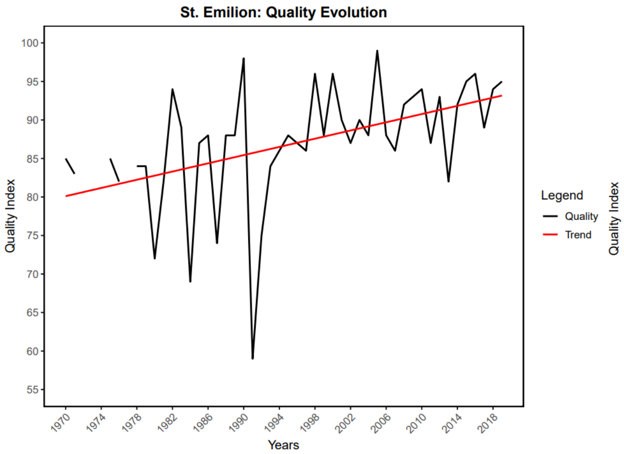
Figure 3: Evolution of seasonal temperatures and their trend

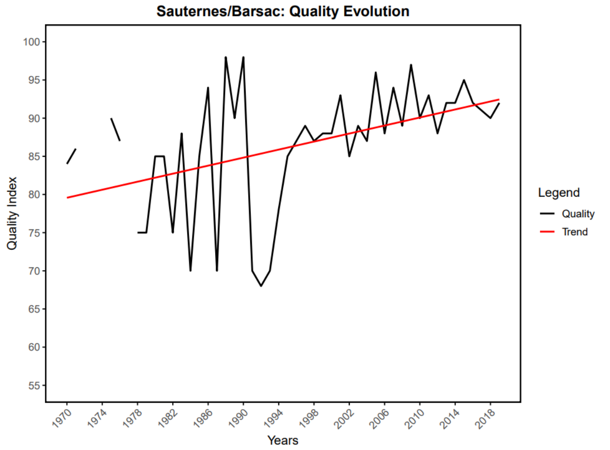


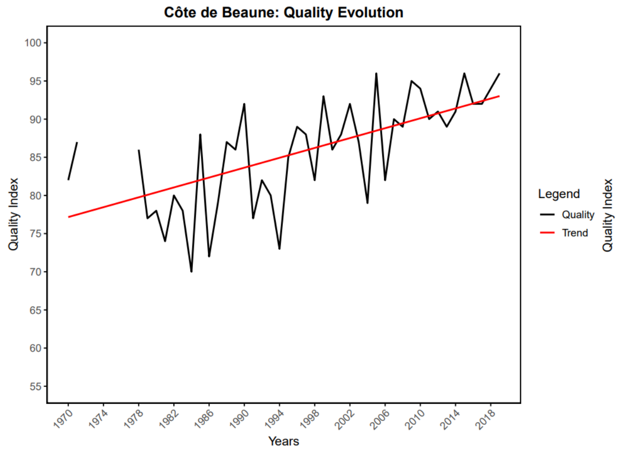

*Source: Graphs prepared by the authors*

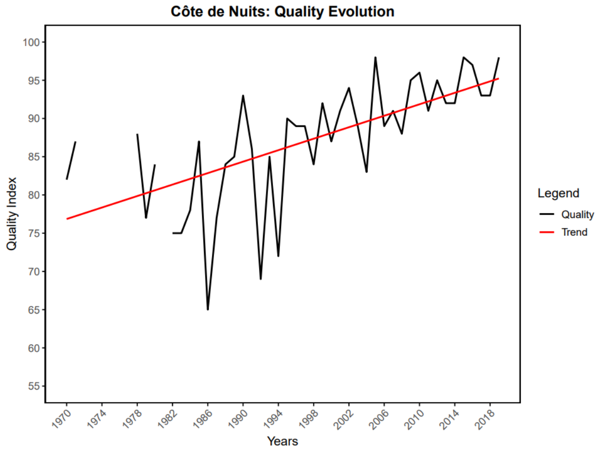
Figure 4: Evolution of quality indexes and their trend

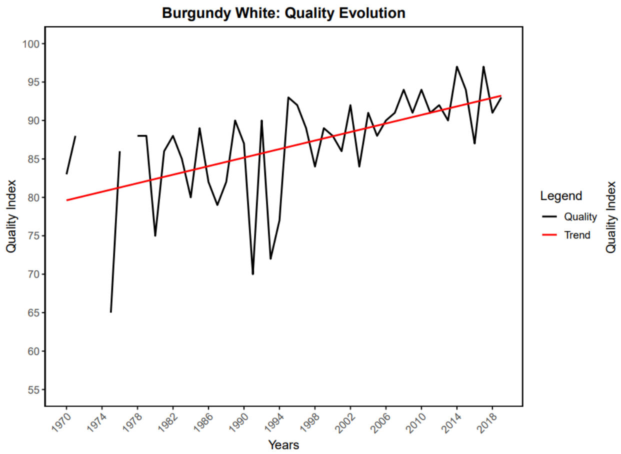


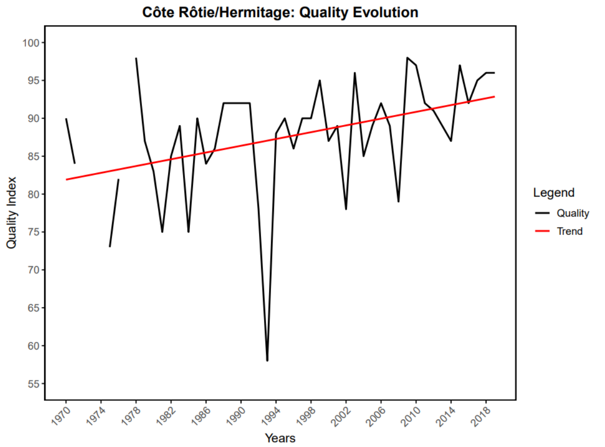

St. Emilion: Quality Evolution
Quality Index
Years
Legend
Quality
Trend

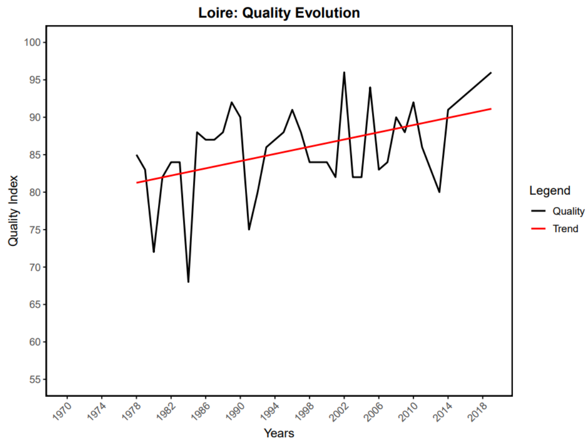

Sauternes/Barsac: Quality Evolution
Quality Index
Years
Legend
Quality
Trend


Côte de Beaune: Quality Evolution
Quality Index
Years
Legend
Quality
Trend


Côte de Nuits: Quality Evolution
Quality Index
Years
Legend
Quality
Trend


Burgundy White: Quality Evolution
Quality Index
Years
Legend
Quality
Trend

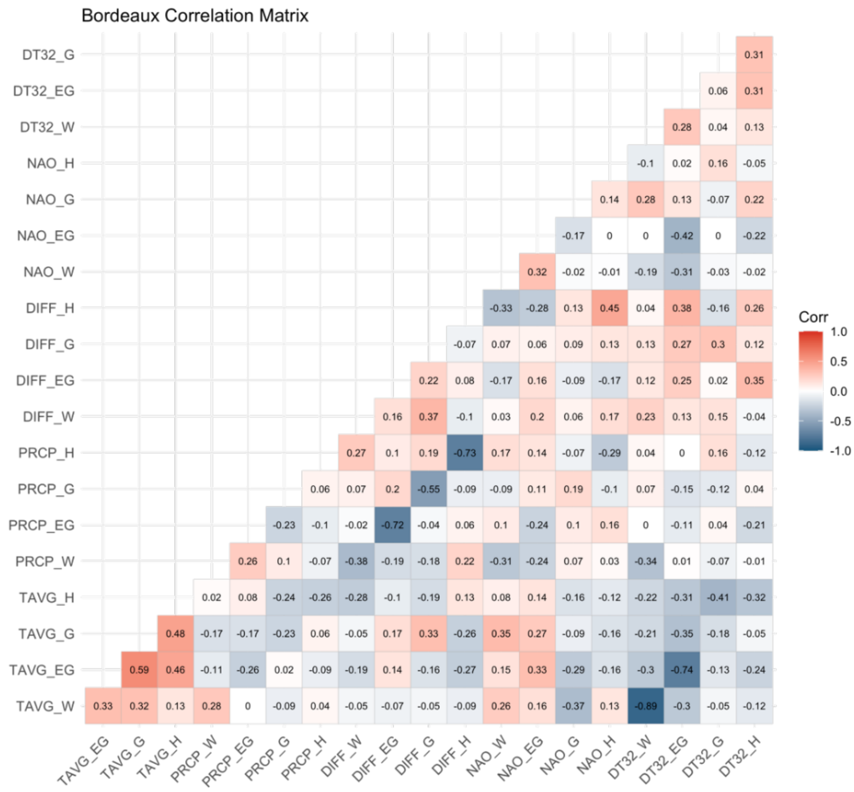

Côte Rôtie/Hermitage: Quality Evolution
Quality Index
Years
Legend
Quality
Trend




*Source: Graphs prepared by the authors*

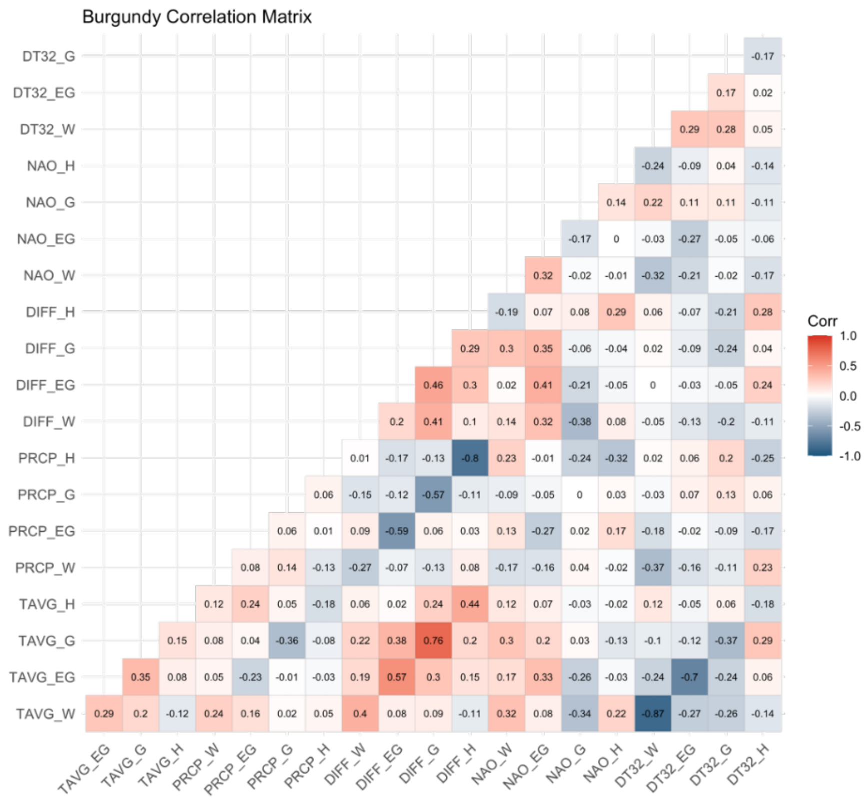
## Appendix 6

Figure 5: Bordeaux Correlation Matrix



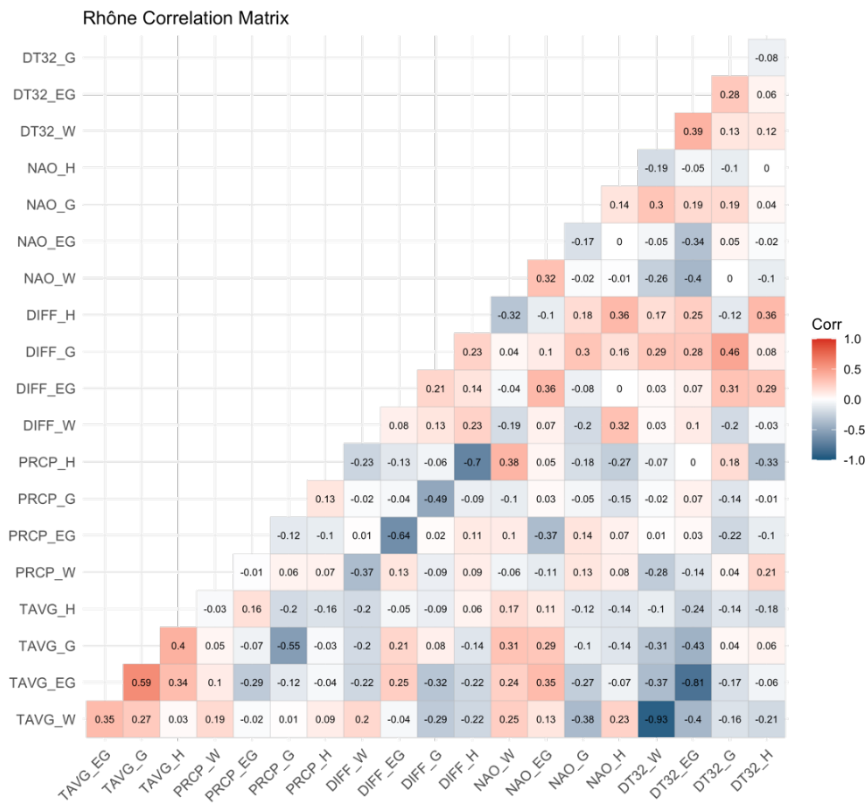

*Source: Matrix prepared by the authors*

Figure 6: Burgundy Correlation Matrix



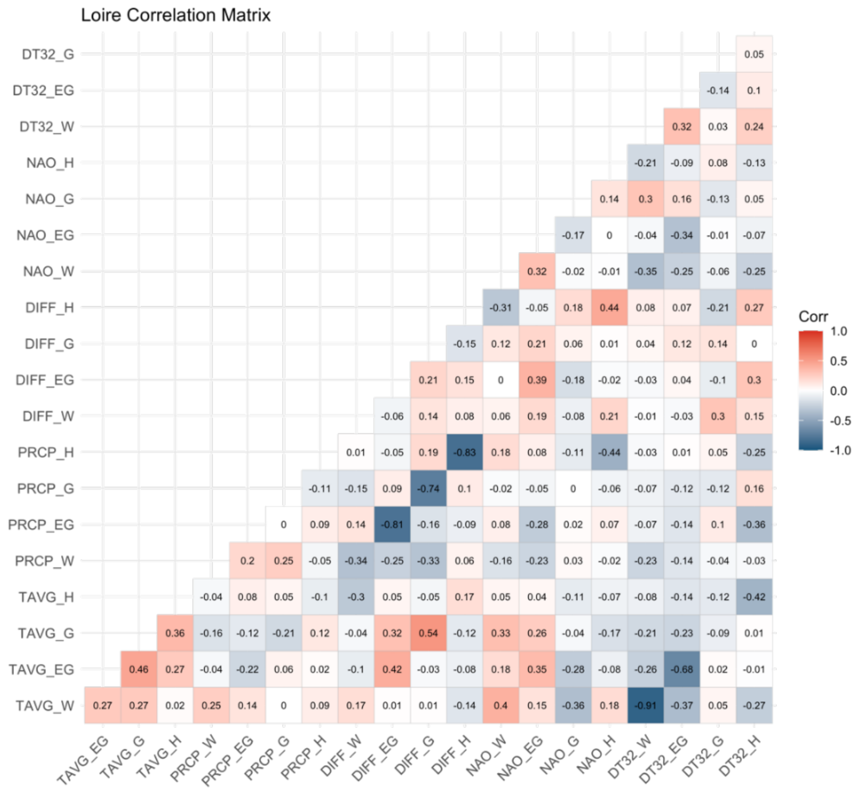

*Source: Matrix prepared by the authors*

Figure 7: Rhône Correlation Matrix




*Source: Matrix prepared by the authors*

Figure 8: Loire Correlation Matrix




*Source: Matrix prepared by the authors*

## Appendix 7

Table 10: Summary Linear Regressions Results : Model 1

| Linear Model | St. Emilion | St. Julien Paulliac St. Estephe | Pomerol | Sauternes Barsac | Côte de Beaune | Côte de Nuits | Burgundy White | Côte Rotie Hermitage | Loire White |
|---|---|---|---|---|---|---|---|---|---|
| *Intercept* | 15.36 | 49.39* | 10.70 | 46.34* | 41.36*** | 59.75*** | 43.91* | 102.66*** | 15.34 |
| | (19.14) | (20.38) | (19.61) | (19.58) | (8.64) | (15.61) | (21.63) | (16.94) | (23.88) |
| *Trend* | | 0.17* | | 0.14 | 0.28*** | 0.41*** | 0.18* | | 0.17* |
| | | (0.08) | | (0.09) | (0.07) | (0.10) | (0.08) | | (0.08) |
| ***Winter Season (Nov - Feb)*** | | | | | | | | | |
| $TAVG_W$ | | | | | | | | | |
| $PRCP_W$ | | | | | | | | | |
| $DIFF_W$ | | | 3.16* | | | | | -2.82* | 4.31* |
| | | | (1.52) | | | | | (1.28) | (1.97) |
| $NAO_W$ | | | | | | | | -2.75* | |
| | | | | | | | | (1.29) | |
| $DT32_W$ | -0.94** | -0.44 | -0.69* | -0.66(.) | | | 0.55* | -0.60** | |
| | (0.31) | (0.28) | (0.33) | (0.33) | | | (0.23) | (0.22) | |
| ***Early Growing Season (Mar - Apr)*** | | | | | | | | | |
| $TAVG_{EG}$ | -1.12 | -2.45(.) | -1.80(.) | | | -6.20** | | | |
| | (0.90) | (1.22) | (0.93) | | | (1.99) | | | |
| $PRCP_{EG}$ | 0.09* | | 0.06* | | | | | | |
| | (0.04) | | (0.03) | | | | | | |
| $DIFF_{EG}$ | 1.81(.) | 1.23 | | | 0.98 | 4.79*** | | | |
| | (1.03) | (0.89) | | | (0.76) | (1.31) | | | |
| $NAO_{EG}$ | | | | | | -3.05(.) | | | |
| | | | | | | (1.58) | | | |
| $DT32_{EG}$ | | -0.80 | | 1.23* | | -1.59* | | -0.84* | |
| | | (0.64) | | (0.52) | | (0.68) | | (0.31) | |

Table 10 – continued from previous page

| Linear Model | St. Emilion | St. Julien Paulliac St. Estephe | Pomerol | Sauternes Barsac | Côte de Beaune | Côte de Nuits | Burgundy White | Côte Rotie Hermitage | Loire White |
|---|---|---|---|---|---|---|---|---|---|
| ***Growing Season (May - Aug)*** | | | | | | | | | |
| $TAVG_G$ | 3.80*** | 2.13* | 4.06*** | 2.47* | | | 1.80 | | 1.49 |
| | (0.99) | (0.95) | (0.97) | (1.02) | | | (1.12) | | (1.00) |
| $PRCP_G$ | -0.07 | -0.10* | | -0.07 | | | 0.11(.) | -0.14*** | |
| | (0.04) | (0.04) | | (0.04) | | | (0.06) | (0.03) | |
| $DIFF_G$ | | | | | | | | | |
| $NAO_G$ | -1.94 | | -3.45** | | | -2.69(.) | -1.68 | | |
| | (1.22) | | (1.21) | | | (1.54) | (1.40) | | |
| $DT32_G$ | | | | | | | | | |
| ***Harvest Season (Sep - Oct)*** | | | | | | | | | |
| $TAVG_H$ | | | | | | | | 0.74 | |
| | | | | | | | | (0.60) | |
| $PRCP_H$ | -0.05** | | -0.07** | -0.07** | | | -0.13*** | -0.04(.) | -0.06 |
| | (0.02) | | (0.02) | (0.02) | | | (0.03) | (0.02) | (0.06) |
| $DIFF_H$ | | 1.85** | | | 2.78*** | 3.23** | | 1.77(.) | 1.80 |
| | | (0.64) | | | (0.77) | (0.93) | | (0.94) | (1.24) |
| $NAO_H$ | | | | | | | | | -1.90 |
| | | | | | | | | | (1.23) |
| $DT32_H$ | | | | | | -2.47(.) | -2.08(.) | | -4.44* |
| | | | | | | (1.45) | (1.16) | | (1.95) |
| **Ajdusted *R*-squared** | 0.56 | 0.48 | 0.49 | 0.54 | 0.54 | 0.63 | 0.52 | 0.66 | 0.42 |
| **Model *P*-values** | 2.83E-06 | 4.75E-05 | 1.68E-05 | 1.41E-06 | 6.64E-08 | 1.57E-07 | 7.10E-06 | 2.80E-08 | 3.83E-04 |

**NOTE :** Standard Deviation is shown below each variable. "***", "**", "*", and "(.)" indicate significance levels : 0.001, 0.01, 0.05 and 0.10 respectively. Tables are prepared by Authors

Table 11: Summary Quadratic Regressions Results : Model 2

| Quadratic Model | St. Emilion | St. Julien Paulliac St. Estephe | Pomerol | Sauternes Barsac | Côte de Beaune | Côte de Nuits | Burgundy White | Côte Rotie Hermitage | Loire White |
|---|---|---|---|---|---|---|---|---|---|
| *Intercept* | -267.00 | -226.00 | -304.00 | -316.00 | -385.60* | -65.50 | 47.28* | 85.87** | -214.00 |
| | (213.20) | (198.93) | (220.46) | (209.76) | (180.00) | (40.00) | (19.89) | (12.10) | (183.60) |
| *Trend* | | | | | 0.35*** | 0.32** | 0.17* | | 0.16(.) |
| | | | | | (0.08) | (0.10) | (0.08) | | (0.08) |
| ***Winter Season (Nov - Feb)*** | | | | | | | | | |
| $TAVG_W$ | | | | | | | | | |
| $TAVG^2_W$ | | | | | | | | | |
| $PRCP_W$ | | | | | | | | 0.51* | |
| | | | | | | | | (0.19) | |
| $PRCP^2_W$ | | | | | | | | -0.004* | |
| | | | | | | | | (0.001) | |
| $DIFF_W$ | | | 3.09* | | -2.44 | -2.50** | | -2.82* | 4.49* |
| | | | (1.51) | | (1.64) | (1.86) | | (1.19) | (1.96) |
| $NAO_W$ | | | | | | | | | |
| $DT32W$ | -0.89** | -0.51(.) | -0.65(.) | -0.69* | | | 0.56* | -0.54* | |
| | (0.31) | (0.27) | (0.33) | (0.30) | | | (0.23) | (0.20) | |
| ***Early Growing Season (Mar - Apr)*** | | | | | | | | | |
| $TAVG_{EG}$ | | | -1.74(.) | | | 24.61** | | | |
| | | | (0.91) | | | (8.65) | | | |
| $TAVG^2_{EG}$ | | | | 0.07 | | -1.55** | | | |
| | | | | (0.05) | | (0.49) | | | |
| $PRCP_{EG}$ | 0.10** | | 0.06* | | | | | | |
| | 0.04 | | 0.03 | | | | | | |
| $PRCP^2_{EG}$ | | | | | | | | | |
| $DIFF_{EG}$ | 2.06(.) | | | | | 2.68** | | | |
| | (1.02) | | | | | (0.91) | | | |
| $NAO_{EG}$ | | | | | | | | | |
| $DT32_{EG}$ | | | | 1.38* | | | | -0.82** | |
| | | | | (0.54) | | | | (0.27) | |

Table 11 – continued from previous page

| Quadratic Model | St. Emilion | St. Julien Paulliac St. Estephe | Pomerol | Sauternes Barsac | Côte de Beaune | Côte de Nuits | Burgundy White | Côte Rotie Hermitage | Loire White |
|---|---|---|---|---|---|---|---|---|---|
| ***Growing Season (May - Aug)*** | | | | | | | | | |
| $TAVG_G$ | 32.20 | 27.20 | 36.60 | 38.83(.) | 52.46* | | 1.81 | | 2.70 |
| | (22.12) | (20.29) | (22.91) | (21.78) | (20.40) | | (1.10) | | (20.30) |
| $TAVG_G^2$ | -0.76 | -0.63 | -0.85 | -0.94 | -1.43* | | | | -0.71 |
| | (0.57) | (0.52) | (0.59) | (0.56) | (0.55) | | | | (0.57) |
| $PRCP_G$ | -0.08* | -0.07* | | | -0.87* | | | | |
| | (0.04) | (0.52) | | | (0.36) | | | | |
| $PRCP_G^2$ | | | | -0.0006* | 0.0060 * | | 0.0009* | -0.0009*** | |
| | | | | (0.0002) | (0.003) | | (0.0004) | (0.0002) | |
| $DIFF_G$ | | | | | | | | | |
| $NAO_G$ | -1.30 | | -3.35** | | | | 1.73 | | |
| | (1.15) | | (1.20) | | | | (1.39) | | |
| $DT32_G$ | | | | | | | | | |
| ***Harvest Season (Sep - Oct)*** | | | | | | | | | |
| $TAVG_H$ | | | | | | | | | |
| $TAVG_H^2$ | | | | | -0.05 | | | | |
| | | | | | (0.03) | | | | |
| $PRCP_H$ | | 0.13 | | 0.10 | | | -0.13*** | | -0.06 |
| | | (0.08) | | (0.07) | | | (0.03) | | (0.06) |
| $PRCP_H^2$ | -0.0003** | -0.0007(.) | -0.0004*** | -0.0010* | | | | -0.0003*** | |
| | (0.00002) | 0.0003 | (0.00004) | (0.00001) | | | | (0.00001) | |
| $DIFF_H$ | | 2.65* | | | 3.83*** | 3.88*** | | 2.15** | 1.93 |
| | | (1.05) | | | (0.81) | (0.88) | | (0.76) | (1.24) |
| $NAO_H$ | | | | | | | | | -1.79 |
| | | | | | | | | | (1.23) |
| $DT32_H$ | | -3.06 | | | | | -2.17(.) | | -4.26* |
| | | (2.26) | | | | | (1.16) | | (1.94) |
| **Adjusted *R*-squared** | 0.568 | 0.489 | 0.510 | 0.605 | 0.586 | 0.663 | 0.522 | 0.731 | 0.431 |
| **Model *P*-value** | 2.05E-06 | 3.39E-05 | 1.69E-05 | 4.30E-07 | 9.93E-07 | 2.79E-08 | 5.75E-06 | 5.251E-10 | 4.866E-4 |

**NOTE :** Standard Deviation is shown below each variable. "***", "**", "*", and "(.)" indicate significance levels : 0.001, 0.01, 0.05 and 0.10 respectively. Tables are prepared by Authors

Table 12: Summary Semi-Log Linear Regressions Results : Model 3

| **Semi-Log Linear Model** | **St. Emilion** | **St. Julien Paulliac St. Estephe** | **Pomerol** | **Sauternes Barsac** | **Côte de Beaune** | **Côte de Nuits** | **Burgundy White** | **Côte Rotie Hermitage** | **Loire White** |
|---|---|---|---|---|---|---|---|---|---|
| *Intercept* | -6.61** | -2.30 | -8.44*** | -4.54(.) | -1.90 | 2.70 | -3.34 | 4.94** | -5.60** |
| | (2.38) | (3.08) | (2.17) | (2.30) | (2.52) | (2.61) | (2.20) | (1.47) | (1.94) |
| *Trend* | | 0.03* | | | 0.04** | 0.07*** | 0.02* | | 0.03*** |
| | | (0.01) | | | (0.01) | (0.01) | (0.01) | | (0.01) |
| ***Winter Season (Nov - Feb)*** | | | | | | | | | |
| $TAVG_W$ | | | | | | | | | |
| $PRCP_W$ | | | | | | | | | |
| $DIFF_W$ | | | 0.42* | | -0.40(.) | -0.37 | | -0.42** | 0.45* |
| | | | (0.17) | | (0.23) | (0.25) | | (0.15) | (0.20) |
| $NAO_W$ | | | | | | | | -0.41* | |
| | | | | | | | | (0.16) | |
| $DT32_W$ | -0.11** | -0.07 | -0.08* | -0.10* | 0.05 | | 0.05* | -0.07** | |
| | (0.04) | (0.04) | (0.04) | (0.04) | (0.04) | | (0.02) | (0.03) | |
| ***Early Growing Season (Mar - Apr)*** | | | | | | | | | |
| $TAVG_{EG}$ | -0.15 | -0.47* | -0.24* | 0.13 | | -0.80** | | | |
| | (0.11) | (0.18) | (0.10) | (0.13) | | (0.26) | | | |
| $PRCP_{EG}$ | 0.008(.) | | 0.007* | | | | -0.003 | | |
| | (0.005) | | (0.003) | | | | (0.003) | | |
| $DIFF_{EG}$ | 0.19 | 0.29* | | | | 0.43** | | | |
| | (0.13) | (0.13) | | | | (0.15) | | | |
| $NAO_{EG}$ | | | | | | | | | |
| $DT32_{EG}$ | | -0.16 | | 0.15* | | -0.15(.) | | -0.12** | |
| | | (0.10) | | (0.07) | | (0.08) | | (0.04) | |

Table 12 – continued from previous page

| Semi-Log Linear Model | St. Emilion | St. Julien Paulliac St. Estephe | Pomerol | Sauternes Barsac | Côte de Beaune | Côte de Nuits | Burgundy White | Côte Rotie Hermitage | Loire White |
|---|---|---|---|---|---|---|---|---|---|
| ***Growing Season (May - Aug)*** | | | | | | | | | |
| $TAVG_G$ | 0.45*** | 0.24 | 0.51*** | 0.29* | | | 0.20(.) | | |
| | (0.12) | (0.14) | (0.11) | (0.12) | | | (0.11) | | |
| $PRCP_G$ | -0.010* | -0.014* | | -0.007 | | -0.014(.) | 0.012* | -0.018*** | |
| | (0.005) | (0.006) | | (0.005) | | (0.008) | (0.006) | (0.004) | |
| $DIFF_G$ | | | | | 0.22 | | | | 0.16 |
| | | | | | (0.16) | | | | (0.10) |
| $NAO_G$ | -0.25 | | -0.49*** | | -0.22 | -0.32 | -0.23 | | |
| | (0.15) | | (0.13) | | (0.19) | (0.21) | (0.14) | | |
| $DT32_G$ | | | | | | | | | |
| ***Harvest Season (Sep - Oct)*** | | | | | | | | | |
| $TAVG_H$ | | | | | -0.19 | | | | |
| | | | | | (0.13) | | | | |
| $PRCP_H$ | -0.004(.) | | -0.008** | -0.008** | | | -0.014*** | -0.004 | -0.006 |
| | (0.002) | | (0.002) | (0.002) | | | (0.003) | (0.003) | (0.006) |
| $DIFF_H$ | | 0.22* | | | 0.40** | 0.33** | | 0.22(.) | 0.19 |
| | | (0.10) | | | (0.12) | (0.12) | | (0.11) | (0.13) |
| $NAO_H$ | | | | | | | | | -0.24(.) |
| | | | | | | | | | (0.13) |
| $DT32_H$ | | | | -0.40 | -0.24 | | -0.27* | | -0.47* |
| | | | | (0.31) | (0.18) | | (0.12) | | (0.19) |
| **Adjusted *R*-squared** | 0.525 | 0.402 | 0.553 | 0.478 | 0.505 | 0.633 | 0.554 | 0.645 | 0.485 |
| **Model *P*-value** | 1,01E-05 | 4,358E-04 | 1,77E-06 | 2,67E-05 | 2,03E-05 | 1,23E-07 | 3,50E-06 | 2,904E-08 | 6,70E-05 |

**NOTE :** Standard Deviation is shown below each variable. ”***”, ”**”, ”*”, and ”(.)” indicate significance levels : 0.001, 0.01, 0.05 and 0.10 respectively. Tables are prepared by Authors

Table 13: Summary Semi-Log Quadratic Regressions Results : Model 4

| Semi-Log Quadratic Model | St. Emilion | St. Julien Paulliac St. Estephe | Pomerol | Sauternes Barsac | Côte de Beaune | Côte de Nuits | Burgundy White | Côte Rotie Hermitage | Loire White |
|---|---|---|---|---|---|---|---|---|---|
| *Intercept* | -4.72(.) | -5.06(.) | -43.15(.) | -34.90 | -43.34(.) | -66.97* | -3.34 | 4.14** | -5.76** |
| | (2.57) | (2.89) | (24.35) | (25.84) | (22.80) | (2.04) | (2.20) | (1.19) | (1.84) |
| *Trend* | | 0.03* | | | 0.04*** | 0.07*** | 0.02* | | 0.03** |
| | | (0.01) | | | (0.01) | (0.01) | (0.01) | | (0.01) |
| ***Winter Season (Nov - Feb)*** | | | | | | | | | |
| $TAVG_W$ | | | | | | | | | |
| $TAVG_W^2$ | | | | | | | | | |
| $PRCP_W$ | | | | | | | | | |
| $PRCP_W^2$ | | | | | | | | | |
| $DIFF_W$ | | | 0.40* | | -0.30 | -0.40(.) | | -0.43** | 0.46* |
| | | | (0.17) | | (0.21) | (0.24) | | (0.15) | (0.21) |
| $NAO_W$ | | | | | | | | -0.39* | |
| | | | | | | | | (0.15) | |
| $DT32W$ | -0.12** | -0.06 | -0.07* | -0.09* | 0.05 | | 0.05* | -0.07** | |
| | (0.04) | (0.04) | (0.04) | (0.04) | (0.03) | | (0.02) | (0.03) | |
| ***Early Growing Season (Mar - Apr)*** | | | | | | | | | |
| $TAVG_{EG}$ | | | | | | | | | |
| $TAVG_{EG}^2$ | | -0.02* | -0.01* | 0.01 | | -0.03** | | | |
| | | (0.01) | (0.01) | (0.01) | | (0.01) | | | |
| $PRCP_{EG}$ | 0.009* | | 0.007* | | | | -0.003 | | |
| | (0.004) | | (0.003) | | | | (0.002) | | |
| $PRCP_{EG}^2$ | | | | | | | | | |
| $DIFF_{EG}$ | 0.23(.) | 0.30* | | | | 0.36** | | | |
| | (0.13) | (0.13) | | | | (0.12) | | | |
| $NAO_{EG}$ | | | | | | | | | |
| $DT32_{EG}$ | | -0.16(.) | | 0.14* | | | | -0.12** | |
| | | (0.09) | | (0.07) | | | | (0.04) | |

Table 13 – continued from previous page

| Semi-Log Quadratic Model | St. Emilion | St. Julien Paulliac St. Estephe | Pomerol | Sauternes Barsac | Côte de Beaune | Côte de Nuits | Burgundy White | Côte Rotie Hermitage | Loire White |
|---|---|---|---|---|---|---|---|---|---|
| ***Growing Season (May - Aug)*** | | | | | | | | | |
| $TAVG_G$ | 0.29** | 0.24 | 3.97 | 3.51 | 4.87(.) | 7.24* | 0.20(.) | | |
| | (0.10) | (0.14) | (2.53) | (2.69) | (2.56) | (2.85) | (0.11) | | |
| $TAVG_G^2$ | | | -0.09 | -0.08 | -0.13(.) | -0.20* | | | |
| | | | (0.07) | (0.07) | (0.07) | (0.08) | | | |
| $PRCP_G$ | -0.04* | -0.01* | | -0.01 | -0.1* | -0.03** | 0.01* | | |
| | (0.02) | (0.01) | | (0.01) | (0.01) | (0.01) | (0.01) | | |
| $PRCP_G^2$ | 0.0002(.) | | | | 0.0006(.) | | | -0.0001*** | |
| | (0.0001) | | | | (0.34) | | | (0.0001) | |
| $DIFF_G$ | | | | | | | | | 0.15 |
| | | | | | | | | | (0.10) |
| $NAO_G$ | -0.19 | | -0.48*** | | | | -0.23 | | |
| | (0.14) | | (0.13) | | | | (0.14) | | |
| $DT32_G$ | | | | | | | | | |
| ***Harvest Season (Sep - Oct)*** | | | | | | | | | |
| $TAVG_H$ | | | | | | | | | |
| $TAVG_H^2$ | | | | | | | | | |
| $PRCP_H$ | | | | | | | -0.01*** | | |
| | | | | | | | (0.00) | | |
| $PRCP_H^2$ | -0.00002(.) | | -0.00004*** | -0.00005*** | | | | -0.00002* | -0.00005 |
| | (0.00001) | | (0.00001) | (0.00010) | | | | (0.00001) | (0.00001) |
| $DIFF_H$ | | 0.23* | | | 0.35*** | 0.35** | | 0.22* | 0.20 |
| | | (0.10) | | | (0.10) | (0.11) | | (0.10) | (0.12) |
| $NAO_H$ | | | | | | | | | -0.23(.) |
| | | | | | | | | | (0.12) |
| $DT32_H$ | | | | -0.35 | | | (-0.27)* | | (-0.46)* |
| | | | | (0.30) | | | (0.12) | | (0.19) |
| **Adjusted *R*-squared** | 0.542 | 0.410 | 0.569 | 0.516 | 0.526 | 0.658 | 0.554 | 0.673 | 0.487 |
| **Model *P*-value** | 5.38E-05 | 3,50E-05 | 1.95E-06 | 1.35E-05 | 9.81E-06 | 3.57E-08 | 3.50E-06 | 6.71E-09 | 6.30E-05 |

**NOTE :** Standard Deviation is shown below each variable. ”***”, ”**”, ”*”, and ”(.)” indicate significance levels : 0.001, 0.01, 0.05 and 0.10 respectively. Tables are prepared by Authors

# Appendix 8

Table 14: Linear Model Regressions Hypothesis : Model 1

| **Wine Region** | **AOC** | **Linearity** | **Homoscedasticity of residuals** | **Independence of residuals** | **Normality of residuals** |
|---|---|---|---|---|---|
| Bordeaux | St. Emilion | OK | OK | OK | OK |
| Bordeaux | St. Julien/Paulliac/St. Estephe | OK | OK | OK | OK |
| Bordeaux | Pomerol | KO | OK | OK | KO |
| Bordeaux | Sauternes/Barsac | KO | KO | OK | OK |
| Burgundy | Côte de Beaune | OK | OK | OK | OK |
| Burgundy | Côte de Nuits | KO | OK | OK | OK |
| Burgundy | All over | OK | OK | OK | OK |
| Rhône | Côte Rôtie/Hermitage | KO | OK | OK | OK |
| Loire | All over | OK | OK | OK | OK |

Table 15: Quadratic Model Regressions Hypothesis : Model 2

| **Wine Region** | **AOC** | **Linearity** | **Homoscedasticity of residuals** | **Independence of residuals** | **Normality of residuals** |
|---|---|---|---|---|---|
| Bordeaux | St. Emilion | KO | OK | OK | OK |
| Bordeaux | St. Julien/Paulliac/St. Estephe | OK | OK | OK | OK |
| Bordeaux | Pomerol | KO | OK | OK | OK |
| Bordeaux | Sauternes/Barsac | OK | KO | OK | OK |
| Burgundy | Côte de Beaune | OK | OK | OK | OK |
| Burgundy | Côte de Nuits | KO | KO | OK | OK |
| Burgundy | All over | KO | OK | OK | OK |
| Rhône | Côte Rôtie/Hermitage | OK | OK | OK | OK |
| Loire | All over | OK | KO | OK | OK |

Table 16: Semi-Log Linear Model Regressions Hypothesis : Model 3

| **Wine Region** | **AOC** | **Linearity** | **Homoscedasticity of residuals** | **Independence of residuals** | **Normality of residuals** |
|---|---|---|---|---|---|
| Bordeaux | St. Emilion | OK | OK | OK | OK |
| Bordeaux | St. Julien/Paulliac/St. Estephe | OK | OK | OK | OK |
| Bordeaux | Pomerol | OK | OK | OK | OK |
| Bordeaux | Sauternes/Barsac | OK | OK | OK | KO |
| Burgundy | Côte de Beaune | KO | OK | OK | OK |
| Burgundy | Côte de Nuits | KO | OK | OK | OK |
| Burgundy | All over | OK | OK | OK | OK |
| Rhône | Côte Rôtie/Hermitage | OK | OK | OK | OK |
| Loire | All over | OK | OK | OK | OK |

Table 17: Semi-Log Quadratic Model Regressions Hypothesis : Model 4

| **Wine Region** | **AOC** | **Linearity** | **Homoscedasticity of residuals** | **Independence of residuals** | **Normality of residuals** |
|---|---|---|---|---|---|
| Bordeaux | St. Emilion | OK | OK | OK | OK |
| Bordeaux | St. Julien/Paulliac/St. Estephe | OK | KO | OK | OK |
| Bordeaux | Pomerol | OK | OK | OK | KO |
| Bordeaux | Sauternes/Barsac | OK | OK | OK | KO |
| Burgundy | Côte de Beaune | KO | OK | OK | KO |
| Burgundy | Côte de Nuits | KO | OK | OK | OK |
| Burgundy | All over | OK | OK | OK | OK |
| Rhône | Côte Rôtie/Hermitage | OK | OK | OK | OK |
| Loire | All over | OK | OK | OK | OK |

*Source: Tables prepared by the authors*

# Appendix 9

Table 18: Adjusted *R*-squared from all regressions without *Trend*

| **Wine Region** | **AOC** | **Linear** | **Quadratic** | **Semi-log Linear** | **Semi-log Quadratic** |
|---|---|---|---|---|---|
| Bordeaux | St. Emilion | 55.9% | 56.8% | 52.5% | 54.2% |
| Bordeaux | *St. Julien* | *46.78%* | *48.89%* | *38.74%* | *38.84%* |
| Bordeaux | Pomerol | 49.2% | 51% | 55.3% | 56.9% |
| Bordeaux | Sauternes/Barsac | 54.0% | 60.5% | 47.8% | 51.6% |
| Burgundy | *Côte de Beaune* | *48.35%* | *51.12%* | *42.72%* | *45.57%* |
| Burgundy | *Côte de Nuits* | *54.52%* | *63.04%* | *52.89%* | *59.50%* |
| Burgundy | *All over* | *47.65%* | *48.27%* | *52.03%* | *52.07%* |
| Rhône | Côte Rôtie/Hermitage | 66.3% | 73.1% | 64.5% | 67.3% |
| Loire | *All over* | *36.58%* | *40.18%* | *40.05%* | *41.30%* |

*The impacted Adj. *R*-squared from the withdrawal of the variable *Trend* are in *italic*

*Source: Table prepared by the authors*