In search of the New Bordeaux

How will climate change effect the suitability of the Bordeaux region for fine wine? A predictive modelling approach to future climate mapping

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August 2019

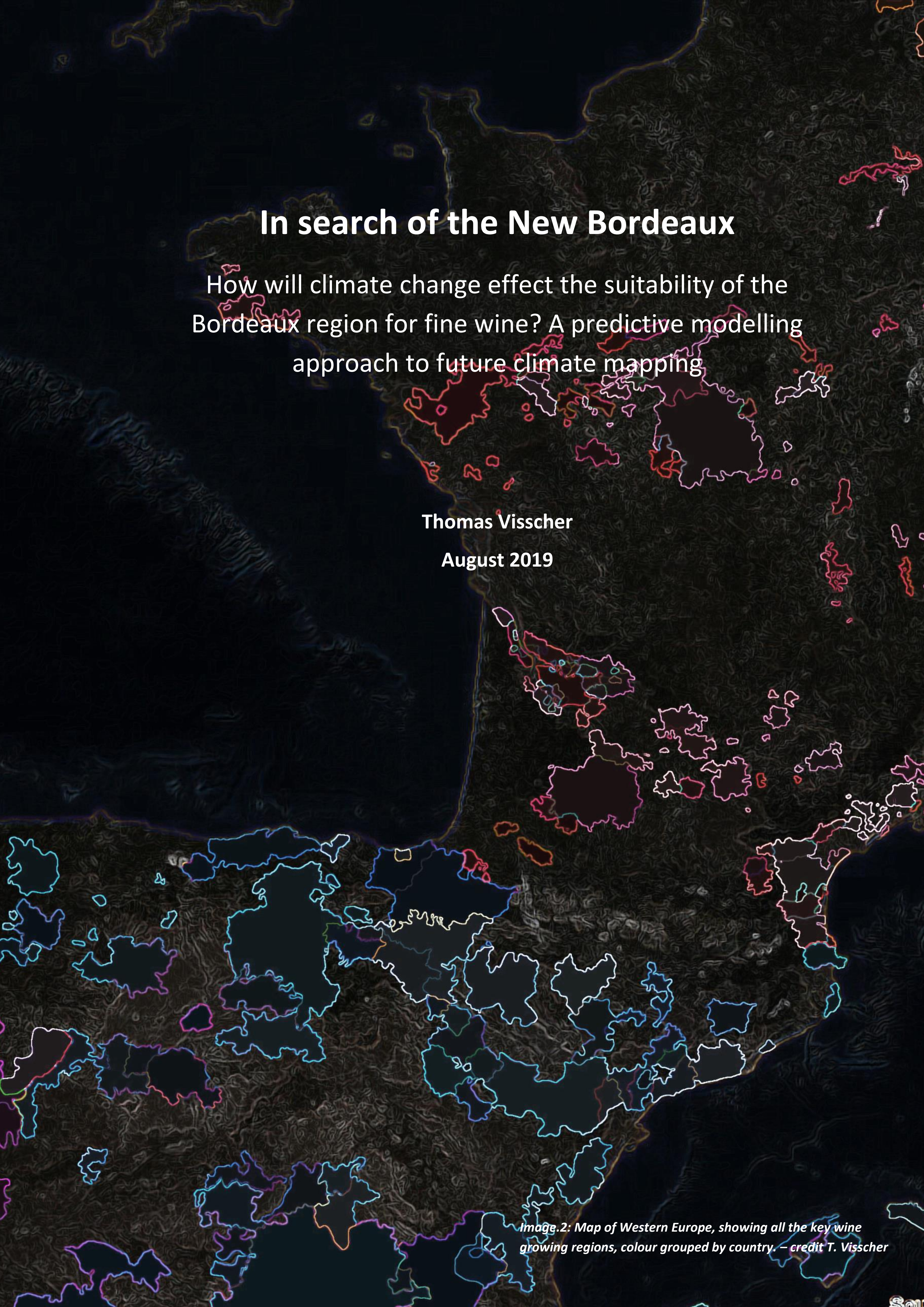

Image.2: Map of Western Europe, showing all the key wine growing regions, colour grouped by country. – credit T. Visscher

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30 August 2019

A letter to the future

"Ok is the first Icelandic glacier to lose its status as a glacier. In the next 200 years all our glaciers are expected to follow the same path.
This monument is to acknowledge that we know what is happening and what needs to be done.
Only you know if we did it."

August 2019
415ppm CO_2

Inscription on a memorial commemorating the loss of Okjökull glacier in Iceland which has already disappeared due to the impact of anthropogenic climate change.

Image.3: 'Ok' is losing it's ice. - credit PHOTOGENIC/ALAMY STOCK PHOTO

Abbreviations

Acronym and abbreviation	Definition
GIS	Graphical information system
GCM	General Circulation Models
RCP	Representative Concentration Pathway
NCDC	National Centre for Environmental Information Website
WO	Wine Owners ® ™ (Wine Owners Limited, London, UK)
PS	Phenological Stage
TAVG	Average Daily Temperature
TMAX	Maximum Daily Temperature
TMIN	Minimum Daily Temperature
PRCP	Daily Precipitation total
Dorm	Dormancy
Bud	Bud Break
Rsq	R Squared Value
aRsq	Adjusted R Squared Value
CI	Confidence Interval
IQR	Interquartile range
OR	Odds ratio
mm	millimetres

Abstract

Almost 2000 years ago between the years A.D 30 - 60, the Roman writer Columella was one of the first people in recorded history to address the topic of climate change (Lamb 1977). He drew inspiration from another writer, Saserna, born c.100 years before him, relaying that;

'The position of the heavens has changed – regions which previously on account of the regular severity of the weather could give no protection to any vine planted there, now that the weather is warmer produce crops and vintages in the greatest abundance'

Since Saserna's work documented the early spread of viticulture upwards through Italy and that by Columella's time, vines now existed north of Rome and were being established even as far as newly conquered Britain, Columella reasoned that the climate could undergo long term changes and warned that agricultural methods might not always be up to date to the latest conditions. Although, the warmer climate that existed around this time was not caused by human input, Columella's warning seems remarkably pertinent to a contemporary society facing the reality of a dramatically warming future. Moreover, Saserna's use of viticulture as marker of climate change still has enormous potential today.

Academics have produced numerous studies on the subject. Some of the best examples show the historical link between vintage quality and climate (Baciocco, Davis, and Jones 2014), examine why vines in their sensitivity to weather conditions are a good indicator of climatic changes (Teixeira et al. 2013), discuss current changes affecting viticulture (Chevet, Lecocq, and Visser 2011), and try to predict how wine growing areas will adapt to future changes (G. V. Jones and Webb 2010). Some studies have a direct focus on outcomes for wine growers or consumers, whereas others frame the topic within the wider literature addressing the global climate change crisis, yet altogether they provide a rich resource in context, data, and applicable statistical and analytical methods for future researchers in the fields of climate, agriculture and economics.

By employing statistical science methodologies and well as Geographic Information Systems (GIS), this dissertation aims to deepen the field of research in wine and climate change in three distinct ways. First to explore an associative model which highlights key explanatory climate variables in wine quality and yield. Secondly, to create an original predictive model to predict wine quality and yield from wine growing regions, when inputting specific projected future climate conditions across the wine growing season. Thirdly, by using an understanding of the key explanatory variables, to project the ideal future wine growing regions, based on models that predict climate change.

We hypothesise that by 2070, rising temperatures and extremes of rainfall will damage the current suitability for producing fine wine in Bordeaux, forcing an adaption of current grape varieties and growing practices. However, if Bordeaux is to change in the future, we might also expect new regions to become favourable to Bordeaux grapes. We must cast our imaginations back to the Roman Britain of Columella, where during a period of warmer centuries (Manning 2018), vines dotted the gently rolling hills of the south coast. Perhaps then 50 years ahead from now, somewhere in northern Europe, a 'New Bordeaux' will emerge to challenge the fame of the old.

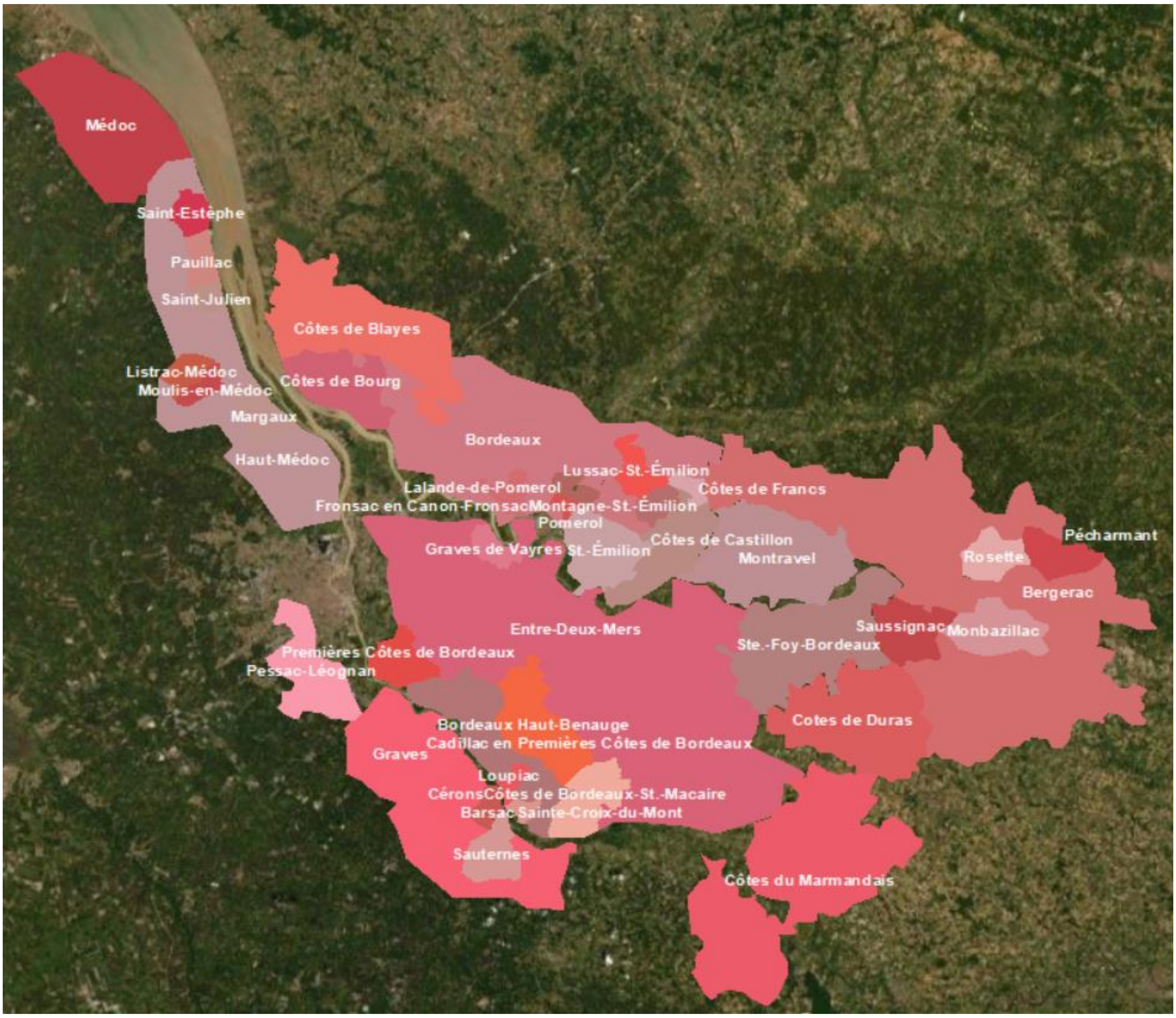

Image.4: Map of Bordeaux wine region, showing the main appellations. – credit T.Visscher

Image.5: Bordeaux grapes - credit T.Visscher

1. Introduction

How to apply climate science to Bordeaux viticulture?

1.1 Global warming and new realities

It is probably already too late to avoid the negative future consequences of anthropogenic climate change (Sanford et al. 2014). For decades, the scientific community has warned governments that action needed to be taken on reducing carbon dioxide and other greenhouse gas emissions in order to keep global warming below dangerous levels. At the Paris Climate conference in 2015 a target was set to keep warming below 1.5^0C by creating zero carbon emissions sometime between 2030 and 2050 (Roehrdanz and Hannah 2016). Despite this, global greenhouse gas emissions continue to rise year on year. It is now estimated that to reach this target of less than 2.5^0C warming, a figure that scientists predict will already cause catastrophic environmental social and economic damage, all fossil fuel exploitation will have to cease by 2025 (Sanford et al. 2014). Ultimately, until 2019 very little has been done by policy makers to realistically reach their own targets, with governments reacting to climate change with acknowledgement but not action (Galbreath 2015).

The reality is that no one quite knows how future society will respond to the crisis. Will we move to radically change our lifestyles and economy? Some experts predict that seismic changes in the nature of work and the global economic model will be required (N. K. Jones 2012). At the same time, due to the vast complexity of earth's weather system, we don't yet know how exactly climate change will affect our climate and ecosystems. Melting icecaps, sea level rise, species extinction and extreme weather are expected to continue (Flato 2013) but the extent of the damage depends on society's actions now.

1.2 Why is wine so interesting and what makes Bordeaux special?

The impact of global warming on agriculture and crop production has already forced largescale changes in many regions (Leeuwen et al. 2013) and is predicted to decrease the viability of agriculture in future (Mayer 2013). In the case of viticulture, climate change could bring many risks such as increased damage from invasive species, pests, increased pollution from socio economic collapse and exacerbation of local microclimate differences in an environment (Clavero, Villero, and Brotons 2011).

Higher temperatures could also lead to greater vine contamination by mycotoxigenic fungi which damage crops and may pose health risks (Paterson et al. 2018). Furthermore, agriculture in the Mediterranean region, where most of the world's wine is produced, including Bordeaux wine, is expected to be particularly vulnerable to climate change. The knock-on effects of this change will also impact the wider local ecology e.g. increased water use for irrigation and to cool grapes may damage potential for freshwater conservation (Hannah et al. 2013). The precited impact on wine is however, not one of total devastation and there is much uncertainty, for example Hannah's modelling shows a large variation between the upper and lower limits of area loss (25%- 73%), (Hannah et al. 2013). The effects are also likely to vary locally.

In this study we will focus on viticulture because it is an exceptionally good proxy for how climate change affects agriculture in general. The majority of wine grapes are grown between 12.C and 22.C, while other varieties, such as those found in Bordeaux are even more sensitive and can only grow within a much smaller temperature range in order to produce quality wines. (G. Jones et al. 2005). There is also reason to believe viticulture might be especially in peril, as 'the wine industry is surprisingly conservative when it comes to considering longer term planned adaptation for substantial climate change impacts' (Meztger and Rounsevell 2011). Since viticulture is concentrated in Mediterranean climate regions which are 'global biodiversity hotspots' (Hannah et al. 2013), it becomes ever more pressing to study them.

The taste of wine, or its phenology, is highly sensitive to climate, with various combinations of weather patterns across the growing season leading to subtle differences in the taste and texture of wines. Higher temperatures in the veraison and ripening period generally produce smaller, denser grapes which give more flavour than grapes which are well-watered and thus larger (Stockham et al. 2013). Therefore, low precipitation in this period is preferred. Drought, however is problematic since, 'water stress increases the content of flavonols' but too much water stress can lead to overly bitter flavours (Teixeira et al. 2013). Earlier in the year, high precipitation is required for growth and yield, yet excessive rain in dormancy and bud-break can cause mildew and thus ruin a harvest (Stockham et al. 2013). According to Holland the highest quality wines are associated with, 'low frost damage in mild winters, early and even budburst, flowering and development during warm springs, and optimal maturation with low summer temperature variability' (Holland and Smit 2010). Thus, the ideal growing conditions are characterised by a balance between climate factors, with a large contrast between early and late in the growing season.

Soil composition or 'terroir' is also very important to wine quality. However, unlike climate, this is not anticipated to change significantly in the future so is a constant in predictive modelling. In addition, there are a minutia of other details involved in the winemaking process such barrel type that can differ vineyard to vineyard and affect the taste, but these are beyond the scope of this study. Below (Table.1) is a summary of the main climate factors involved in Bordeaux wine.

Factor	**Description**	**Used in study?**
Precipitation (mm)	Feeds vines to grow more grapes early in the growing season	Yes
Temperature (deg. C)	Higher temperatures produce smaller, more flavourful grapes	Yes
Soil type	Terroir, helps certain vines thrive and subtlety affects taste	Yes (chapter 4)
Terrain elevation	Important for water runoff properties and increasing sunlight	Part (chapter 4)
Sunlight hours	Helps grapes gain in flavour in the period called veraison	No
Hail	Hailstorms have previously destroyed entire vintages	No
Fog	Too much fog can cause rot and mildew in unripe vines	No

Table.1: Bordeaux Wine quality factors

We have established the key conditions in producing good wine in any large quantity. There is however currently a shortage of evidence on how specific regions with niche production methods will be impacted. In order for this study to establish a link between climate change and Bordeaux wine specifically, we need to employ a more exact measure of the quality of a wine. Bordeaux is regarded as producing the finest red wines in the world (Ashenfelter 2007). In some parts of Bordeaux, the traditional viticulture is so regulated and protected that artificial watering of vines is forbidden (Bois et al. 2008) and thus, Bordeaux appears especially sensitive to climate change. Thus, Bordeaux provides an ideal candidate region to look at the future of viticulture in general, since it garners more attention than other wine regions. Bordeaux also provides a wealth of data relating to fine wines and we can use this data to develop a closer correlation of climate and quality.

We worked with Wine Owners ® ™ (Wine Owners Limited, London,UK) (WO), a company which runs an online wine trading platform in order to create the database used in this study, which records thousands of Bordeaux wines over time and includes a score matrix for each individual vintage. We took wine scores dating from 1950 (there is much less data for earlier vintages) till 2016 (the latest vintage on record). Data on historical yields was found separately. Wine scores are roughly consistent over time, with slightly higher scores in recent decades (Fig.1). Average yields also increase with time (Fig.2). This may be due to adaptive technological advances in the wine industry as well as higher average temperatures (Almaraz 2015). We can also see that maximum daily temperature (Fig.2) and daily precipitation (Fig.3) for each vintage's veraison period (as an illustration) also fluctuate with time. However, the slight increase in temperature and decrease in precipitation reveal the trend caused by global warming, and these trajectories are forecast to continue.

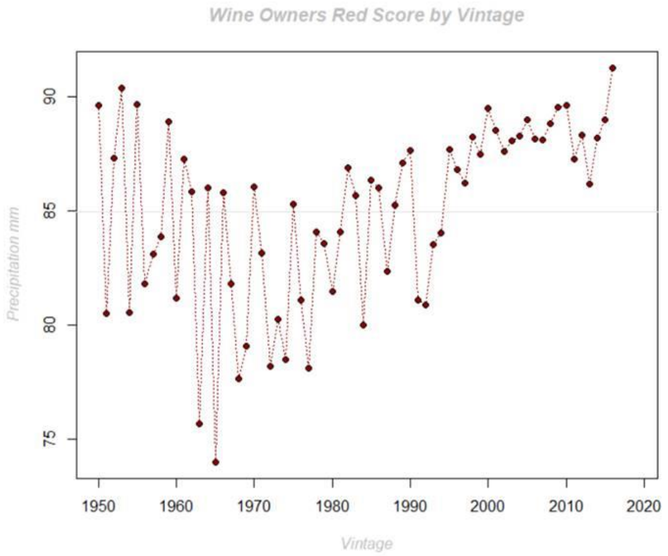

Fig.1: Average wine scores across all Bordeaux wines per year over time - credit T.Visscher

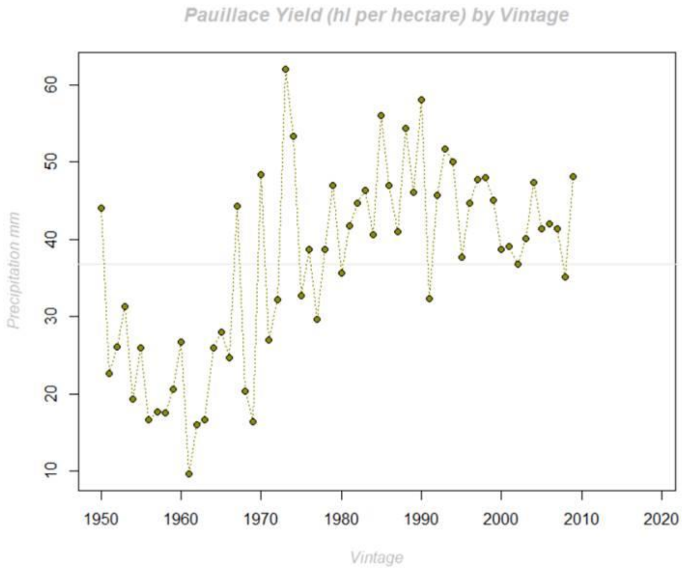

Fig.2: Average yields for Pauillac appellation per year over time - credit T.Visscher

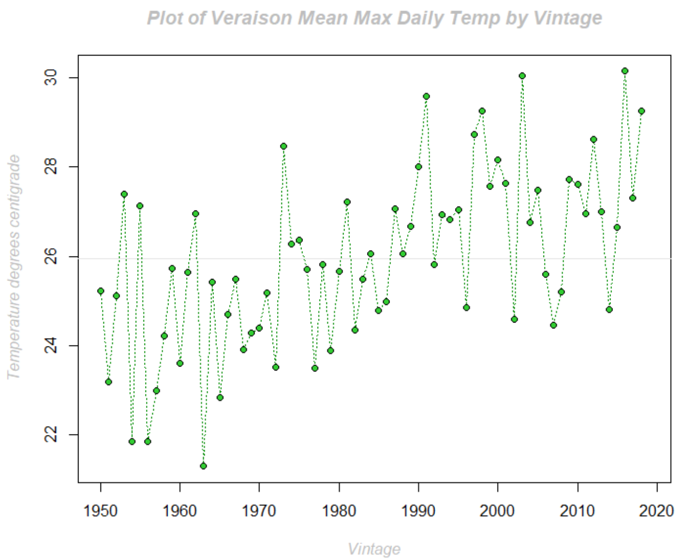

Fig.3: Average Maximum Daily Temperature in degrees C in Veraison by Vintage - credit T.Visscher

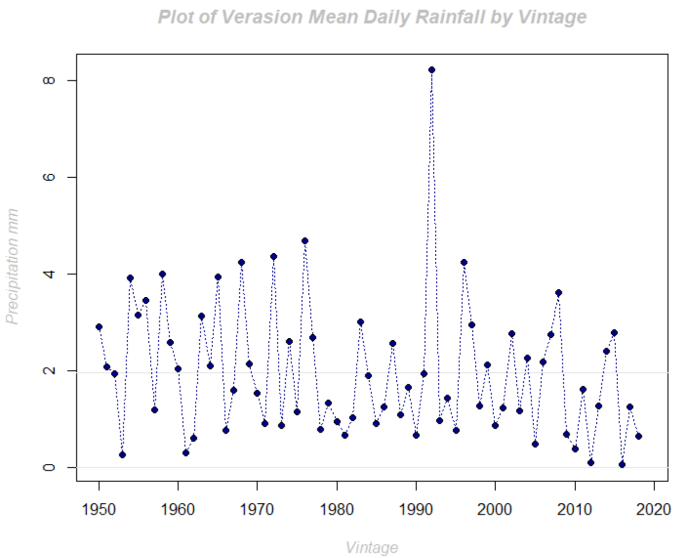

Fig.4: Average Daily Rainfall in mm in Veraison by Vintage - credit T.Visscher

1.3 Summary and Aims

My study will first bring recent research, that looks at the historical association between wine quality scores and yield and climatic data, up to date using an industry recognised wine evaluation methodology. Using this model, the 'optimal' climactic conditions and the most important predictive factors can be identified (Chapter 2).

I will then go on to use climate prediction models to forecast the wine growing conditions in the Bordeaux region in 50 years' time. Three global climate models and two future emissions projections will be used to illustrate the potential variability in results. Using the model built in Chapter 2 we will predict the likely impact of future climate conditions on both yield and quality of Bordeaux wine, (Chapter 3)

Finally, global climate predictions will be used to identify new regions that may approximate the 'optimal' Bordeaux conditions in future. They will be assessed for other fixed factors such as soil composition to identify the 'New Bordeaux', (Chapter 4).

1.5 Ethics

The study is solely concerned with data related to wine, agriculture and meteorological data. There is no personally identifiable data used and no individuals were impacted in where the data was accessed from and how it was permissibly used. In a couple of places, we focus in on data relating to the historical records of specific vineyards but these, coming from published journals were allowed to be referenced and again do not identify any individuals only organisations. In addition, specific permission was granted by Wine Owners to allow us to use their entire database for our research.

Image.6: Barrels of Red in Bordeaux wine cellar - credit T.Visscher

2. Exploring the relationship between climate and wine in Bordeaux

A multi-factorial predictive modelling approach using aggregated wine scores and yields

2.1 Rationale

'Wine grapes are among the most sensitive agricultural products to changes in climatic conditions - as little as a two-degree centigrade increase in average temperature, for example, can have a dramatic effect on what varieties can best be ripened where, the quality of grape that can be achieved, and the yields that can be produced' (Galbreath 2011).

The purpose of this part of the study is to understand how different climate measurements in Bordeaux have affected wine scores and yields in the past and to use these predictive variables to build a model that will allow us to predict wine scores and yields in the future as well as understand which factors are most important. Our choice of predictive variables will be partly informed on the basis of previous research. We aim to build a parsimonious model in order to enable the greatest amount of utility for wider applications.

2.2 Study design

The methodology of our study involved the following steps:

1. Identifying Phenological Stages (PS)
2. Aggregate datasets into Phenological Stages
3. Explore data distributions and perform necessary transformations
4. Examine crude correlations between different climate and wine score variables
5. Multiple linear regression to build a full model
6. Identifying key variables using subtraction method in regression models
7. Examining goodness of fit using adjusted R Squared (aR^2) and P values
8. Creating parsimonious predictive model with key predictive variables
9. Verifying models using "dredging" function

The following software tools were used to process the data:

- SQL – for data extraction from Wine Owners database
- WebPlotDigitizer - for deriving yield data from existing graphical presentations
- Excel – for data cleansing and table production
- R –statistical processing, graphs and linear regression
- Chart.Correlation() for R - for creating the distribution and correlation matrices
- Plotly Library for R – for graphical presentation
- MuMLn package for R – for dredge method of linear regression analysis

Exclusions and assumptions:

We excluded white wine scores in this study because white wine is not as historically important to Bordeaux, only comprising of around 5% of Bordeaux production (Liv Ex 2019). In addition white wine grapes require different phenological conditions, so might have confounded our results if included (Baciocco, Davis, and Jones 2014).

2.3 Data preparation

Historical Climate Data

The historical meteorological data set for the Bordeaux-Merignac station was accessed from the open source NCDC website (National Centres for Environmental Information 2019). This included daily maximum, minimum and average temperatures, in degrees Celsius and total daily rainfall in mm for each day from 1950 to 2018.

In order to create a more accurate model for predicting wine outcomes, it was necessary to break up the monthly climate data into 5 key sequential growing periods, as studies have demonstrated that a time-varying coefficients approach model statistically outperforms the previously used constant regression models (Almaraz 2015). We decided to employ a Bordeaux specific definition of these growing periods, or phenological stages (PS). We used the same PS date ranges as Baciocco and Urhausen (Baciocco, Davis, and Jones 2014) and (Urhausen et al. 2011), which also focus on Bordeaux wine quality. These ranges can be seen below (Table 2). The raw historical daily weather data was reorganized and aggregated into these phenological stages. An average daily precipitation (PRCP) in mm was calculated for each PS. Mean maximum temperature (TMAX), mean minimum temperature (TMIN) and mean daily average temperature (TAVG) was calculated for each PS. This was achieved using a script in R.

Dormancy	Bud Break	Bloom	Veraison	Ripening
1 Nov – 31 March	15 march - 15 April	25 May - 20 June	5 August - 5 September	6 September - 30 September

Table.2: Bordeaux phenological stages

We discounted TAVG and TMIN, only using TMAX as our temperature measure because, as Baciocco demonstrates, TMAX and TMIN are most important for Bordeaux Wine (Baciocco, Davis, and Jones 2014). Since TMAX and TMIN are highly correlated, the decision was taken to select TMAX as our measure. It was reasoned that TMAX might also reflect the impact of sunny days better than minimum temperatures, another important factor in wine (Table.1).

To check this assumption, we looked at the correlation between, TAVG, TMAX and TMIN in each of the growing seasons. All growing seasons displayed a very similar pattern. Fig.5 and Fig.6 show this correlation using Dormancy and Veraison as examples (Fig.5), (Fig.6). Although there seemed to be greater fluctuation between TMAX and TMIN in Veraison than dormancy, both seasons show a very strong correlation between daily temperature measures.

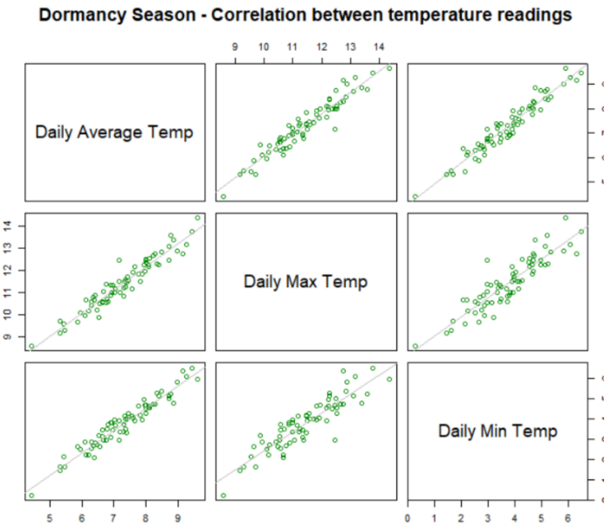

Fig.5: Correlation between temperature in Dorm - credit T.Visscher

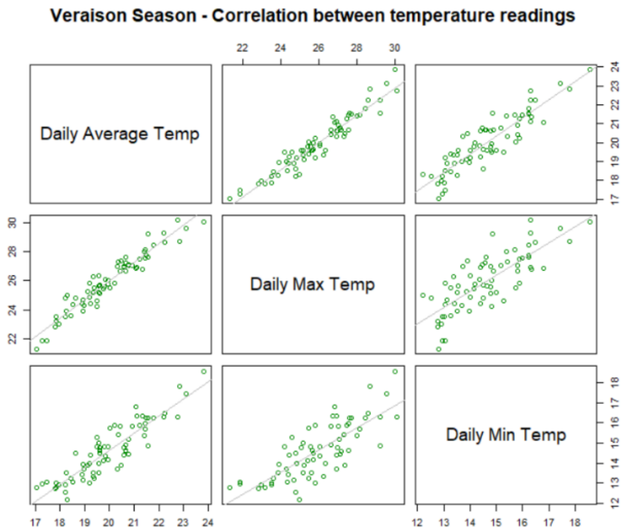

Fig.6: Correlation between temperature in Veraison - credit T.Visscher

The clean table of historical weather data organised by PS, formed the basis of our master data table. Note that, since the entire Bordeaux growing season overlaps year-end (ranging from November to September the next year), we assigned a wine "vintage" to each row in our dataset, rather than a calendar year. Thus, the row relating to the 2015 vintage in our master table contains all the PSs ranging from 2014 to 2015 that produce that vintage.

Wine scores

Of key interest to our study was discovering how climate affects the taste or 'quality' of wine, as this is after all the defining feature of wine as product. Maintaining high quality is especially important for the very fine wines of Bordeaux. Therefore, we created a measure of quality using the scores of reviewed wine brands.

The data for wine scores was provided by Wine Owners™ (Wine Owners 2019) directly from their own wine trading and information database. 20,000 Bordeaux classified red wine ratings (numerical scores) for individual wines for each year dating from 1950 to 2016 were extracted collected using a SQL script. Ratings for vintages after 2016 have not yet been released.

We produced our overall vintage wine score by averaging the ratings for each individual rated wine per vintage. We decided to include no vintages older than 1950, as there are few rated wines from this time to average, and this avoids the bias that could result from a small sample of wine-ratings. Each vintage in our data set reflects a minimum of 40 individual wines, but the more recent vintages have averages calculated from hundreds of individual wines.

The wine scoring metric created by Wine Owners uses a weighted average of 5 different well-established rating systems to lessen the impact of bias. This consensus approach provides a level of stability in the assessment of vintage quality. Implicit to our approach is the understanding that wine ratings stay roughly consistent over time (Fig.1).

We also considered the use of wine prices as recorded by the Wine Owners trading platform for our study as a comparative measure alongside rating. However due to prior research it was determined that wine prices are too heavily affected by market forces unrelated to wine quality such as scarcity driving up prices exponentially (Agnoli, De Salvo, and Capitello 2015), a particular problem for wines pre 1980. This problem was compounded by our focus on Bordeaux which due to its prestige, has the most heavily inflated prices of all fine wines.

We then verified the score against a different measure of vintage quality to check validity. An alternative scoring system for vintages from 1950 to 2013 was gathered from wine tasting website Vin Vigne (Vin-Vigne 2019). The results of this showed a moderately strong correlation between WO score (red score) and VV score with a R^2 value of 0.48 and a very low P value (Fig.7). This also confirmed our decision to use an average WO score instead of the less detailed categories or a ranking system for vintages. VV score was not incorporated into the design of the predictive model for the same reasons of lack of detail, as it gave only 8 different possible data points.

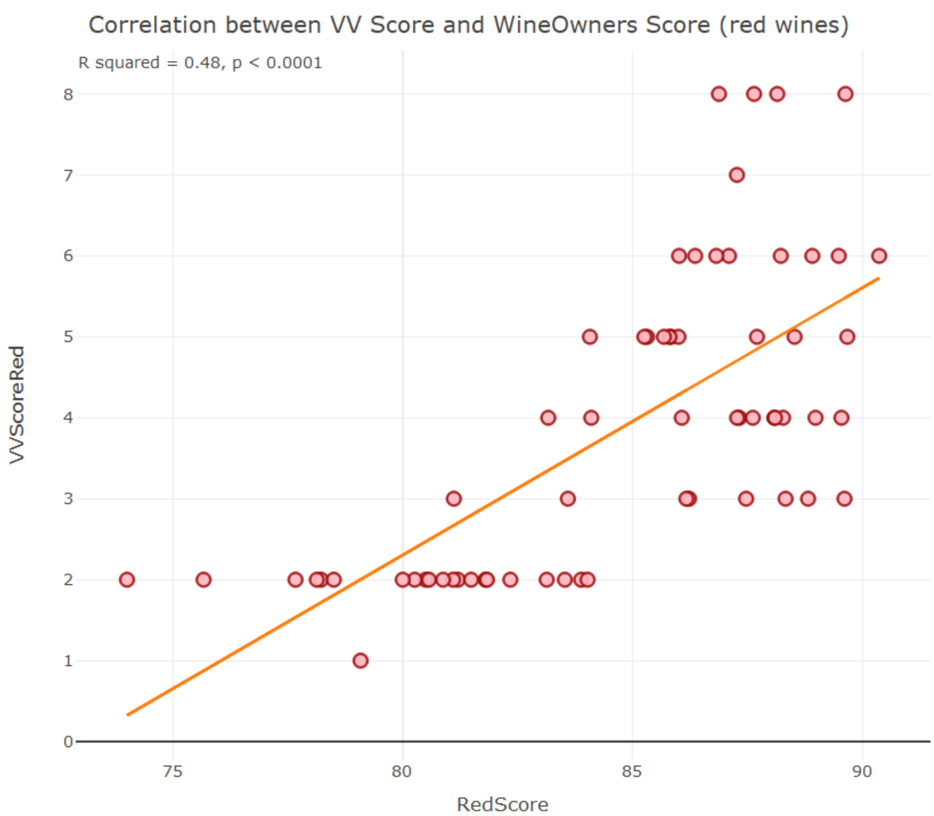

Fig.7: Correlation between WO score and VV score to check accuracy of WO score - credit T.Visscher

Wine Yields

We also wished to consider how climate affects the wine yield potential of the Bordeaux region. Adverse conditions in the growing season can severely lower the total volume of wine that can be produced at the end.

It was harder to create the dataset of Bordeaux yields, since very little historical data relating to the wine output of Bordeaux as a whole was available. Therefore, average yields in hectolitres per hectare of the Pauillac appellation (Image.4), a famous Bordeaux red wine type, were taken from the study by Chevet (Chevet, Lecocq, and Visser 2011). These average yields, for vintages dating between 1950 and 2009, were used as a proxy for average wine yield across all Bordeaux vineyards. In order to test if Pauillac could be representative of Bordeaux as a whole, Pauillac data was correlated with a smaller dataset reflecting average Bordeaux yields (Liv Ex 2019). Although there were only a few datapoints that could be compared to the Pauillac yields, there was still a significant close correlation with a R^2 value of 0.74 (Fig.8), suggesting that Pauillac could serve as a good proxy for Bordeaux as a whole.

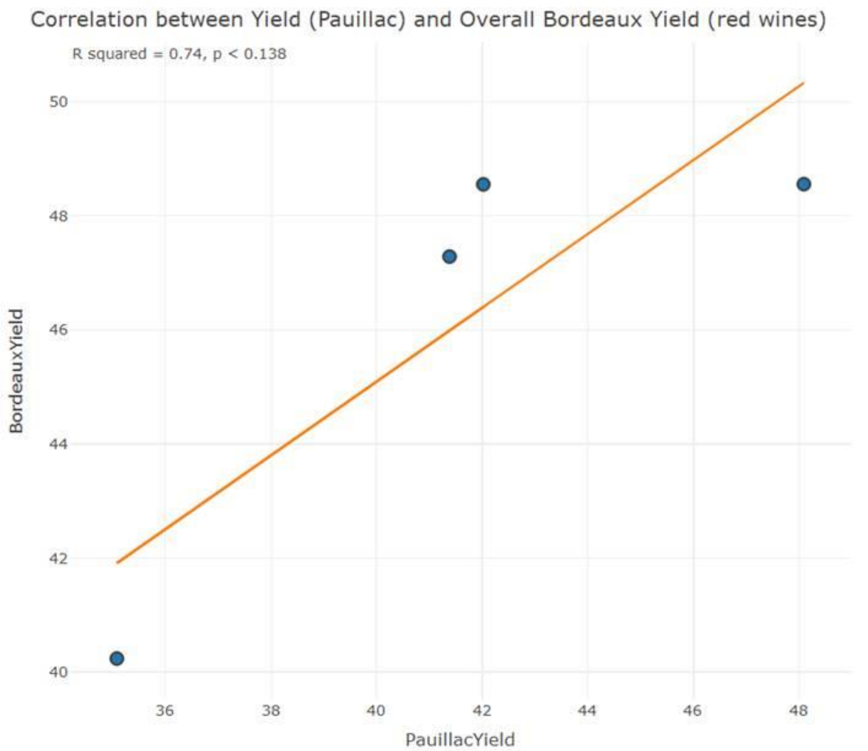

Fig.8: Correlation between Pauillac yield and Overall yield - credit T.Visscher

2.4 Statistical analysis

Overview of statistical analysis

Baciocco's work on modelling Bordeaux wine quality with climate was a key inspiration for this part of our study, and we have redesigned core aspects of this work to fit our aims. Baciocco used correlation and regression modelling to find the most significant climate variables over the growing season. His work suggests that low precipitation and high temperatures during veraison are the most important factors in high quality wine, with 9 of top 10 red wine vintages having less than 40 mm of precipitation in this period (Baciocco, Davis, and Jones 2014).

Baciocco's paper develops an associative model for Bordeaux wine. We will take a broadly similar approach in our study, however whilst we employ the same concept of linking wine score and climate, we have adjusted Baciocco's method and will look to produce a best fit linear regression model, which can also be employed as predictive model, as well as highlighting the key associative relationships between the variables. We will also run this predictive model to predict both score and yield.

Summary Characteristics

First, we looked at summary characteristics of the key predictive variables of interest and the 2 key outcomes red score and yield these are summarised below (Table.3). The red scores range show that Bordeaux is generally a high scoring wine with the worst vintage scoring 74 to the best vintage of 91.26. In contrast the yield varies much more over the period, ranging from 9.67 hectolitres per hectare to 62.04 hectolitres (Fig.2).

Mean for all vintages 1950 to 2016 (66 Vintages)	Mean (SD)	Range
Red scores	84.97 (3.93)	74.00 - 91.26
Red scores last 20 years only	88.37 (1.14)	86.23 - 91.28
yield (Pauillac) hectolitres per hectare	36.75 (12.38)	9.67 - 62.04
yield (Pauillac and Bordeaux) last 20 years only	43.79 (5.12)	33.82 - 52.00
Dormancy temperature mean daily max °c	11.4 (1.17)	8.6 - 14.3
Dormancy mean daily precipitation mm	3.0 (0.86)	1.2 - 5.2
Bud temperature mean daily max °c	15.7 (1.74)	11.2 - 19.6
Bud mean daily precipitation mm	2.4 (1.2)	0.23 - 6.1
Bloom temperature mean daily max °c	23.0 (2.0)	18.8- 28.1
Bloom mean daily precipitation mm	2.4 (1.3)	0.03 - 6.1
Veraison temperature mean daily max °c	26.0 (1.96)	21.3 - 30.1
Veraison mean daily precipitation mm	2.0 (1.40)	0.1 - 8.2
Ripening temperature mean daily max °c	23.4 (2.04)	18.1 - 27.5
Ripening mean daily precipitation mm	2.9 (2.02)	0.1 - 9.9

Table.3: summary characteristics of scores, yield and PS with mean and range

There is more variation in temperature during the summer months (Bloom to Ripening) and less variation in both precipitation and temperature during Dormancy.

Distributions and transformations

We used histograms of key variables to check for normality of distributions. Maximum temperatures are approximately normally distributed (Fig.9), (Fig.11). Similarly, Precipitation was normally distributed (Fig.10), (Fig.12) with the exception of PRCP during ripening. Likewise score and yield were approximately normal. Overall the data was considered close enough to normal for the purposes of this study. Therefore, no log transformations were required.

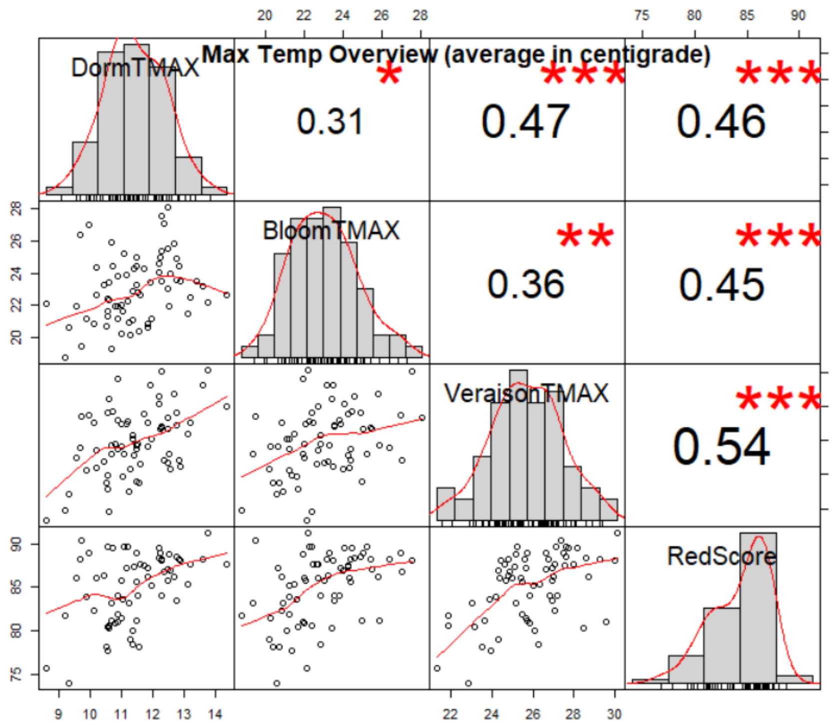

Fig.9: TMAX histogram and correlations with score - credit T.Visscher

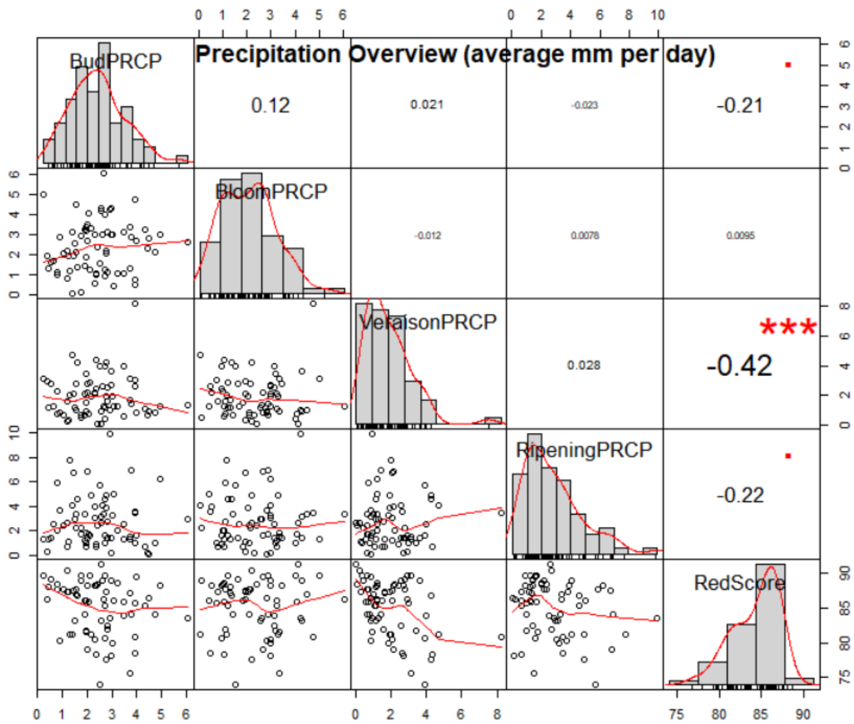

Fig.10: PRCP histogram and correlations with score - credit T.Visscher

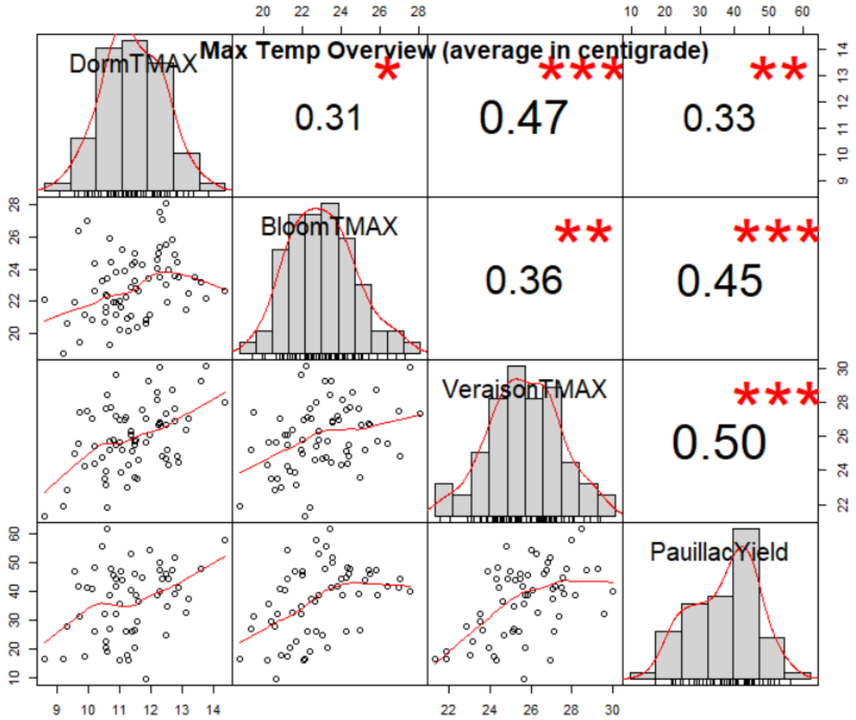

Fig.11: TMAX histogram and correlations with yield - credit T.Visscher

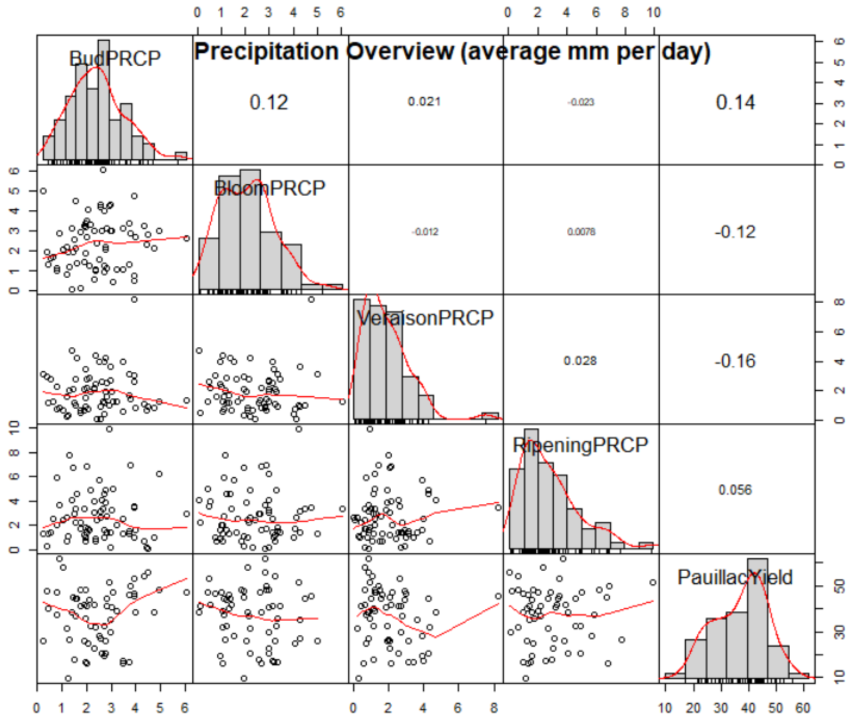

Fig.12: PRCP histogram and correlations with yield - credit T.Visscher

Exploring associations between variables

Scatter plots (Fig.8 – Fig.12), were used to explore the associations between explanatory climate variables and outcome measures (score and yield). This was done for all PS variables, but the key associations only are shown in the scatter plot matrices above. Pearson's r correlation coefficients were used to compare the strength of these crude associations. These coefficients are displayed in the same correlation matrix charts. For example, when looking at score and temperature, there is a strong positive correlation between TMAX in veraison and score; $r = 0.54$ (Fig.8). Moreover, the 3 stars against this figure indicate that the p-value is low, ($p < 0.001$) thus indicating that the relationship is significant at the 99.9% confidence level. Two stars indicate a p value of $p < 0.01$ (99%) and one star, $p < 0.05$ (95%). The temperature matrix also indicated that Bloom TMAX was moderately/strongly correlated with Red score, $r = 0.45$. Dormancy TMAX was also moderately highly correlated with Red score, $r = 0.46$.

This finding supports previous studies which found that heat accumulation in veraison is particularly important (Baciocco, Davis, and Jones 2014), (Teixeira et al. 2013). Note however that there is a moderately strong and significant correlation between Dormancy TMAX and Veraison TMAX ($r = 0.47$, $p <0.001$). Therefore, it is not clear which is the main causal factor.

For precipitation the only factor that had a strong and significant correlation with Red score was Veraison PRCP which was negatively correlated with score ($r = -0.42$, $p <0.001$) (Fig 12). There were also weak negative correlations between Bud PRCP and score ($r = -0.22$, $p <0.05$) and Ripening PRCP and score ($r = -0.21$, $p <0.05$).

The associations between the temperature explanatory variables and yield were similar to those with score, with the strongest correlation being between Veraison TMAX and yield ($r = 0.50$, $p <0.001$), (Fig 13). In addition, Bloom TMAX ($r = 0.45$, $p <0.001$) and to a lesser extent Dormancy TMAX ($r = 0.33$, $p <0.01$) were moderately positively correlated with yield. In contrast there were no clear strong or significant correlations between individual precipitation factors and yield (Fig. 14).

We also wanted to check how closely related score and yield were, in order to decide if the creation of separate predictive models was necessary. We plotted this using the R Plotly library (Fig.13). Our investigations show that yield and score are not barely correlated; the r value for this relationship was only r = 0.06. This fits in with our general understanding of Bordeaux wine practices. Although superficially we might expect yield and high quality to be correlated, often the best historical vintages had low yields, (Liv Ex 2019) as generally more concentrated grapes produce better tasting wines (Almaraz 2015). Generally, any yield of wine can be a range of different quality, so we must carry out the analysis of these outcomes in entirely separate models. Nonetheless, we have seen that Veraison TMAX is crucial for both yield and quality in its own right.

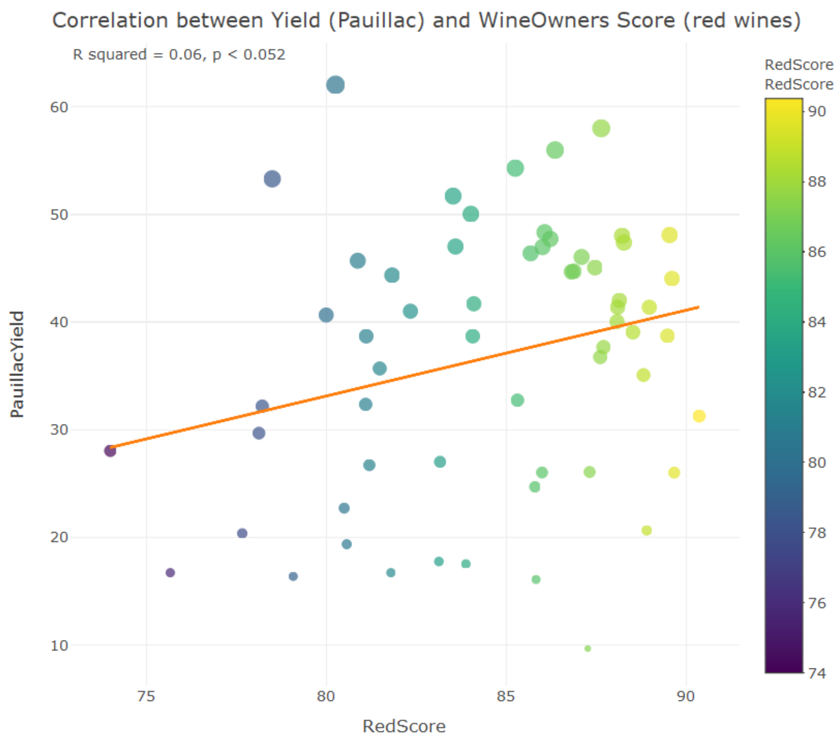

Fig.13: Correlation of yield and score - credit T.Visscher

Creating the linear regression model

Having identified the likely key associations from our crude correlation charts, we now used these to build our multiple linear regression model. A series of models was built using imported libraries in the program R, in order to identify the best fit linear regression model (using adjusted R^2) and the most parsimonious regression model. We used the subtraction method in our modelling approach, starting with more variables in a model and then removing variables with small or insignificant coefficients, in order to improve the 'adjusted R^2' (aR^2) value. The same process for modelling was applied to score and yield separately, to create 4 models for each outcome (8 models in total).

1. **All parameters model**
   This model used all 10 climate parameters (i.e. TMAX and PRCP for each PS)
   We did this a baseline position for the subtraction method and to sense check the data.

2. **Simple model (no quadratic terms)**
   This model shows the end result of the subtraction process, with the most parsimonious model available with fewest parameters and highest R^2 score.

3. **Most parsimonious model (with quadratic terms)**
   Before building the models, we identified some possible polynomial relationships in the scatter plots of our PS against score and yield (Fig.8 – Fig.12). Therefore, it was decided to include extra quadratic terms for the following variables: Bloom TMAX, Bud Break PRCP, and Veraison TMAX.

   This pattern was seen for both score and yield. Polynomial trends indicate there is a turning point in the curve somewhere. This makes logical sense since our research indicates that increasing temperatures may be beneficial but extremely high temperatures will begin to have a negative effect on vine growth. This is key because the historical data we use does not include temperatures likely to occur in the future due to climate change and thus it would be wrong to assume a straight linear trend. We also made this version as parsimonious as possible by subtracting PS variables with insignificant coefficients.

4. **Pragmatic model (with quadratic terms)**
   The final model and the version used in our further experiments was an adaption of model 3. It was not quite the most parsimonious because we decided, based on background research to retain Bud PRCP in the wine score model. The yield model was the same. It was deemed that inclusion of this variable was not detrimental to the overall fit of the model since they did not decrease the adjusted R^2 value by a significant amount. It was also anticipated that including this PS would lead to more successful future predictions modelling. This model gave also gave the highest (unadjusted) R^2 value. Retaining Bud RPCP also meant that our model had at least one variable from each PS and previous research suggests that all climate in each PS may have some impact on the quality of wine (Ashenfelter 2007).

The four models presented, show the sequential stages of this approach for score and yield respectively. The list of all variables in the regression models and their individual coefficients and p values are in the following tables (Table.4), (Table.5).

Table 4. Linear Regression analysis of different wine score prediction models

Model Name	Adjusted R^2	*Overall p-value*	Predictive Variable	Estimated Coefficient	*p-value*
1. All Parameters	0.483	*p<0.0001*	Dorm TMAX	0.67	*0.07*
			Dorm PRCP	0.17	*0.70*
			Bud TMAX	0.14	*0.58*
			Bud PRCP	-0.22	*0.53*
			Bloom TMAX	0.71	*< 0.01*
			Bloom PRCP	0.45	*0.15*
			Veraison TMAX	0.35	*0.18*
			Veraison PRCP	-0.68	*0.03*
			Ripening TMAX	0.12	*0.59*
			Ripening PRCP	-0.45	*0.03*
2. Simple Model (no quadratics)	0.503	*p<0.0001*	Dorm TMAX	0.69	*0.05*
			Bud PRCP	-0.29	*0.33*
			Bloom TMAX	0.75	*0.12*
			Bloom PRCP	0.48	*< 0.01*
			Veraison TMAX	0.39	*< 0.01*
			Veraison PRCP	-0.75	*0.09*
			Ripening PRCP	-0.51	*< 0.01*
3. Most Parsimonious	0.545	*p<0.0001*	Dorm TMAX	0.60	*0.07*
			Bud PRCP	-0.34	*0.24*
			Bloom TMAX	0.74	*< 0.01*
			Bloom PRCP	0.55	*0.07*
			Veraison TMAX	9.12	*0.01*
			Veraison $TMAX^2$	-0.19	*0.01*
			Veraison PRCP	-0.74	*< 0.01*
			Ripening PRCP	-0.52	*< 0.01*
4. Pragmatic Model	0.530	*p<0.0001*	Dorm TMAX	0.63	*0.08*
			Bud PRCP	-0.42	*0.68*
			Bud $PRCP^2$	0.02	*0.91*
			Bloom TMAX	-0.64	*0.86*
			Bloom $TMAX^2$	0.02	*0.71*
			Bloom PRCP	0.57	*0.06*
			Veraison TMAX	9.35	*0.01*
			Veraison $TMAX^2$	-0.17	*0.01*
			Veraison PRCP	-0.75	*< 0.01*
			Ripening PRCP	-0.51	*< 0.01*

Footnotes:
Precipitation in average daily precipitation per day in mm during the named phenological period
Max temperature is average daily average in centigrade during the named phenological period
Coefficients represent the change in score per 1^{o} temperature change or 1mm precipitation change

Table 5. Linear Regression analysis of different wine yield prediction models

Model Name	Adjusted R^2	*Overall p-value*	Predictive Variable	Estimated Coefficient	*p-value*
1. All Parameters	0.294	*p<0.01*	Dorm TMAX	1.1	*0.44*
			Dorm PRCP	-1.07	*0.53*
			Bud TMAX	-0.69	*0.51*
			Bud PRCP	2.49	*0.06*
			Bloom TMAX	2.18	*0.02*
			Bloom PRCP	0.16	*0.90*
			Veraison TMAX	2.42	*0.02*
			Veraison PRCP	-0.08	*0.94*
			Ripening TMAX	0.14	*0.87*
			Ripening PRCP	0.11	*0.89*
2. Simple Model (no quadratics)	0.365	*p<0.0001*	Bud PRCP	2.83	*0.01*
			Bloom TMAX	2.10	*< 0.01*
			Veraison TMAX	2.69	*< 0.01*
3. Most Parsimonious	0.394	*p<0.0001*	Bud PRCP	-2.74	*0.50*
			Bud $PRCP^2$	0.94	*0.17*
			Bloom TMAX	1.10	*< 0.01*
			Veraison TMAX	28.67	*0.04*
			Veraison $TMAX^2$	-0.51	*0.06*
4. Pragmatic Model	0.389	*p<0.0001*	Bud PRCP	-2.98	*0.02*
			Bud $PRCP^2$	0.94	*0.46*
			Bloom TMAX	11.14	*0.17*
			Bloom $TMAX^2$	-0.20	*0.48*
			Veraison TMAX	26.80	*0.06*
			Veraison $TMAX^2$	-0.48	*0.09*

Footnotes:
Precipitation in average daily precipitation per day in mm during the named phenological period
Max temperature is average daily average in centigrade during the named phenological period
Coefficients represent the change in yield in hectolitres per hectare per 1^o temperature change or 1mm precipitation change

2.5 Results

Wine score

For wine score, Model 1 had an aR^2 score of 0.48 suggesting that 48% of the variation in score could be explained by a model which included all available PS variables. However, there were very few PS variables that clearly showed significant associations in this model as shown by the non-significant p values, probably due to collinearity (Table.4).

After 3 predictor variables were removed, Model 2 showed an improved fit with an aR^2 score of 0.50. We began to get a sense of the most important PS variables involved in score. In particular, the coefficients for Veraison TMAX and Veraison PRCP were large and significant (Table.4).

The introduction of quadratic terms in score Model 3 greatly improved the fit to 0.55 aR^2. Interestingly the only quadratic necessary for this model was for Veraison TMAX, suggesting this is a crucial stage (Table.4).

In Model 4, adding back in quadratics for pragmatic reasons was not very detrimental to the overall fit, reducing it to 0.53. Many PS variables such as Bud PRCP and Bloom TMAX were highly correlated thus making it difficult to interpret individual coefficients. However, since Bloom PRCP and VeraisonTMAX generally had very high coefficients, it is probable that these periods have the biggest impact on score. (Table.4).

Yield

For yield, Model 1 gave a fairly low aR^2 of 0.294. There were many PS variables that had very high and thus non-significant p values, such as Veraison PRCP (0.94) and Ripening TMAX (0.87) suggesting they could be omitted from future versions of the model (Table.5).

Applying the subtraction method to variables in Model 2 greatly improved the aR^2 to 0.365. In addition, the p value for each of the PS variables was 0.01 or below suggesting these associations were significant (Table.5).

In Model 3 we added quadratic terms for Bud PRCP and Veraison TMAX which slightly increased the aR^2 to 0.394 (Table.5).

Model 4 was very similar to 3 but was less parsimonious as we included the quadratic for bloom TMAX back into the model. This better reflected the reality that there is an upper limit for heat tolerance during bloom. This gave a fairly good overall aR^2 of 0.389 (Table.5).

As a last step we attempted to verify the logic of our final pragmatic models. We employed another modelling technique similar to a Bayesian modelling approach (Merloni et al. 2018). We used the "dredge()" function within the MuMIn package to fit all combinations of the most plausible models and then rank all the models on the basis of AICc. AICc is AIC corrected for small sample sizes. The results showed that the most parsimonious AIC models very similar for both score and yield to our models in choice of PS variables to be included. The AIC projections most closely matched with the Model 3 designs.

2.6 Limitations

Most significantly, we can't guarantee the applicability of this model outside of the context of Bordeaux. Although the significant PS variables employed in our final linear regression model are likely to be similar across all wines, because we calculated the coefficients only based on Bordeaux wines and scores, different grape varieties in different wine regions may react very differently to the same conditions. There is also a problem with timing, as the definitions of the PS in this study were calculated for Bordeaux practices specifically and may not match other regions whose harvest times vary across the years and across producers.

Another possible source of error is our use of precipitation rather than a water balance approach to gauge growing conditions. As Baciocco suggests: 'future research might benefit from the use of a soil dryness index (based on data availability) to characterize soil moisture status throughout the growing season.' (Baciocco, Davis, and Jones 2014). Other factors such as hail and fog were not included in the modelling since there is no available predictive data.

In the future we could improve this study by having better access to yield data across more Bordeaux vintages, so as to gain a fairer impression of Bordeaux as a whole. Despite this, we believe that this study succeeds in its aims with the data we had available.

2.7 Findings

Overall, this study clearly demonstrates the vital impact climate in the growing season has on Bordeaux wine. Regarding the quality of wine, 53% of the variation in score could be explained by the PS variables in the pragmatic model. Although this value may seem moderate, when one considers that there are many other known factors that influence wine quality (terroir, barrel type, producer finesse, etc.), that do not relate to climate, we can say that, in practice, climate is incredibly important and explains over half of what makes a good wine. The fact that most significant conditions for better wine are high maximum temperature during veraison and high precipitation during the bloom period matches which corroborates previous research (Baciocco, Davis, and Jones 2014). In addition, in model 4 we can see that rainfall in veraison is moderately negatively correlated with quality.

We also discovered that accurately predicting yield is more difficult. Our best yield model explains 39% of the variation in yield and is thus moderately useful. One reason for this, also noted by Baciocco (Baciocco, Davis, and Jones 2014), may be that many of the PS variables are highly inter-correlated and thus are less effective as a whole in accounting for changes to yield. In addition, yields are often regulated by French Wine Classifications or AOC Law, thus making them less affected by climate conditions (The Wine Cellar 2019).

It is likely that this predictive accuracy of the model could have been greatly improved if we had access to more historical yield data for Bordeaux as a whole. On the other hand, considering that the Pauillac yields were increasing over time and perhaps slightly confounding results (Fig.2), our pragmatic model shows a reasonable best fit. It also reveals that Bloom and Veraison maximum temperature are highly significant for high yields, a plausible finding. Unlike for score, for yield, the only truly significant time period relating to precipitation seems to be the positive association between precipitation and yield in the Bud-Break PS, although this was not very significant. This perhaps reflects the associated risk that mildew (damp rot) can pose to vines in the earlier period (Centofanti et al. 2008).

Cautiously, we have identified an associative relationship of variables in our models but our results are somewhat affected by colinearity making indidivual coefficeients hard to interpret. However, taken together, we can say that the final set of PS varaibles are relevant to the quality and yield of any Bordeaux vinatge in our dataset. Another valuable result of this part of the study, is that the resulting regression models can now be employed in reverse as predictive models, in order to predict possible future scores and yields, given climate input variables. Thus this work provides an effective foundation for our following reaserch and predictive GIS analysis.

Image.7: Fermentation of grapes in Bordeaux Vineyard - credit T.Visscher

3. How will Bordeaux be affected by climate change in the future?

Predicting future wine quality and yield for the 2070 Bordeaux vintage under various future climate projection scenarios

3.1 Rationale

'Area suitable for viticulture decreases 25% to 73% in major wine producing regions by 2050 in the higher RCP 8.5 concentration pathway and 19% to 62% in the lower RCP 4.5' (Hannah et al. 2013).

In this section we will use the final pragmatic linear regression models designed in Part 2 to provide predictions for both score and yield, given future predicted climate data for Bordeaux, for the relevant phenological stages. In doing so we will aim to predict how climate change might affect wine scores and wine yields in Bordeaux by 2070 and discuss the wider implications of this for Bordeaux as a viticulture region.

3.2 Study design

The methodology of our study involved the following procedures:

1. Choosing a balance of GCMs for our projected climate data
2. Choosing which RCPs to focus on
3. Downloading future climate data for 2070 from WorldClim and converting GeoTiff to shapefile in R
4. Aggregating the future climate data into PS using R and adding quadratic variables to table
5. Extracting climate data which relates to the Bordeaux area only using coordinates to create Future Bordeaux climate data
6. Running our 2 final pragmatic regression models to set up prediction models
7. Running the R predict function on the Future Bordeaux climate data file for score and yield models respectively
8. Comparing future predicted Bordeaux scores and yields to contemporary average scores and yields

The following software tools were used to process the data:

- Excel – for data cleansing and table production
- R – statistical processing, linear regression and converting raster to shape files
- raster (R library package)
- rgdal (R library package)
- sf (R library package)
- rgeos (R library package)
- xlsx(R library package)
- sp (R library package)
- ARC GIS for plotting the mapped output

3.3 Selecting a model for predicting future climate?

In order to input future climate data into the predict functions of our regression models we had to find a source for detailed future climate predictions. There are a wide range of models available, however they generally use similar data and show similar projections. We used WorldClim (one of the most widely used datasets for ecological predictions), to provide monthly predicted climate outcomes for 2070 (WorldClim 2019). It was selected because it provides data at a high resolution (30 arc sec to 10 arc minutes or roughly 1km × 1km to 20km X 20km) and it provides global grids for the periods that we are interested in (projecting each month for 2050 and 2070).

For each grid there are many different climate models, known as general circulation models (GCMs) (Fig.14). Based on the previous research of Flato, we decided to take an average of the 3 most recent and most popular GCMs: HadCM3, MIROC-ESM-CHEM and NorESM1-M (Flato 2013) to reach a more balanced future projection. We tried to find a consensus amongst academics for the best models and the three models employed here were recommended in other studies (Moriondo et al. 2013), (Chen 2011) and (Smith 2017) respectively.

To allow for how anthropogenic action may continue to affect climate change in the future, the GCM's are run with different scenarios for future greenhouse gas emissions, known as Representative Concentration Pathways (RCPs). These model only the concentration of CO_2 emissions. In the best-case scenario, RCP 2.6, global emissions decline by 2025, whereas emissions following current trends without change lead to RCP 8.5 (Fig.15). Modelling two or more RCP scenarios appears to be an industry standard approach (Fraga et al. 2016). Thus, we decided to download projection data for the 6.0 RCP pathway and the 8.5 RCP pathway, the two highest possibilities, based on the reasoning that pessimistic emission scenarios are looking increasingly likely. Global average temperatures are likely to rise above the 2 °C policy target, allowing us to completely dismiss RCP 2.6 as a possibility for example (Sanford et al. 2014). Current emissions trends match or even exceed the RCP 8.5 emissions scenario, thus we employ the assumption that future emissions scenarios will fall somewhere between RCP 6.0 and RCP 8.5. This approach is also supported by other studies (Briche et al. 2014).

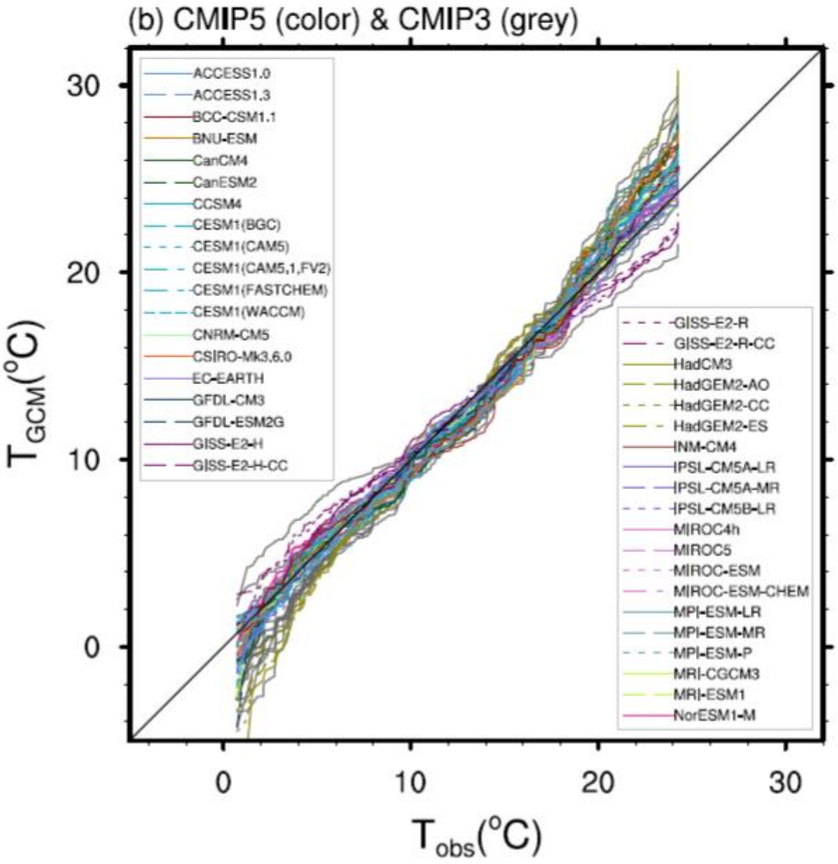

Fig.14: Mapping different GCM's against control variable. - credit (Flato 2013)

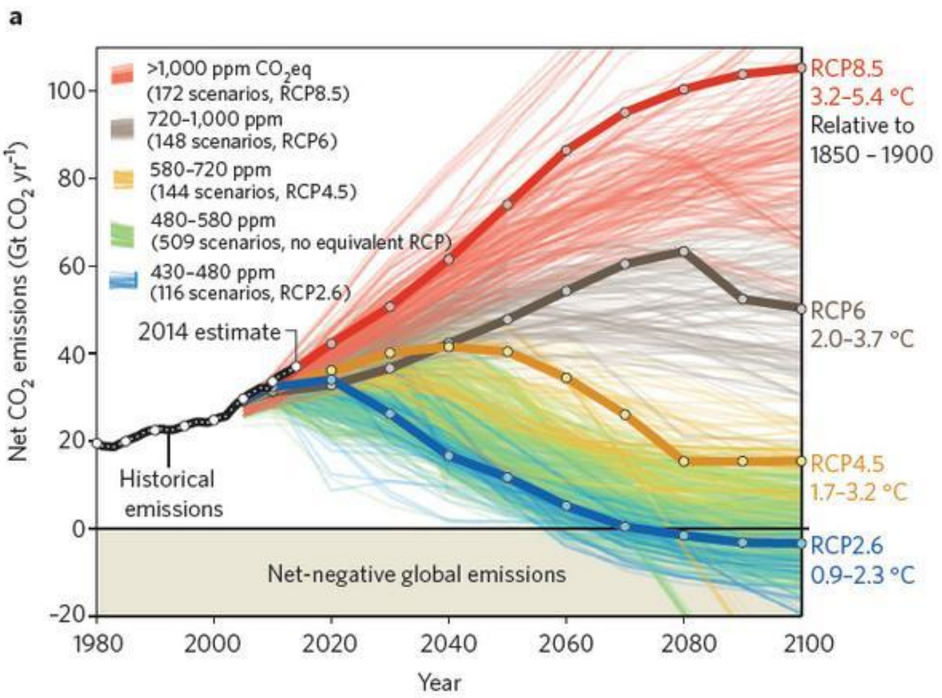

Fig.15: Possible future RCPs and warming outcomes. - credit (Impacts – II 2017)

3.4 Data preparation

The WorldClim, climate prediction datasets were downloaded from WorldClim as GeoTiff raster files, contain average climate for monthly precipitation, mean, minimum and maximum daily temperatures. The grids were produced by spline surface fitting spatial interpolation using data on latitude, longitude and elevation from weather station (WorldClim 2019). We downloaded the 2070 projection data at 10-minute (lat/long degree) spatial resolution. This resolution was considered sufficient, since we planned to intersect this layer with a soil composition polygon layer, clipping the results to the boundary of the soil layer, and thus higher resolution data was not necessary.

We also needed to convert the climate data in the spatial database to match our Phenological Stages for predicting purposes. Since the WorldClim data gave TMAX (x10) and PRCP for every month, we aggregated those months using a weighting index, into our PS using R code as follows:

```
Temp.dorm <- mean(europe.temp11,europe.temp12,europe.temp1, europe.temp2, europe.temp3)/10
Temp.bud <- mean(europe.temp3, europe.temp4)/10
Temp.bloom <- (europe.temp5*.25 + europe.temp6*.75)/10
Temp.veraison <- (europe.temp8*.84 + europe.temp9*.16)/10
Temp.ripening <- (europe.temp9)/10
```

In addition, for precipitation we had to convert values from monthly rainfall total into average PRCP per day in mm, so divided each value by the total number of days in that month:

```
Prcp.dorm <- mean(europe.prcp11,europe.prcp12,europe.prcp1, europe.prcp2, europe.prcp3)/30.2
Prcp.bud <- mean(europe.prcp3, europe.prcp4)/30.5
Prcp.bloom <- (europe.prcp5/31*.25 + europe.prcp6/30*.75)
Prcp.veraison <-(europe.prcp8/31*.84 + europe.prcp9/30*.16)
Prcp.ripening <- (europe.prcp9/30)
```

We added additional columns for the PS quadratic variables using R, which the predictive regression model requires. Lastly, we converted the GeoTiffs for RCP 6.0 and RCP 8.5 2070 (combined average of our 3 GCMs) to asci and saved them as a normal shape file using the 'raster', 'rgdal' and 'rgeos' libraries. We only exported polygons covering Europe, to speed up processing. Thus we ended up with a total of 20 different climate shapefile layers (Table.5).

RCP 6.0 2070.shp	RCP 8.5 2070.shp
TMAX.dorm	TMAX.dorm
TMAX.bud	TMAX.bud
TMAX.bloom	TMAX.bloom
TMAX.veraison	TMAX.veraison
TMAX.ripening	TMAX.ripening
PRCP.dorm	PRCP.dorm
PRCP.bud	PRCP.bud
PRCP.bloom	PRCP.bloom
PRCP.veraison	PRCP.veraison
PRCP.ripening	PRCP.ripening

Table.6: Climate 2070 projections shapefiles

3.5 Statistical Analysis

We began by mapping some of our 2070 projections into ArcGIS alongside layers for climate data 1970-2000, also from WorldClim, which had been cleaned and aggregated in the same way. This way we could sense check our method and see some general climate trends for Europe as a whole (Fig.16) – (Fig.19).

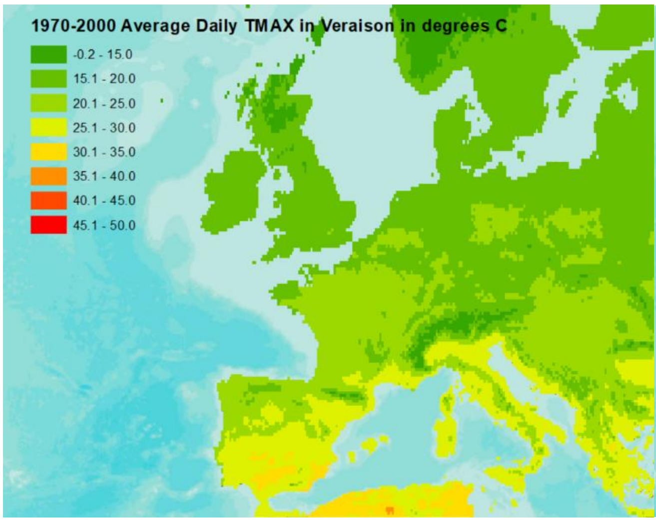

Fig.16: Map of Europe TMAX average 1970-2019 - credit T.Visscher Source: WorldClim

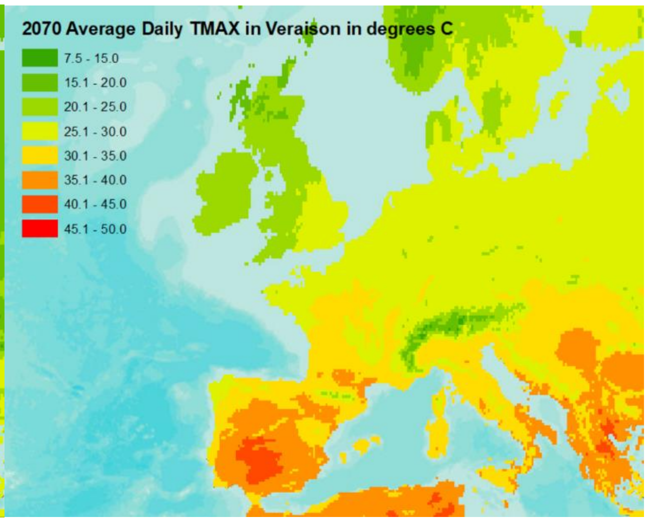

Fig.17: Map of Europe TMAX 2070 (average of RCP 6.0 and 8.5) - credit T.Visscher Source: WorldClim

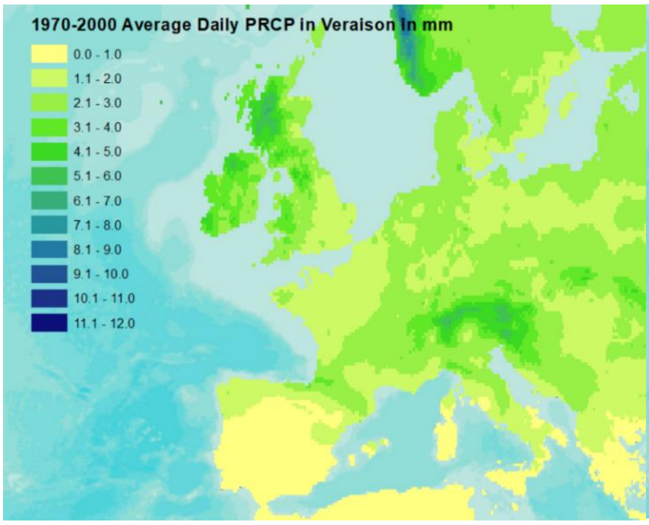

Fig.18: Map of Europe PRCP 2019 - credit T.Visscher Source: WorldClim

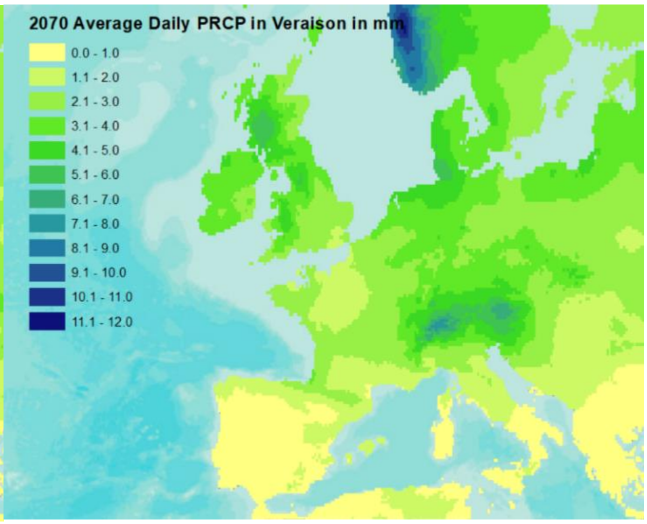

Fig.19: Map of Europe PRCP 2070 (average of RCP 6.0 and 8.5) - credit T.Visscher Source: WorldClim

From these ArcGIS layers we extracted the averaged TMAX and PRCP figures for the 2070 Phenological Stages for the Bordeaux area only, to create the Future Bordeaux climate data (Table.6), (Table.7). We also compared this data to the 1970-2000 data for TMAX (Fig.20) and RPCP (Fig.21).

RCP	Vintage	Dorm PRCP	Dorm TMAX	Bud PRCP	Bud TMAX	Bloom PRCP	Bloom TMAX	Veraison PRCP	Veraison TMAX	Ripening PRCP	Ripening TMAX
6	2070	2.9073	13.08	2.197	17.95	1.973	25.575	1.93428	28.836	2.26667	26.4

Table.7: Bordeaux climate predictions for PS for 2070, RCP 6.0

RCP	Vintage	Dorm PRCP	Dorm TMAX	Bud PRCP	Bud TMAX	Bloom PRCP	Bloom TMAX	Veraison PRCP	Veraison TMAX	Ripening PRCP	Ripening TMAX
85	2070	2.947	15.42	2.082	20.05	2.182	28.8	2.28482	33.004	2.93333	30.4

Table.8: Bordeaux climate predictions for PS for 2070, RCP 8.5

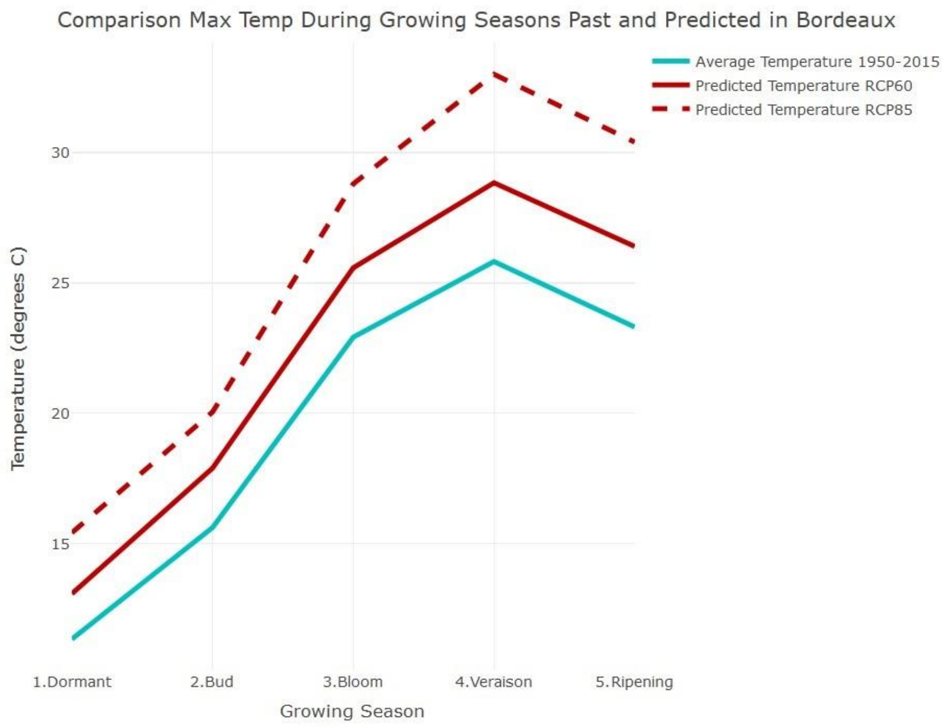

Fig.20: Average TMAX by PS for historical, RCP 6 and RCP 85 - credit T.Visscher

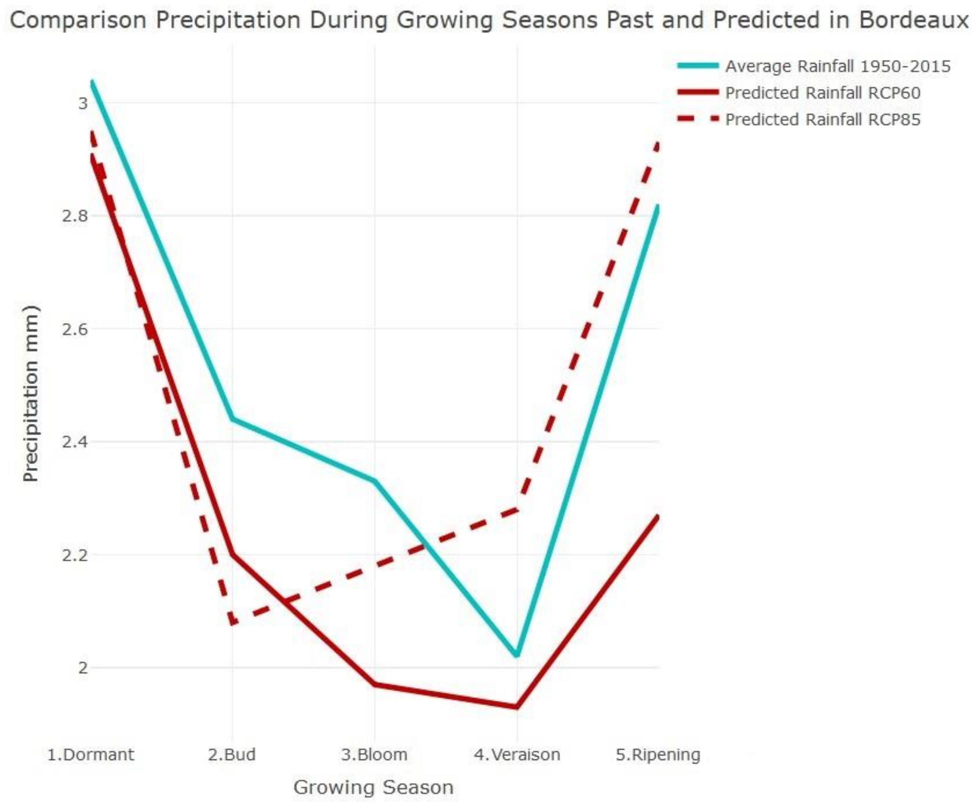

Fig.21: Average PRCP by PS for historical, RCP 6 and RCP 85

We utilised the ability to turn the linear regression models created in Chapter 2 into predictive models. We ran the different versions of the regression models and saved the model definitions locally. Then we use the inbuilt 'predict()' function as part of the default R library in order to predict the score or yield outcomes of these models, given the input of the Future Bordeaux climate data for RCP 6.0 and RCP 8.5 respectively. Lastly, we compared the scores and yields for our future predictions with average Bordeaux scores and yield from the last 25 years. The results of these predictions for various versions of the regression model are as follows: (Table.5).

Prediction Parameters	***Predicted Value***	**Lower Bound**	**Upper Bound**
score RCP 6.0 without quadratics (simple model) regression results	89.49	87.92	91.06
score RCP 6.0 with quadratics (pragmatic model) regression results	88.52	86.55	90.50
score RCP 8.5 with quadratics (pragmatic model) regression results	87.09	78.44	95.75
yield RCP 6.0 without quadratics (simple model) regression results	50.22	44.11	56.32
yield RCP 6.0 with quadratics (pragmatic model) regression results	44.50	36.50	52.51
yield RCP 8.5 with quadratics (pragmatic model) regression results	34.89	1.41	68.38
Average score last 25 years	89.13		
Average yield last 25 years	44.35		

Table.9: Prediction results and average Bordeaux score and yields from last 25 years

3.6 Results

Climate predictions show that, in general, Europe and southern Europe in particular, is expected to get considerably hotter by 2070 (Fig.16), (Fig.17). Rainfall is expected to increase across Central Europe but leave Southern Europe more prone to drought (Fig.18), (Fig.19). We can thus expect Bordeaux to get much hotter and slightly wetter in the key PS periods (veraison is used in Fig.20 and Fig.21 as an illustration).

Generally the RCP 6.0 and RCP 8.5 projections follow similar seasonal fluctuation patterns to current climate as shown by their identical trend line shape for TMAX (Fig.20). RCP 8.5 also gives higher predictions across all PSs for TMAX than contemporary conditions with RCP 6.0 lying between the two extremes. This is similar for PRCP, however, RCP 8.5 PRCP in Veraison, is expected to increase dramatically in comparison to contemporary conditions, whereas in 6.0 it is expected to be lower than it is presently the case in Bordeaux, by far the biggest difference between the two scenarios. RCP 6.0 also predicts a much sharper drop off in PRCP between Dormancy and Bud than is currently the case.

Utilising the quadratic PS variables for our regression models gave slightly lower predictions for scores and yields than the projections without. The future projections both show slightly worse score predictions compared to the last 25 years average, although the difference wasn't very large at all; only 2 score points overall between this and the lowest predictions of RCP 8.5. The RCP 8.5 prediction had an especially large gap between upper and lower bounds than the contemporary results. The only model to predict a reduction in yield by 2070 was the RCP 8.5 pragmatic model, which predicts a quite large reduction of 10 hectolitres per hectare (Table.5).

3.7 Limitations

The main limitation with this study is that future predictions will always remain uncertain and can only tell us so much about the topic we are interested in. This uncertainty is exacerbated by the fact that the regression models used are only able to explain around half of the relationships at best for score and even less for yield and that the extremes seen in future predicted climate models may lie outside the range of our historical models. As Urhausen points out, 'due to the high sensitivity of wine phenology it is hard to predict with certainty exactly how flavors will be affected by new conditions and palettes may in fact change with the times as well (Urhausen et al. 2011). Thus, future changes in taste may plausibly account for some of the change in Bordeaux score.

Also, we did not take into account the variety of different grape varieties in Bordeaux and the possibility that they may react differently to different climate changes. This is not a huge problem since, 88.5% of Bordeaux grapes are either Merlot or Cabernet Sauvignon (The Wine Cellar 2019), yet further research may consider attempting to model future Bordeaux on a more granular level, generating more specific predictions for individual vineyards or grape varieties.

A statistical limitation is that the WorldClim climate predictions are only given by month and only for 1 year (2070). This is understandable considering the complexity of future climate modelling. However, being able to map the changing Bordeaux climate over time (2020-2070) would be immensely useful to future wine producers.

3.7 Findings

We have come to expect that future higher temperatures and greater extremes of rainfall (as shown by our WorldClim datasets (Fig.16 – 19) are bad news for wine in general (Hannah et al. 2013). In Bordeaux our findings, particularly for the worst case scenario, seem to support this idea: If PRCP in ripening and veraison is higher than now, under the 8.5 projection, then it will likely be problematic for quality, since we know from Chapter 2 that both these variables are highly negatively correlated with score (Table.4). In addition, the much higher average temperatures we expect to see, (5^0C increase at certain times) under RCP 6.0, and 10^0C under 8.5 (Fig.20), could be responsible for the lower score predictions we see. As Galbreath points out, 'A warmer climate will impact directly on wine-grapes through over-ripening, drying out, rising acidity levels, and greater vulnerability to pests and disease' (Galbreath 2011).

However, on balance, the predicted scores do not decrease as much as excepted (only 1 and 2 points for 6.0 and 8.5 respectively), considering the huge changes in temperature and rainfall. This might not be so surprising. Leeuwen makes the crucial observation that due to warming, some areas will actually become better for growing high quality wine through changes such as faster grape ripening and more intense veraison, giving the example that Burgundy continues to produce great wines although the average seasonal temperatures are already above the previously assumed upper limit (Leeuwen et al. 2013).

The problem is that we don't know if Bordeaux has reached it's 'peak' in terms of winegrowing potential and when those maximum potential climate conditions will be reached. Therefore, it is quite possible that our predictive results reflect a mix of changes that will in some ways improve Bordeaux wine quality and in other ways damage it, thus leaving wine scores only slightly lower than they are now. Based on similar climate predictions, Mozell suggests that practical adaptive management strategies could be employed to adjust for the impact on wine quality such as managing the vine canopy to provide additional shade and reduce sugars and increase acids where necessary (Mozell and Thach 2014).

Yield seemed the factor most heavily affected by extreme climates (with a 10-hectolitre per hectare reduction) but only when considering the RCP 8.5 projection, as the RCP 6.0 pragmatic model was almost identical to the last 25 years average score. The lower yield prediction for the 8.5 projection can perhaps be explained by the fact that PRCP in bud-break drops to 2.082, in this projection, whereas the 6.0 projection it is a nearly 1mm higher at 2.971. Our studies show that PRCP is positively correlated with yield in bud-break (Table.5) and we know that in this period, vines require much water to grow as fast as possible (Baciocco, Davis, and Jones 2014), thus supporting this interpretation.

On the other hand, we know from Chapter 2 that yield is harder to predict and this is reflected in the much larger range between the upper and lower bounds for yield than score in the quadratic predictive models (Table.5). The results seem to show that timing of the Phenological Stages are crucial for yields as extremes of weather too early or too late in the season can ruin crops. Perhaps Bordeaux could adapt to this by harvesting earlier as the period of drought before harvesting could be compensated by quicker ripening during early veraison' (Cook and Wolkovich 2016). Alternatively a switch to night-time harvesting could avoid spoilage' (Mozell and Thach 2014).

It seemed that the use of quadratics for PS variables was a good decision as the models with them showed lower scores and yields for future predictions, something that we were expecting to find, whereas the prediction without quadratics actually predicted an increase in both score and yield (Table.5). This demonstrates the crucial observation that the relationship between temperature and wine quality is not a straight-line linear association but that eventually, very high temperatures will damage the quality, and the same pattern applies to yield. Overall, the future of Bordeaux will be affected by climate change but at the same time the outlook is not apocalyptic if producers can adapt.

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Image.8: Bordeaux Vines - credit T.Visscher

4. Finding the New Bordeaux

Using an integrated GIS and predictive modelling approach to predict which European region will be most suitable for producing fine wine in 2070

4.1 Rationale

'The two main responses to these warmer and drier conditions are 1) progressive shifts of existing grapevine cultivated area to the north-northwest of their original ranges, and 2) expansion or contraction of the wine regions due to changes in within region suitability for grapevine cultivation. Wine regions with climatic conditions from the Mediterranean basin today - were shown to potentially shift the most over time' (Moriondo et al. 2013).

Our final aim was to visualise the potential 'shifting' nature of the Bordeaux wine area, by predicting where the areas of ideal climate suitability and landscape composition for growing Bordeaux grape varieties are likely to lie in 2070. Previous research has suggested an approach for identifying these areas using spatial GIS techniques (Moriondo et al. 2013). We will use a similar method, to help designate our 'New Bordeaux'. We will identify the geographical intersection of the ideal climate conditions for the key PS layers and matching soil composition.

4.2 Study design

1. Importing Future climate GeoTiff files into ArcGIS
2. Downloading European Soil Database and importing into ArcGIS
3. Identifying soil types that best match the profile of Bordeaux in ArcGIS
4. Identifying the key associative PS variables and choosing these as climate layers
5. Finding the areas which best match the PS characteristics of the top 20 historical Bordeaux vintages and exporting these as 'New Bordeaux Climate layers'
6. Using R to find intersection of 'New Bordeaux Climate layers' and Bordeaux soil type
7. Importing the intersect layer into Google Earth to sense check and check elevation profiles.
8. Use Google Earth to select and define favourite candidate regions and tidy up boundaries

The following software tools were used to process the data:

- ARC GIS for creating the intersections between layers and mapping output
- Google Earth for providing the underlying map layers

4.3 Data preparation

For this section of our project, we had most of the data we needed already prepared. However, in order to make an accurate analysis of wine growing capability, we needed to create a measure representing the terroir of Bordeaux. Prior research had established a precedent for including soil type and ground water content as a key part of viticultural spatial analysis (Moriondo et al. 2013).

We downloaded the European Soil Database (National Centres For Environmental Information 2019), an open source and highly detailed spatial dataset. We used ArcGIS to explore this database and were able to produce a rough profile of Bordeaux's terroir from selecting the 4 soil types that almost entirely make up the Bordeaux wine region. These soil types were the following:

- Arenosol - Sandy soil
- Rendzina - A fertile lime-rich soil
- Podzoluvisol - A fertile clay like soil
- Fluvisol - Comprised of river sediment deposits

We confirmed that these soil types accurately reflected the gravelly, silty, sandstone and fluvial ground composition of Bordeaux, created over time by the deposits of the Gironde river (Centofanti et al. 2008), and thus could be a good proxy for Bordeaux's terroir. The clay like quality of Podzoluvisol is particularly important to Bordeaux, since the expansion and contraction of the clay provides space for vine roots do delve deep into the ground and get more water (The Wine Cellar 2019).

4.4 GIS analysis

The analyis was fairly simple and could be entirely completed within ArcGIS. In ArcGIS we first created spatial subsets of our 2070 climate layers which only covered areas which matched our percieved 'ideal' climatic conditions for Bordeaux.

To get these we calculated for each PS, an average of the TMAX and average of the PRCP for the top-20 rated vintages from our orginal master database. We also calculated the standard deviation for each PS Variable. A band 1-Standard deviation either side of the mean was used to create a range within which conditions could be described as 'optimal'. Finding only areas which matched the exact values for each PS would not have worked since very few squares of the 2070 climate grid would have exactly the same temperatures and precipitation levels. The results of estimation of the 'ideal' Bordeaux climate specifications can be seen below (Table.12):

(yellow)	*= PS Variable relating to Score*
(orange)	*= PS Variable realting to Score **AND** Yield*

	dorm prec top 20	dorm tmax top 20	bud prec top 20	bud tmax top 20	bloom prec top 20	bloom tmax top 20	veraison prec top 20	veraison tmax top 20	ripening prec top 20	ripening tmax top 20
Average	2.85094	11.9515	2.0886	16.727	2.32315	24.308	1.49898	27.1525	1.83379	24.1619
SD	0.90898	1.05045	1.0629	1.4389	1.48801	1.8543	1.01639	1.6503	0.89626	1.68903
Lower Range	1.94195	10.901	1.0257	15.288	0.83514	22.4537	0.48259	25.5022	0.93753	22.4729
Upper Range	3.75992	13.0019	3.1515	18.166	3.81116	26.1623	2.51537	28.8028	2.73005	25.851

Table.11: Average of top 20 vintages of Bordeaux PS conditions with upper and lower bounds

The biggest decision was choosing which PS layers from the 20 possible future climate layers (10 each for RCP 6.0 and 8.5 respectively) to inlcude in our spatial analysis. It became apparent that intersecting too many different climate layers would confound our results because many of the variables actually have little or no impact on wine score or yield (e.g ripening TMAX) from our findings in Chapter 2. In the final analyis we used only variables that were the most significant in an associative sense to both score and yield, as informed by Chapter 2 (Table.4), (Table.5). The final PS Variable layers were Bloom TMAX, Veraison TMAX, Bud PRCP and Veraison PRCP.

The aim was to weight the analysis slightly towards identifying an area that optimises score since intrinsically the designation of an areas as the 'New Bordeaux' would depend upon wine quality (as measured by score) as opposed to yield. The 'select by attribute' function in ArcGIS was employed to crop these layers within the bounds of the standard deviations. The final layers were exported as separate shapefiles for each RCP (Fig.22).

We exported the 4 desired soil types into a new layer (Fig.23). In order to try and identify candidate regions that would satisfy both the RCP 6.0 and RCP 8.0 pathways, we used the intersect tool to find the intersect of the total of the relevant PS Variable layers for both concentration pathways. Thus, the final composite map layer contained only areas which were predicted to have ideal precipitation and temperature in both projections of RCP. This helped narrow down our candidate areas considerably. Fig.24 shows the climate grid squares highlighted green (Fig.24). Finally, we used the 'select by location' function to the crop the soil layer to the Ideal Climate Layer and saved this as a 'New Bordeaux' layer. The result revealed 3 main candidate locations; The South Downs, The Somme Valley in northern France and the southern French Alps (Fig.25).

Immediately the alpine region was discounted due to logistic impracticality and the other small areas in Normandy were ignored as they were too small to become a grand new wine region. Lastly, we checked the elevation of our prospective regions by importing the South Downs Layer and Somme Valley Layers into GoogleEarth and used an inbuilt function to get elevation profiles for each region (Fig.26). Although this was a rough comparison, it was useful, as a flat or too steep elevation would create conditions impossible for successful viticulture (Chen 2011).

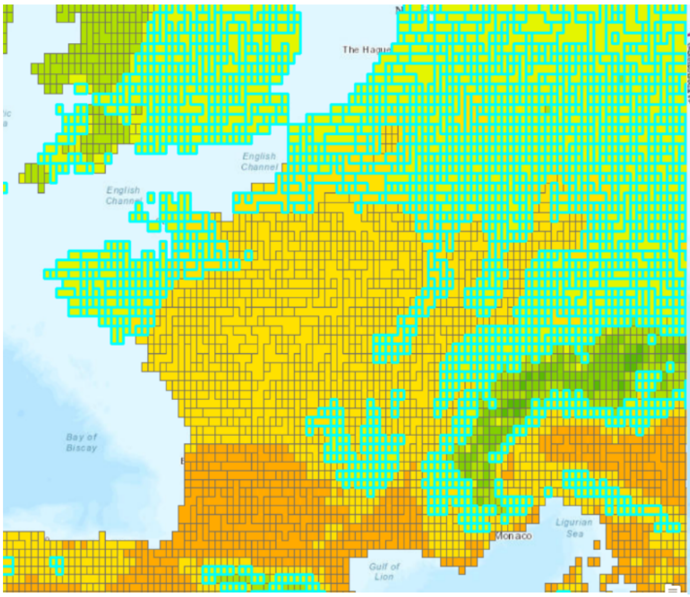

Fig.22: Finding overlap of ideal climatic ranges for each PS - credit T.Visscher ArcGIS

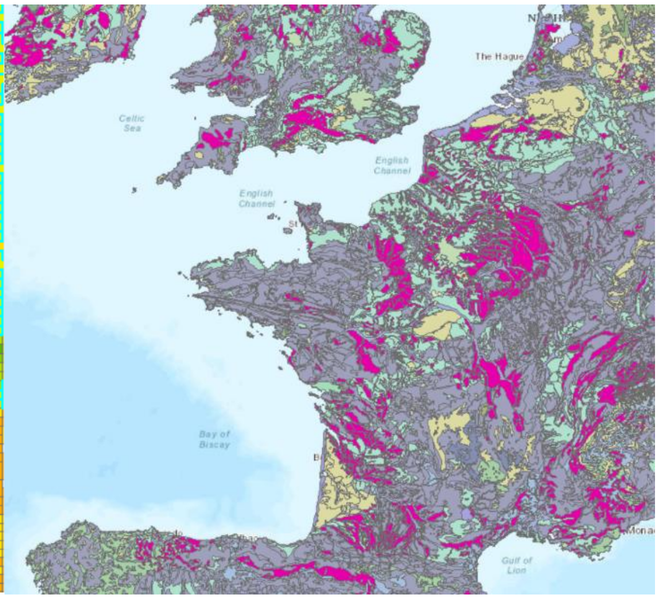

Fig.23: Finding regions which fit same general soil criteria as Bordeaux. Cropped Soil region in pink- credit T.Visscher ArcGIS

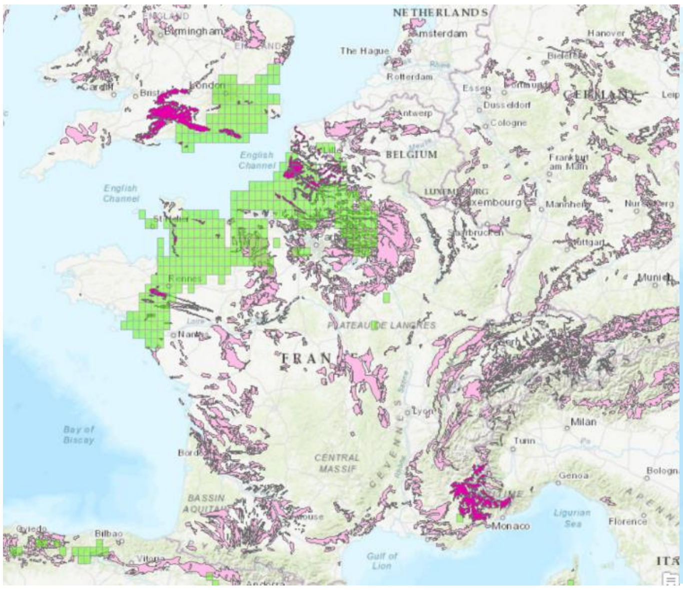

Fig.24: Finding the intersect of ideal climate region and ideal soil composition. Green area is final Ideal Climate Layer- credit T.Visscher ArcGIS

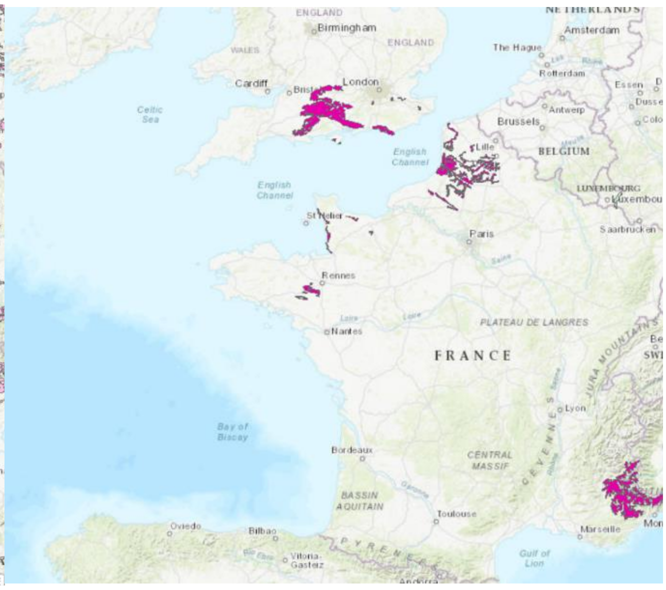

Fig.25: Exporting of regions which fit the profile as a potential 'New Bordeaux' - credit T.Visscher ArcGIS

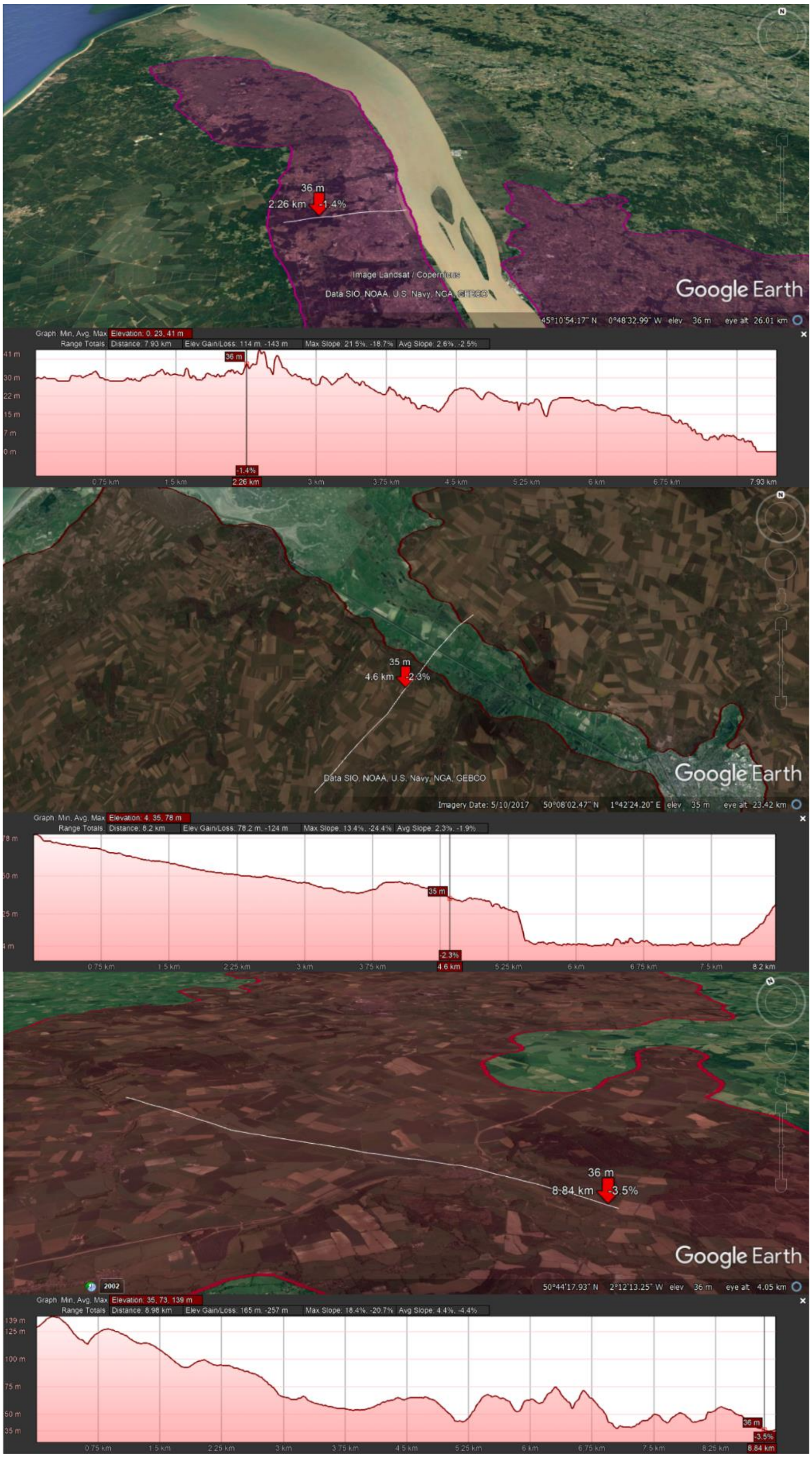

Fig.26: Exploring elevation profiles for new region candidates and original Bordeaux - credit T.Visscher GoogleMaps

4.5 Results

Although we determined in Chapter 3 that viticulture in Bordeaux will not disappear completely by 2070, it is valuable to consider what new regions might become just as suitable as contemporary Bordeaux, for producing fine wines. The South Downs and the Somme Valley (Fig.27) both appear good candidates for future viticulture, in terms of predicted climate and terroir. In addition, both regions have a roughly similar elevation profile to Bordeaux with gently sloping hills providing enough filtration and sunlight. The South Downs may replicate Bordeaux better in this regard since it is more rugged than the Somme Valley landscape (Fig.26). Both regions have a similar total area to Bordeaux (Fig.28), providing room for a viable viticulture region. The proposed regions are shown in maps below (Fig.27 – Fig.31).

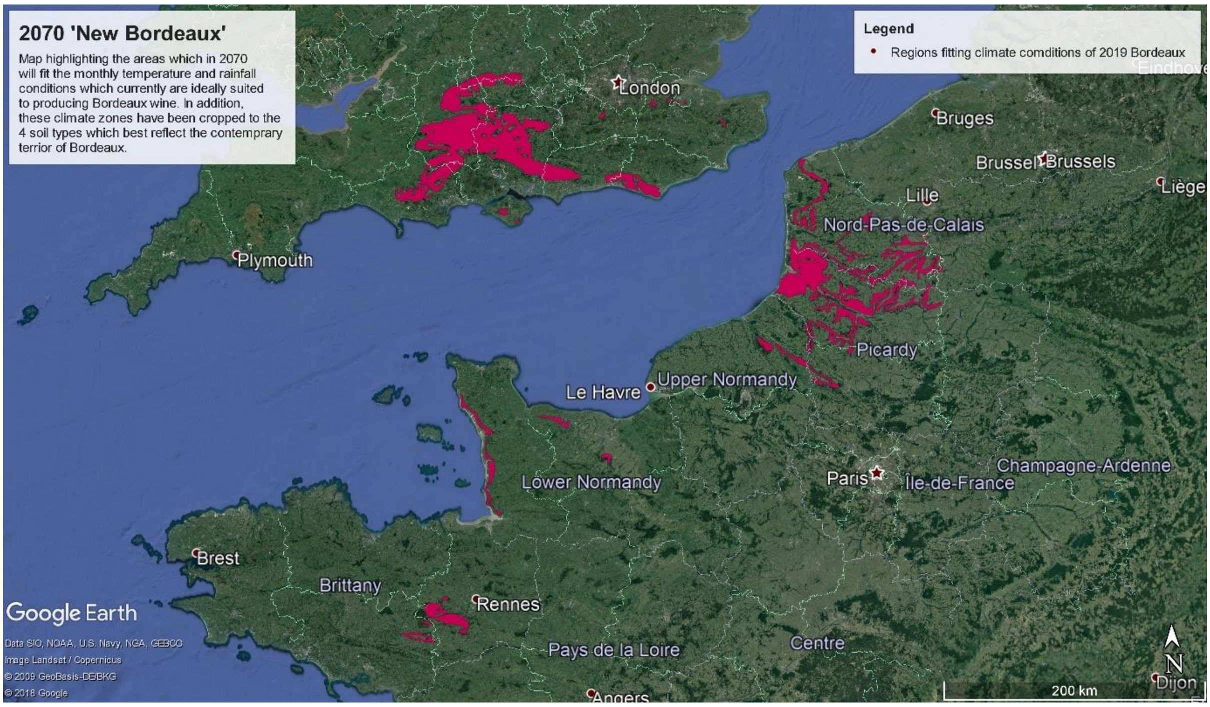

Fig.27: Finalising the 'New Bordeaux' - credit T.Visscher, GoogleEarth

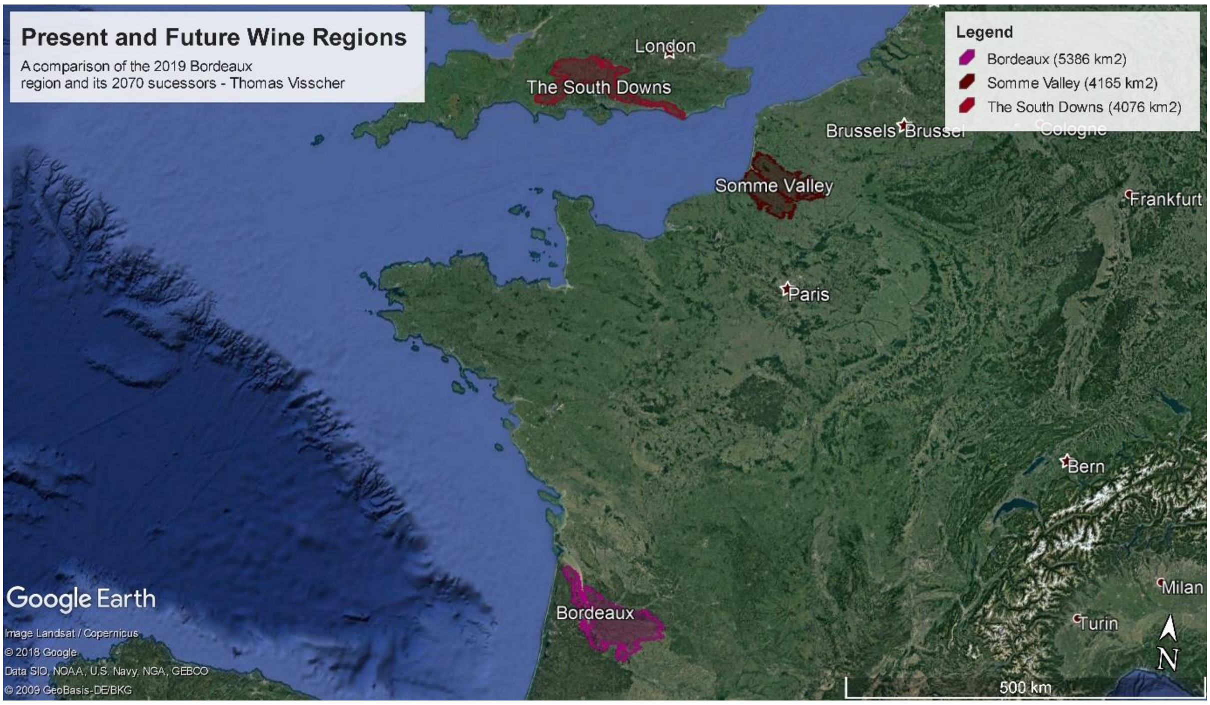

Fig.28: Old and new Bordeaux(s) a comparison - credit T.Visscher, GoogleEarth

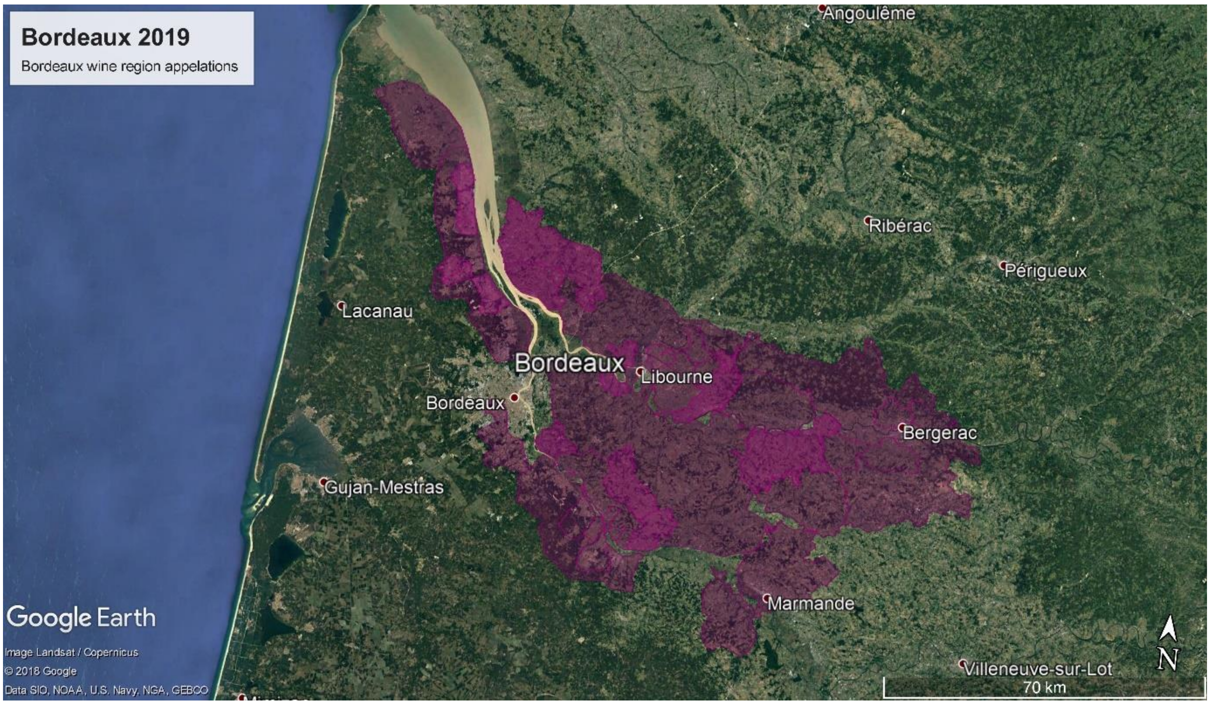

Fig.29: In detail: Bordeaux 2019 - credit T.Visscher, GoogleEarth

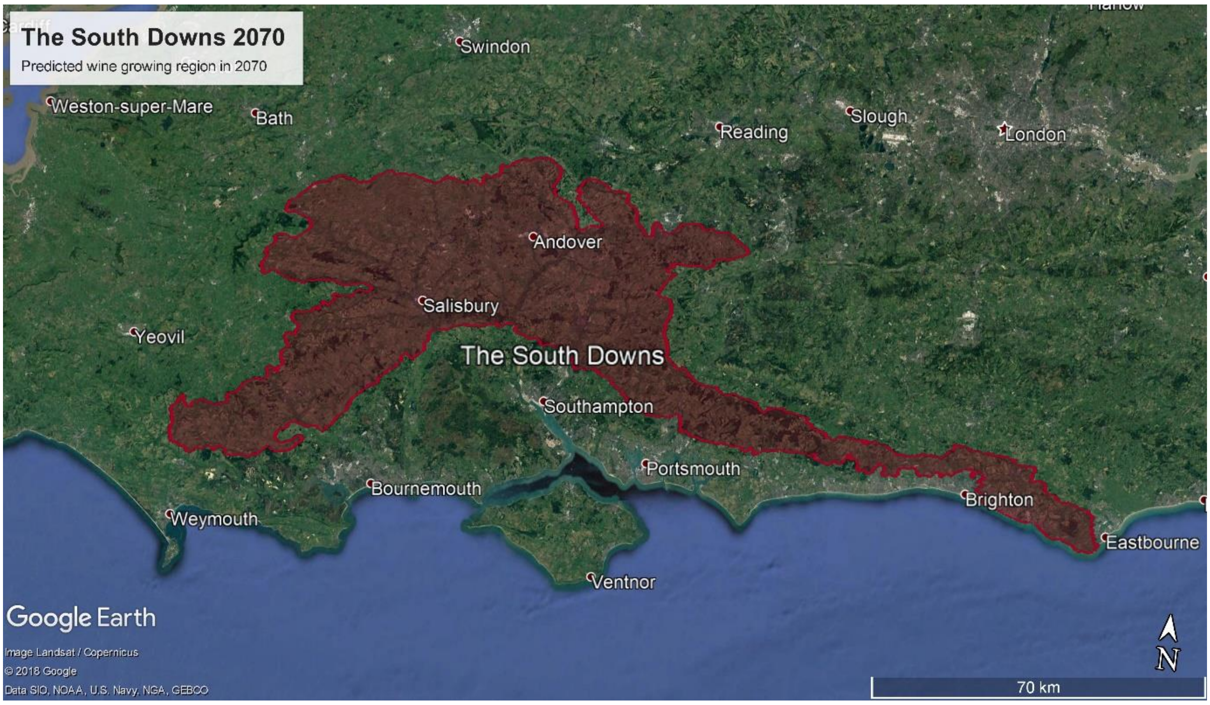

Fig.30: In detail: The South Downs wine region 2070 - credit T.Visscher, GoogleEarth

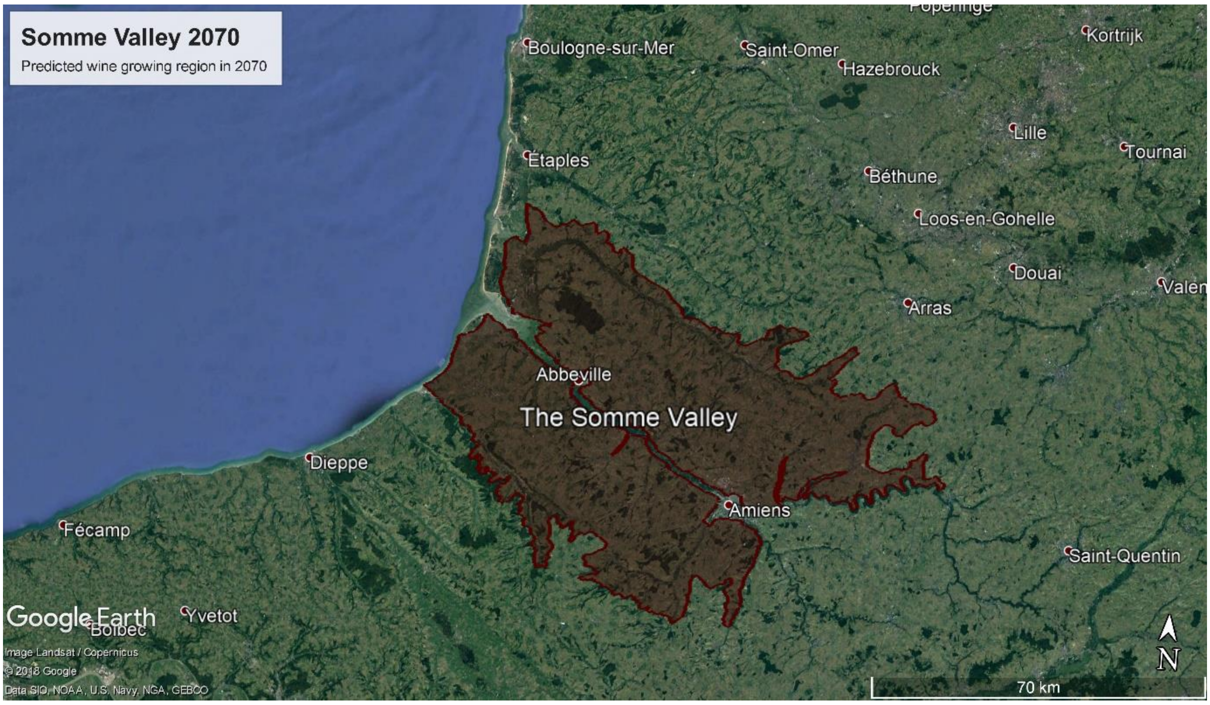

Fig.31: In detail: The Somme Valley wine region 2070 - credit T.Visscher, GoogleEarth

4.6 Limitations

There are many other factors that we haven't considered such as the effects of possible future flooding and sea level rise, which also might have knock on effects for the soil composition. In the future, more attention might also be given to defining a model to reflect terrain characteristics which govern solar radiation data and evapotranspiration (Bois et al. 2018). There is also a historical element to Bordeaux which should not be dismissed.

4.7 Findings

The wine industry is already moving towards new forms of technology such as satellite imaging, in order to monitor and manage crop yields. (Johnson et al. 2003) (Ducati, Bombassaro, and M. G. Fachel 2014) and (Bois et al. 2018). Therefore, this study can be seen within the context of inspiring greater interest in spatial predictive analysis when it comes to viticulture.

Both the South Downs and the Somme Valley seem likely to become excellent regions for viticulture by 2070. It is hard to say which one is better suited than the other, since they both contain sufficient pre-existing agricultural infrastructure to adapt to new forms of agriculture, even in a timespan as short as 50 years. What might tip the balance is the way the Somme Valley in Amiens matches the physical profile of Bordeaux, by having left and right banks alongside a river and being close to the Atlantic (Fig.29), (Fig.8). In addition, the fact that it is in France means the wine industry is already established and it would not be as difficult for Bordeaux producers to move their organisations to this region as to the South Downs. On the other hand, southern England does have some established vineyards which may give it a future head start.

Image.9: Bordeaux grapes and vines- credit T.Visscher

5.
Discussion:
Abandonment or adaption in Bordeaux?

Throughout this study we have taken an interdisciplinary approach to the question of future viticulture in Bordeaux. Our methodology led us through sequential stages of analysis, (chapters 2,3,4) in which each stage built on the statistical findings and research of previous. The statistical regression modelling in Chapter 2 provided the foundation for a reliable and concise original predictive model for Bordeaux wine. Our final climate regression model was reasonably successful in being able to account for 53% of the variation in wine quality, and the 39% result for yield, which, whilst not ground-breaking, is still valuable.

Our findings show that high temperatures and low rainfall in veraison are the most significant climatic factors determining wine quality. This supports Teixeira's understanding of grape phenology, which states that heat, drought and light are crucial for producing the flavonoid chemicals we associate with good tasting wine during veraison and rain during this period can ruin a crop by softening and swelling grapes and diluting flavours (Teixeira et al. 2013). Precipitation was also important for yield during Bud Break. Baciocco sums up the critical aspect of how rain relates to wine quality: 'Over the entire growing season, total rainfall between the extreme vintages is almost identical – the critical factor is the timing of the rain' (Baciocco, Davis, and Jones 2014).

Chapter 3 employed our most pragmatic regression models to predict future outcomes for Bordeaux, whilst blending in wider research to discuss the possible reasons why the predictions were significant and plausible or surprising. We established that Bordeaux will likely experience much higher temperatures (Fig.16) and possible drought early in the season and higher rainfall later in the year (Fig.17). As established in Chapter 2, the exact timing of rainfall is a critical factor for yield and quality and thus unpredictable, extreme rainfall patterns are likely to pose the biggest problem for Bordeaux viticulture. Whilst we predicted average scores to only decrease slightly, yield was dramatically lower for the RCP 8.5 projection and is most at threat. Just as some researchers are not sure whether existing wine regions may experience even better conditions (Leeuwen et al. 2013) or worse (Hannah et al. 2013), the most reasonable conclusion is that since Bordeaux climate is moving to greater weather extremes, quality and yield will simply become more variable vintage by vintage, a characteristic that is already being seen by the 'Jekyll and Hyde' performance of the 2018 Bordeaux season (Liv Ex 2019).

We can better understand the likely impact of climate change on viticulture by employing concepts like Diffenbaugh's 'adaption wedge' which anticipates industry adaptions to climate change where the resulting 'adaption wedge' is the avoided damage relative to the loss that would occur without that adaptation (Diffenbaugh et al. 2011). Under this model, the wine industry in areas like Bordeaux will not disappear overnight but will introduce measures to mitigate the worst effects of changing conditions. However, this adaption wedge cannot completely preserve Bordeaux as it is. Improving the 'heat tolerance' of wines will be necessary but it may lower the quality of wine (Diffenbaugh et al. 2011).

Chapter 4 used our new understanding of the key factors in wine quality and yield as established in Chapter 2 and our spatial analysis of shifting future climate patterns from Chapter 3, to develop a broader, more speculative interpretation of our findings and answer the question which started it all off. Truthfully, we cannot claim to with complete certainty that either The South Downs or the Somme Valley will become the 'New Bordeaux' by superseding the market-share, fame and desirability of the original. The connection between production areas and the agricultural and cultural identity is critical in transforming an ordinary wine into a world-renowned one (Dimson, Rousseau, and Spaenjers 2015). Instead, we use the term 'New Bordeaux' to draw attention to the fact these areas, in our view, will likely at some point in the next 50 – 100 years be ideal for producing the Merlot and Cabaret Sauvignon red wine varieties, so sought after in Bordeaux. Regardless of the fate of Bordeaux itself, we aim to inspire future researchers to consider the promising viticultural potential of northern Europe.

Ultimately the future for fine wine viticulture does not come down to a decision to stay in Bordeaux or abandon it for The South Downs or the Somme Valley. Moreover, changes in the wine sector will not be mediated by physical changes in the climate alone but changes in consumer preferences (Meztger and Rounsevell 2011). This provides an interesting angle to the study; one of human ecology. If as Galbreath suggests, Bordeaux winemakers employ adaptive actions to climate change such as 'purchasing lands in cooler climates' (Galbreath 2011), then our predictive mapping project may provide some starting point or insight into areas of potential for a brand new viticultural industry. In the long term it could even provide purchasing insights for wine futures markets (Baciocco, Davis, and Jones 2014).

Image.10: Grapes
- credit T.Visscher

6.

Conclusions:

A paradigm shift for wine culture

The topic of climate change seems to be ever more present in the contemporary public consciousness. Whilst the reality of climate change may paint a bleak outlook for the future, our intention is not to be pessimistic. On the contrary, we believe it is more important than ever to look facts in the face and be prepared for enormous challenges and changes in our future environment. Ultimately, humans are nothing if not adaptable and thus this study supports the idea that, whilst Bordeaux wine in the future may be forced to change, new opportunities could emerge which will fill that niche.

Our ultimate aim is to inspire interest in the question of how agriculture and society is to adapt to dramatic climate changes and provide a framework for future research into predicting trends and managing risk. Many academics have suggested that the most crucial resource in today's world is information (Smith 2017). Awareness and preparation is crucial for the future of European agriculture. For Merloni, 'The probability to be negatively affected by the effects of climate change is influenced by structural and technical farm characteristics and by farmer readiness to embrace change' (Merloni et al. 2018). Thanks to the rapid growth of the internet, data, information and ideas are both traded and freely shared across the globe at an astounding rate. We anticipate that for viticulture, the sharing of knowledge will be a key 'mitigative tool' in response to the challenges of climate change (Galbreath 2016). It is also an urgent need as there has thus far been little coordinated action from wine industry regulators to plan ahead (Meztger and Rounsevell 2011).

Whilst much depends on the human ecology aspect, interdisciplinary analyses will also become increasingly important in supporting adaptation decision-making. Although highly context-specific, we use Bordeaux viticulture as a proxy for agriculture as a whole. There is some suggestion that the wine industry might be well poised to adapt if its penchant for, 'idiosyncratic actions' and 'a willingness to innovate around new technologies' continues (Galbreath 2015).

Whilst we raise a glass to the future, we hope that some good can come from looking at this one aspect of the bigger picture, as humanity begins to ask itself what it will prioritise, what can be salvaged, and how life can adapt. I wonder what Columella would have thought.

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Image References

Image.2: Map of Western Europe, showing key wine growing regions, colour grouped by country. – credit T. Visscher

Image.3: Ok losing it's ice. - credit PHOTOGENIC/ALAMY STOCK PHOTO

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Figure References

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Image.11: Looking to the future - credit T. Visscher

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