Highlights

???Grape Quality and its Link to Regional Differences in the Australian Winegrowing Industry

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Abstract

1. Introduction

The Australian wine-growing industry is a rich and diverse landscape that is separated into multiple Geographical Indicator Regions. Each region describing unique reputations, qualities and varietals of wine produced there. While a great deal has been done regarding individual regional properties and traits, there has been little statistical insight into broader regional comparisons; due to a lack of cross-regional and in-depth data sources (**??**). In this study we use Classification Trees to compare regional differences and how these differences relate to sustainable practices.

Through the use of classification trees this study aims to highlight the key differences in sustainable practices at a regional level and how these practices relate to the different grades of grape quality.

2. Methods

2.1. Data

Data used in this analysis were obtained from Sustainable Winegrowing Australia. Australia's national wine industry sustainability program, which aims to facilitate grape-growers and winemakers in demonstrating and improving their sustainability (?). Data recorded by the SWA is entered manually by winegrowers using a web based interface tool. A total of 6091 observations were collected from 2012 to 2022. Each observation contained 23 variables reflecting a vineyards account for the given year (see Table ??).

The data originally contained only two multiclass variables: year and region. Variables that measured the same metric from different sources (such as water collected from rivers versus water from dams) were converted into multiclass variables representing the source. The total amount used from these variables was retained as a separate variable. Occurrences of multiple sources were defined as separate classes. As harvest does not run by calendar year, years are in financial years. Region represents one of the 65 Geographical Indicator Regions (GI Region) used to describe different unique localised traits of vineyards across Australia (???). Each region is explicitly defined under the Wine Australia Corporation Act of 1980 (?). Profit was also used as a binary variable, depicting whether a vineyard was profitable or not.

2.2. XGBoosted Trees

XGBoosted (eXtreme Gradient Boosting) trees were created using the XGBoost library (?) in the Python Programming language (?). They were chosen for this analysis as they provide both a high predictive performance and ability to effectively capture complex relationships. An XGBoosted tree was created for each variable to show how they interacted. Each tree included all but the economic variables (profit and operating cost), which were only included once as predicted variables.

Following Chen and Guestrin (?), XGboosted trees predict a value y_i from

Table 1: Summary of variables used in the analysis. The recorded column indicate values that were either greater than zero or that were not missing.

Variable	**Units**	**Recorded**	**Number of Classes**
Water Used	Mega Litres	5846	
Diesel	Litres	5585	
Biodiesel	Litres	25	
LPG	Litres	958	
Herbicide Spray	Times per year	2026	
Year	Class	6091	10
Disease	Class	6091	2
Region	Class	6091	58
Solar	Kilowatt Hours	622	
Irrigation Type	Class	6091	20
Petrol	Litres	4309	
Slashing	Times per year	2290	
Yield	Tonnes	5935	
Irrigation Energy	Class	6091	16
Area Harvested	Hectares	6091	
Electricity	Kilowatt Hours	1015	
Insecticide Spray	Times per year	1092	
Fertiliser	Kilograms of Nitrogen	795	
Fungicide Spray	Times per year	2260	
Cover Crop	Class	6091	32
Water Type	Class	6091	39
Profit	AUD	853	
Operating Costs	AUD	853	

the input x_i. The method of prediction is achieved through a tree ensemble model, using K additive functions to predict the output.

$$\hat{y}_i = \phi(x_i) = \sum_{k=1}^{K} f_K(x_i), f_K \in \mathcal{F}, \tag{1}$$

where each function f_K is a classification or regression tree, such that all functions are in the set of all decision trees $\mathcal{F}$, defined by $f(x) = \omega_{q(x)}(q : \mathbb{R}^m \rightarrow T, \omega \in \mathbb{R}^T)$. Where, f_K corresponds to an independent tree structure q of ω weights. Each tree has T leaves, which contain a continuous score, represented by ω_i for the i-th leaf. The final prediction is determined by the sum of the score of the corresponding leaves, given by ω. The set of functions used by the tree is determined by minimising the regularised objective function, given by:

$$\mathcal{L}(\phi) = \sum_i l(\hat{y}_i, y_i^{t-1} + f_t(x_i)) + \sum_k \Omega(f_K). \tag{2}$$

The difference between the prediction and actual variable is a convex loss function l. To optimise l, the difference is calculated for the i-th instance at the t-th iteration. The function f_t is selected according to which value minimises (**??**). The model complexity is penalised by the function Ω, this acts to smooth weights in an attempt to prevent over fitting.

As predictions are made using additive tree functions, XGboosted trees can be used for classification and regression. Due to the mixture of continuous, binary and multiclass variables in this analysis, both classification and regression trees were created. The difference between the trees created for this analysis was the objective function used. XGBoosted regression trees were created for continuous variables, using the root-mean-square as the objective function. Binary class variables utilised the logistic loss function as the objective. And, Multiclass variable used the soft max function. All objective functions are defined within the SKlearn library (?), linked via an API to the XGBoost library (?).

Chen and Guestrin (?) further illustrate, using Taylor expansions, that for a fixed structure $q(x)$ the optimal weight ω_j^* for a leaf j can be derived. Furthermore, they show the loss reduction after the split is given by the function:

$$\mathcal{L}_{split} = \frac{1}{2}\left[\frac{(\sum_{i\in I_L} g_i)^2}{\sum_{i\in I_L} h_i + \lambda} + \frac{(\sum_{i\in I_R} g_i)^2}{\sum_{i\in I_R} h_i + \lambda} - \frac{(\sum_{i\in I} g_i)^2}{\sum_{i\in I} h_i + \lambda}\right] - \gamma, \tag{3}$$

with the tree structure defined using left I_L and right I_R instance sets of nodes, with $I = I_L \cup I_R$. Instead of enumerating all possible tree structures, a greedy algorithm iteratively adds branches to the tree minimising $\mathcal{L}_{split}$ in (??). The frequency of a variable's occurrence within a tree is directly attributed to the minimisation of the objective function (or loss) through the minimisation of $\mathcal{L}_{split}$.

The frequency of a variable appearing as a node within the ensemble was used as a measure of importance. This measure was chosen as it connected a variable to the minimisation of its associated objective function, translating the value into a simple count metric. Creating XGBoosted trees for each variable allowed the use of importance to show how strongly variables were associated with each other. The importance of predictor variables to economic variables was illustrated through the use of Sankey diagrams constructed using the Holoviews python library (?). Other variable's interconnectedness was demonstrated through the use of a chord diagram also created using Holoviews.

Each variable utilised 80% of the data to train the XGBoost ensemble, with 20% reserved for testing and validation. Testing was done through the iterative minimisation of the respective objective function for the variables type. For continuous variables 20% was used as testing data, minimising the root-mean-square function. The final model was validated using repeated k-fold cross validation for 10 folds, repeated 10 times. For binary and multiclass variables data was split into 80% training, 10% testing and 10% validation data. Due to class disparity in multiclass variables (most prominently in region) data was stratified into each subset at the same ratio of class occurrence. Validation was summarised through confusion matrices and their associated accuracy

The use of the XGBoost library incorporates regularisation techniques built into the software to mitigate over-fitting and enhance model generalisation. The further use of cross validated grid search functions allowed for the selection of better performing hyperparameters when selecting the final model. The performance measure for model selection was root-mean-square error for continuous variables. The receiver operator characteristic's area under the curve was used for category variables (?). Multiclass variables utilised the one verse one approach to minimise sensitivity to class disparity (??).

2.3. Classification and Regression Trees

Classification and Regression Trees were created for region, year, profit and operating cost. These models describe the partitions that are useful in predicting these variables; giving insight into the trees that make up the ensembles created by XGBoost. These trees were created using the rparts and caret packages (**??**) in the R statistical programming language (**?**).

Classification trees were validated using K-fold cross validation. Each model was validated using 10 folds, utilising a random selection of different samples ten separate times to validate each of the classification trees. A summary confusion matrix was then constructed to show the class bias and overall accuracy of each tree.

3. Results

3.1. Region

Region classification performed at 32.34% (3.67% standard deviation) and 56.82% accuracy (50.58% validation accuracy), for the classification tree and XGBoosted ensemble respectively. The most prominent features used to classify regions with the classification tree was water sources (see Figure **??**). This differed from the variables that illustrated the greatest importance for the XGBoosted ensemble (see Figure (**??**), with predictor variables being highly interrelated in importance. Area, water, fuel and yield were more determining factors when predicting region using XGBoost. Although water and diesel were two of the three most frequently occurring variables in predicting region, they were not as connected to the other predictor variables as Yield and area harvested were.

It is reasonable that regions, being subjected to different rainfalls and temperatures, would require different amounts of water, and would have access to different water sources. The relation of area harvested and fuel (particularly petrol) is prominent with other predictors. Due to the wide variety of uses of petrol and diesel, it is likely that they are representative of other activities within the vineyard, such as pruning and harvesting. With predictors such as yield and area being highly interconnected as they likely operate as proxy variables to other factors, possibly other present variables.

Many of the regions had significantly lower reporting rates, resulting much poorer classification performance. The regions with the most samples performed the best. Notably bordering regions were routinely grouped together and misclassified as the same region. Two areas taht suffered the most from this, specifically with the classification tree were the lime coast (cool coastal areas in South Australia) and the warmer inland regions along the Murray Darling. The classification tree likely had more difficulty discerning vineyards closer to the river using only water sources due to the greater access to river water in these areas.

3.2. Year

0.35196134 0.0628483907157039

The classification tree and XGBoosted ensemble performed similarly for classifying year with 35.20% (6.28% standard deviation) and 51.81% (42.20% validation accuracy) respectively. Electricity and the type of irrigation were highly influential within the classification tree. Similarly, electricity was the most frequently occurring node in the XGBoost ensemble. However, other variables such as slashing passes, and fungicide and herbicide spraying were

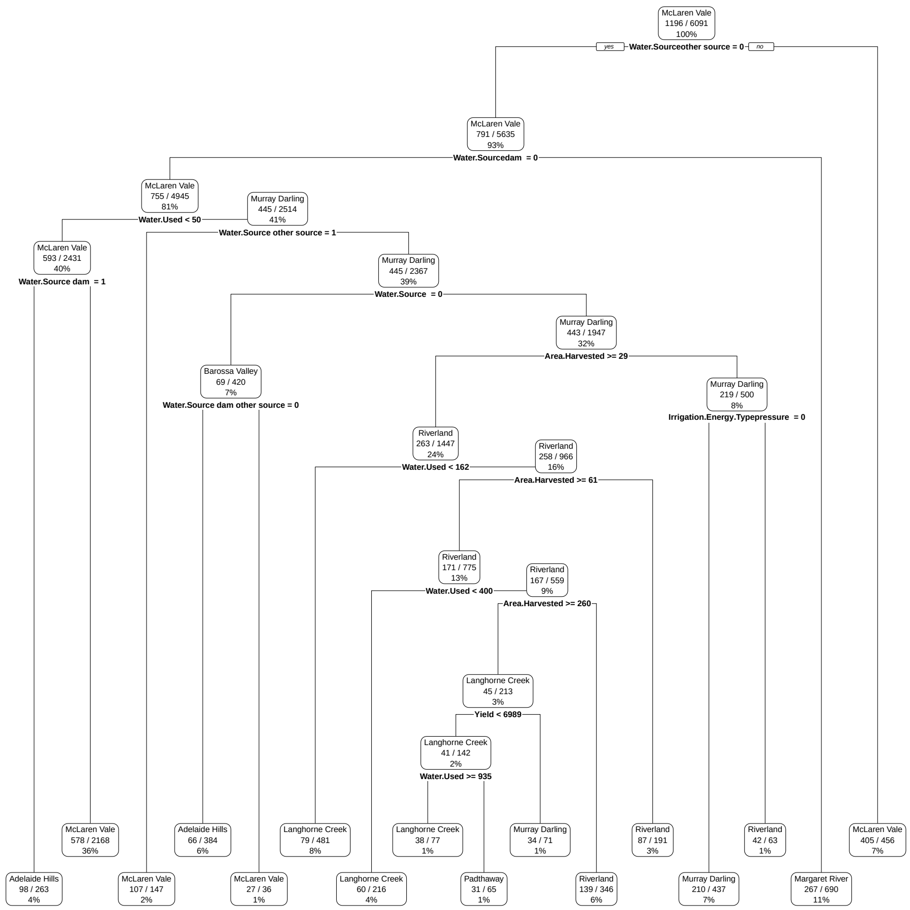

Figure 1: Decision tree predicting Region. Each node indicates the class predicted, and the proportion of elements agreeing with nodes partitioning, with the left direction indicating a yes to the nodes rule.

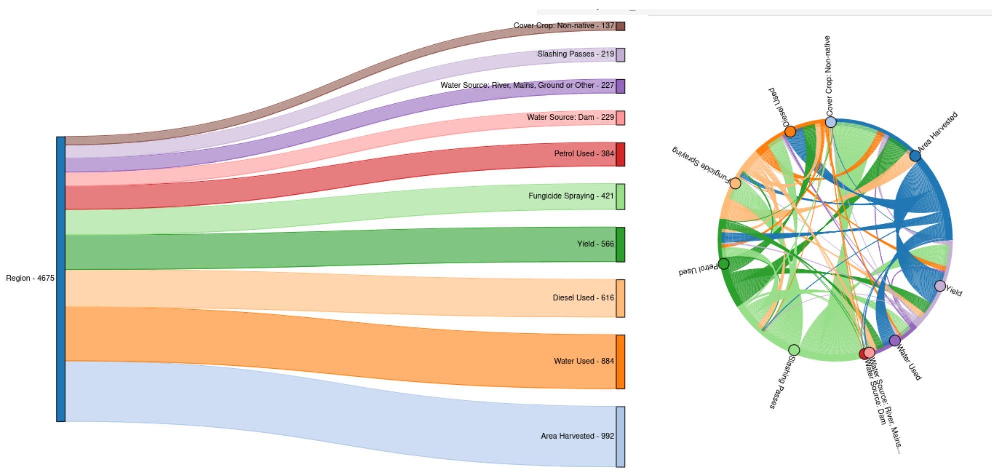

Figure 2: The left-hand side depicts the 10 most important variables in predicting Region using XGBoosted trees as a measure of node occurrence, using a Sankey diagram. The right-hand side depicts the interrelated importance of the ten predictor variables using a chord diagram.

more prevalenct than in the classification tree. Weed and disease outbreaks are likely an influential factor when classifying different years, making the decisions to spray and slash unique factors that differ year to year. Climatic differences between years are likely tied to the influence of yield and water use.

Over half of the interrelated importance of the predictor variables is dominated by area harvested, yield and slashing passes. Although all the predictor variables are highly connected, their relative importance is not as prominent as the three major variables. It is of particular note of the relative importance of slashing to area, fuel and yield; as these are not directly related activities. The connection between slashing and spraying is that those who do a set number of spraying or slashing passes tended to do that many passes for all slashing and spraying activities.

3.3. Operating Costs

There was a pronounced difference in accuracy between the regression tree and the XGBoost model when predicting Operating costs. With the regression tree achieving an R^2 of 0.0931 (with a standard deviation of 0.0197) in its cross validation. The XGBoosted regression ensemble achieved an R^2 of 0.8025 (with a standard deviation of 0.1033).

Within the XGBoost ensemble's nodes for operating costs (see figure **??**) fuel, water, area and yield occurred the most, similarly to region. Both diesel and petrol were of more relative importance (being ranked higher) in operating costs than water was compared with region. It is surprising that electricity, slashing and spraying was not more prominent in operating costs. However, Figure **??** shows that electricity, slashing and spraying are important variables in determining area and yield. Electricity in particular is used predominantly for irrigation and so is related largely to the size of vineyard. However, slashing and spraying are measured in discrete tractor passes and show a surprising connection to the overall size of a vineyard, as they are not scaled to any measure of size. This would mean that, although measured as the same increment, a slashing or spraying pass in a larger vineyard would consume more fuel and wages than in a smaller vineyard.

3.4. Profit

Predictions of profit performed poorly compared to operating costs with the regression tree having an R^2 of 0.1873 (with a standard deviation of

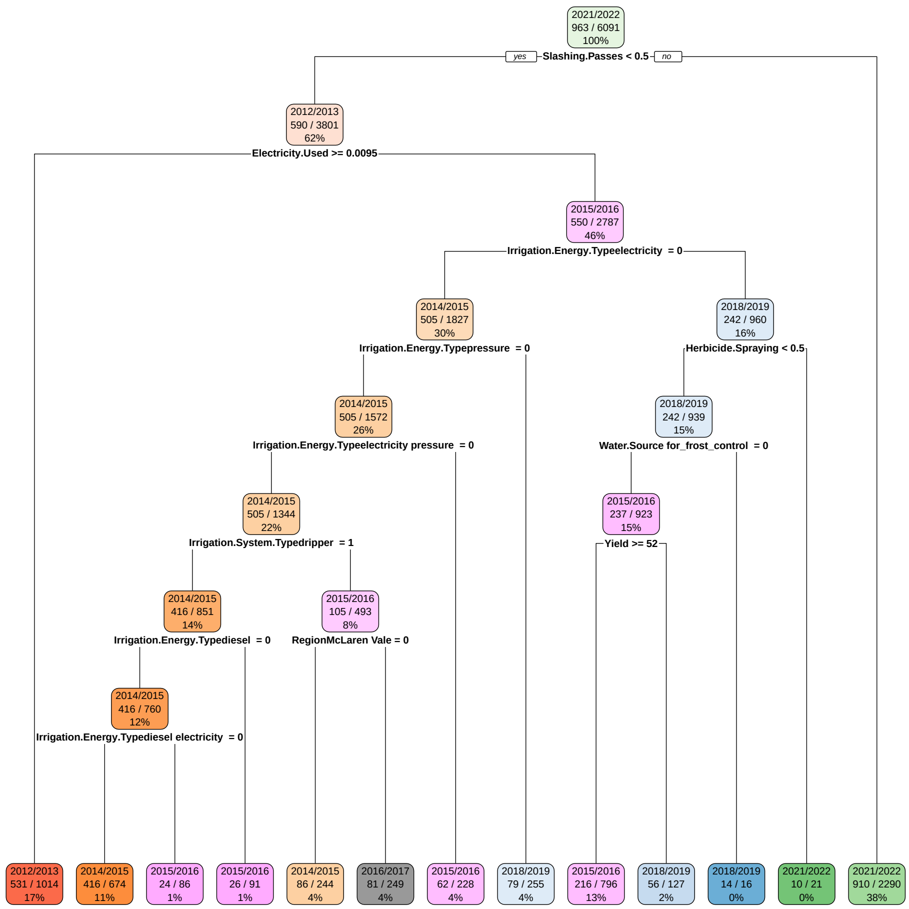

Figure 3: Decision tree predicting Year. Each node indicates the class predicted, and the proportion of elements agreeing with nodes partitioning, with the left direction indicating a yes to the nodes rule.

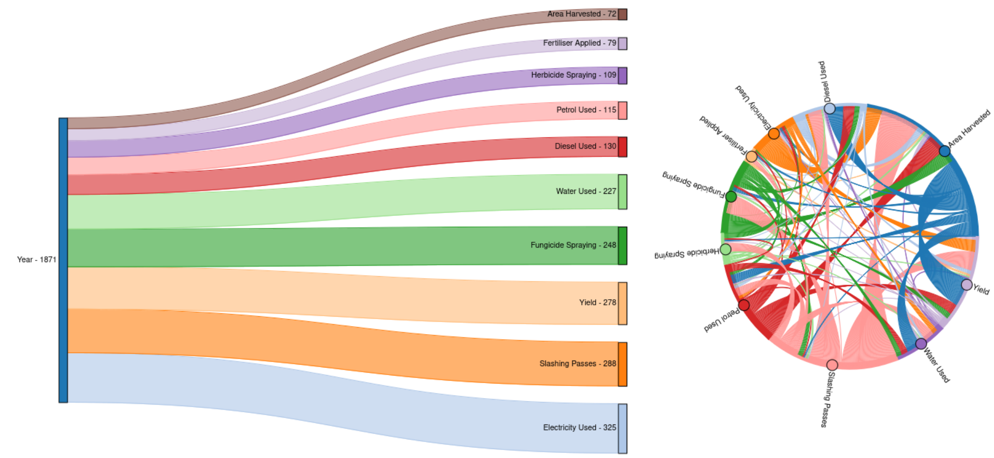

Figure 4: The left-hand side depicts the 10 most important variables in predicting Year using XGBoosted trees as a measure of node occurrence, using a Sankey diagram. The right-hand side depicts the interrelated importance of the ten predictor variables using a chord diagram.

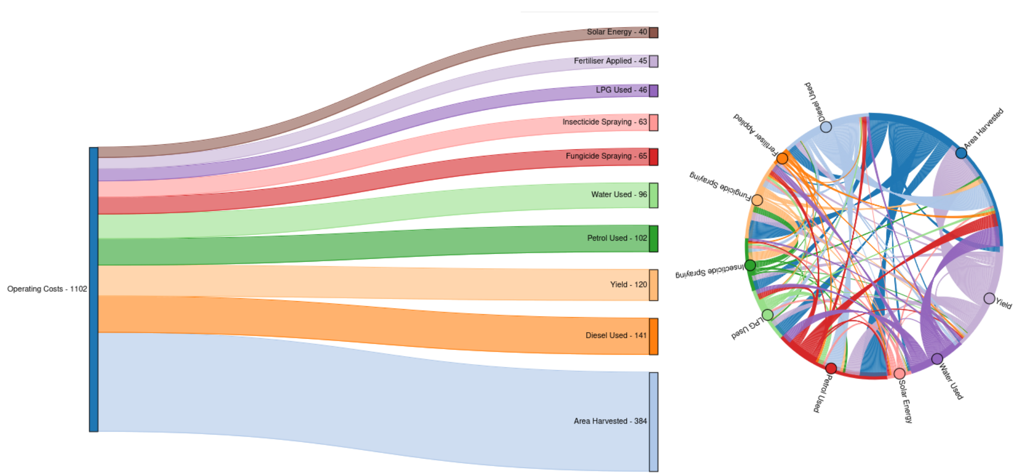

Figure 5: The left-hand side depicts the 10 most important variables in predicting Operating Costs using XGBoosted trees as a measure of node occurrence, using a Sankey diagram. The right-hand side depicts the interrelated importance of the ten predictor variables using a chord diagram.

0.0522) and the XGBoosted ensemble achieving an R^2 of 0.2535 (with a standard deviation of 0.3126). The high standard deviation in the XGBoosted tree was a bias in more accurately predicting vineyards that made profit compared to those that lost money.With much higher R^2 values being achieved in k-folds containing only those that made profits (recording a maximum of 0.7634).

There was a disparity of 66.63% of vineyards recording a profit than those that did not. When predicting if a vineyard would be profitable or not the classification tree and XGBoosted ensemble did not perform considerably differently from this proportion. With the regression tree achieving an accuracy of 68.66% (and a standard deviation of 0.01%) and the XGBoost ensemble achieving 70.59% accuracy (with a validation accuracy of 71.97%).

It was surprising that operating costs performed substantially better in R^2 compared to profit. Interestingly the important variables when attempting to determine profit were similar to those used to classify region (see Figure **??**), with the exception water used. Both the regression tree and the XGBoosted ensemble used region, specifically the Hunter Valley. The regression tree also used Tasmania when determining profit. Both the Hunter valley and Tasmania are known for the production of high quality grapes used in export wines . A major difference between region and profit was the importance given to water use, with water use being a more important variable in predicting region than profit.

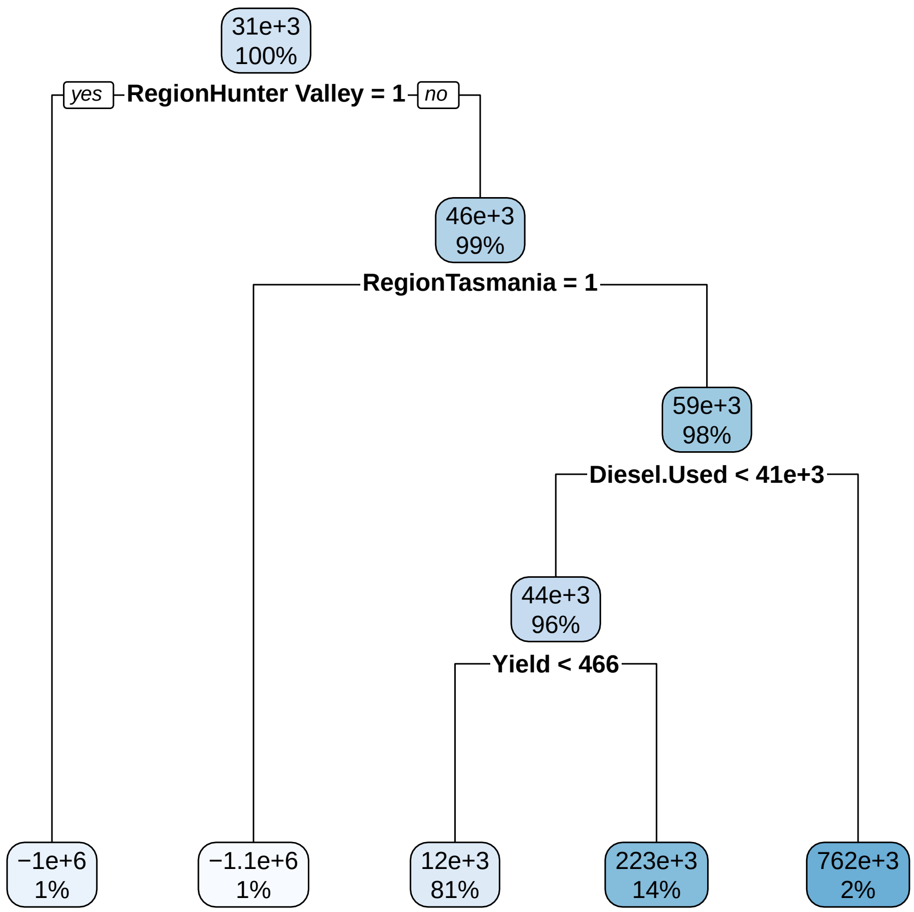

Figure 6: Decision tree predicting Profit. Each node indicates the class predicted, and the proportion of elements agreeing with nodes partitioning, with the left direction indicating a yes to the nodes rule.

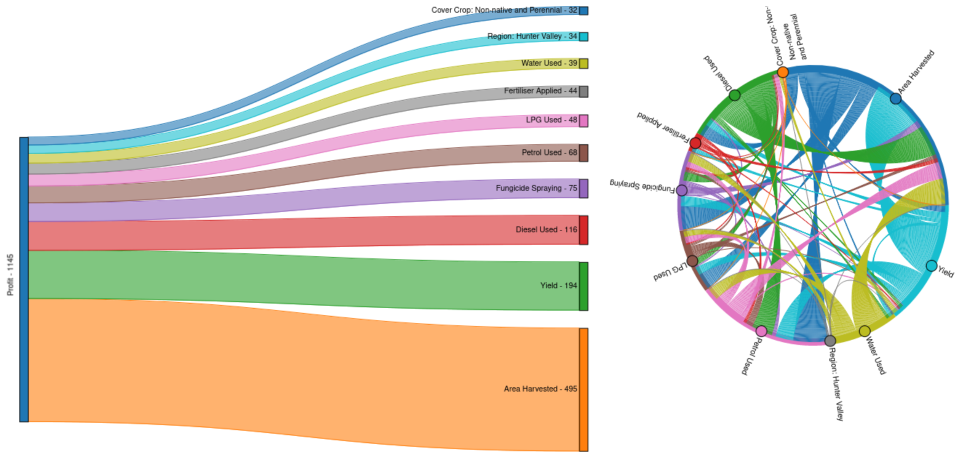

Figure 7: The left-hand side depicts the 10 most important variables in predicting Profit using XGBoosted trees as a measure of node occurrence, using a Sankey diagram. The right-hand side depicts the interrelated importance of the ten predictor variables using a chord diagram.

Table 2: Validation and training accuracies of each multiclass variable.

Variable	Validation	Training
cover crops	0.364086	0.396418
water type	0.742097	0.928905
profitable	0.705882	0.719737
irrigation type	0.841845	0.847554
giregion	0.505824	0.568242
irrigation energy	0.746293	0.836405
data year id	0.422003	0.518059

4. Discussion

4.1. Region

A vineyard's region predetermines several physical parameters, such as: climate, geology and soil; making location a widely considered key determinant of grape yield and quality (???). The association between yield and region is demonstrated by its position as fourth most occurring variable within the nodes of the XGBoosted ensemble which determined region (see Figure ??). The association with area and region is likely a connection to the change in land costs, with inland Australian areas (particularly of lower rainfall) being substantially cheaper to buy than coastal regions, allowing larger areas to be purchased (?).

Regions with lower land costs are also warmer (?), which is known to be beneficial in hastening the ripening process of winegrapes (?). Warmer regions are also associated with lower quality grapes, caused largely due to this hastened ripening (?). In general warmer regions have been associated with lower yields due to their generally lower rainfall, which can be mitigated through applying excess water (?). It is likely that the combination of larger vineyards with higher water use is a determining factor in classifying regions which favour larger production of lower quality grapes; reflected through the variables' importance of water use in the XGBoost ensemble. The practice of utilising larger quantities of water for inland Australian wine crops is partly reflected in the prior use of flood style irrigation to saturate soil (?). This classification can be contrasted with other warmer regions of higher rainfall that use the warmer climate to concentrate their grapes, increasing the flavour profile (and thus quality) (??). This is possibly the connection between the presence of the Hunter Valley within the XGBoost ensemble that determined profit (see Figure ??). With this connection reflecting the restriction of possible strategies employable by winegrowers between different regions.

In part some winegrowing strategies are restricted simply through access to water resources, being reflected through the region classification tree (see Figure ??). Regions are likely to have varying access to different water sources, such as those along the River Murray being able to utilise river water for crops compared with coastal regions. Similarly, the connection between region and fuel is likely an indicator of the level of infrastructure within the region. Where, the need to pressurise irrigation systems from river water or to generate power would require larger amount of diesel and petrol.

Although less important, the variables cover crops, fungicide spraying and slashing are likely linked to broad environmental properties of regions. Rainfall being related to fungal growth and disease, as well as weeds. With cover crops being an effective and sustainable method to alleviate these issues delpuechAdaptingCoverCrop2018. It is difficult to extrapolate findings to these methods and the reason for their use due to the broad and varying definition of the regions. Utilising the Geographical Indicator regions defined by Wine Australia (?) is a limitation, as it is too broad to fully capture a vineyards location and its influence on more granular variables. The reasoning for using approaches such as cover crops can be widely varying.

A cover crop can help to increase soil water retention, reduce erosion, increase biodiversity and reduce weeds (???). However, cover crops can introduce competition with grapevines and may reduce yield depending upon the plants used and the density of the cover crop (**??**). A more granular definition of region may help to better discern the differences in practices, and the reason for employing them.

4.2. Year

This may be particularly important in rainfed areas, like in the study case, due to the lack of irrigation possibilities. The result would be a shortening of the ripening period, with harvest occurring during the period with high temperatures, which could have a negative impact on wine quality (Salazar Parra et al. 2010; Duchne and Schneider 2005; Jones and Davis 2000) and yield (Mira de Ordua 2010; Iglesias et al. 2010). Climate change in the future might move the north and south latitude boundaries of areas suitable for good quality wines (Schultz and Jones 2010), and could even lead to improvements in fruit production and quality in some areas (Olesen and Bindi 2002). However, other areas may be negatively affected by high temperatures and water stress due to a reduction in the amount of water available.

There are several environmental concerns that affect viticulture, including loss of soil quality, lack of rain, hail, disease, fire, and frost; with climate change exacerbating these issues. In 2020, 40,000 tonnes of grapes were lost across 18 different wine regions due to bush fires and smoke taint; the predicted incidence of wildfires is expected to increase (Canadell et al., 2021). In comparison to countrywide pressures such as drought, this damage made up only 3Soil is an important and ongoing consideration for vineyards and interacts with every other practice in various ways at different time scales. For example, cover crops have been shown to be detrimental for soil health in the short term, giving an initial reduction in soil potassium and phosphorus concentrations and no change in nitrogen levels (Gosling and Shepherd, 2005). Conversely, in longer time frames the presence of a cover crop can induce an increase in microorganisms, which can excrete phosphates and potassium, regenerating the soils chemical balance and helping to introduce further organic nitrogen (Coll et al., 2011). The studies that showed this were based in two different countries of similar climate but could have been subject to other underlying conditions not measured. When implementing practices such as cover crops the extent of the practice, the compounding effects and potential alternatives need to also be considered. Alternative options are always available such the use of mulch and wood chips to increase soil health and water retention in place of more involved processes such as crop rotation (Rössert et al., 2022). Crop rotation offers greater benefits than other soil management plans (Brock et al., 2011), however this is often not a viable option for many vineyards although is common practice in some places (Russo et al., 2021). The need to look at the holistic outcomes and interactions of these practices is paramount, however with the existence of many different practices, the outcomes due to interactions are not always known; one such consideration is the use of fungicide and its potential to build up copper, causing a reduction of microorganisms in the soil. Linking copper build up to any particular cause is a difficult endeavour due to the need for multiple reliable soil samples which are equally effected by the same conditions, within soil (Wightwick et al., 2010).

The winegrowing industry holds significant importance for Australia and its economy. There exists many challenges that the industry has to contend against, with disease from sources such as Mildew and Botrytis being a considerable one (Cole, 2010; Magarey et al., 1994). This analysis looks at the prediction of disease in crops across Australia, linking disease pressure and its potential mitigation through the use of sustainable practices. The dataset for this analysis includes multiple vineyard attributes such as water source types, cover crop extents, renewable energy use, and fuel and electricity use. A major consideration within these sustainable practices for this analysis was the use of cover cropping. Cover crops are an example of a sustainable practice in viticulture in which the area between vine rows is seeded with a crop such as grasses or native vegetation. The primary reason for employing cover crops is to increase water retention and reduce the presence of disease and weeds (Delpuech and Metay, 2018). Prior studies have placed an emphasis on optimisations of fungicide sprays through the development of Bayesian models to forecast disease risk (Lu et al., 2020). This analysis investigates at the synergy between spray strategies as a proxy of fuel use to different types of water sources and sustainable strategies with an emphasis on the use of cover crops; allowing for the modelling of interactions between the use of multiple strategies. With the need to balance yield, quality, and combat adversities such as disease; the creation of tools to inform decisions and assist growers with warnings of disease risks is becoming crucial in ensuring sustainable and profitable wine production (Abbal et al., 2016). An interesting observation within the relative importance of variables computed through SHAP values and variable permutation importance, is the similarity between cover crops and the use of contractors to spray herbicide. The presence of a cover crop is known to help in reducing disease and weeds (Capello et al., 2019). Cover crops can further help to increase soil water retention, reducing erosion and water runoff in shallow soils (Capello et al., 2020), which could be the interaction between water and cover crop use in the SHAP variable interactions; where the interaction might be more indicative of how well established a cover crop is, as it would require greater water resources to maintain but potentially offer more protection in return (Capello et al., 2019; Delpuech and Metay, 2018; Gosling and Shepherd, 2005; Monteiro and Lopes, 2007). A further important consideration with this comparison is that diesel vineyard encompasses all vineyard operation aside from irrigation, being a proxy for actions such as weeding and spraying. The disparity between the importance of vineyards being sprayed by owners compared to the use of contractors warrants further investigation; as it would be reasonable to presume similar importance between diesel as a proxy for a vineyard's management of its own disease prevention and the hired preventative strategies of a third party. There is a possibility that the use of contractors may be a vector for disease spread through lax bio-security practices, but would require a rigorous study to inform the matter. There is the potential that the types of herbicides used also have a long term effect on crops, reducing the presence of microorganisms and soil health, making the area more prone to disease in the long run, becoming dependent on these sprays (Coll et al., 2011; Gosling and Shepherd, 2005).

4.3. Operating Costs

The reduction of tillage operations through optimising tractor efficiency is another practice that reduces energy use in vineyards, decreasing running costs, as well as reducing soil compaction (Capello et al., 2019). An increase in soil compaction has been shown to increase water runoff (Capello et al., 2020). Runoff is a significant factor as extreme rain events can cause large scale soil deposition, creating further erosion and removing topsoil. It is important that the interaction of events such as erosion have on other considerations such as soil health.

4.4. Profit

The difference between grape quality is most notable between warm inland regions and coastal regions such as the Riverland and Coonawarra, respectively. Grape quality is only described by a singular variable within this study, however in reality it is driven by market demand and subject to complex forces such as international market pressure, fire, pests and disease (Wine Australia, 2022, 2021, 2020, 2019; Winemakers' Federation of Australia, 2018, 2017, 2016, 2015, 2014, 2013, 2012). The decision trees were able to offer some insights into the factors that influence grape quality and regional contrasts that contribute to different qualities. The most prominent being what readily available resources of each region were, particular the types of water available. Heavy water consumption is often linked to the mass production of grapes, where lower quality grapes are targeted in a quantity over quality strategy. These types of business decisions are unfortunately obfuscated by lack of in-depth data regarding vineyard business plans. Notably the literature shows that there are many complex decisions to be made on the ground depending on many compounding factors that influence both quality and yield ((Abad et al., 2021; Cortez et al., 2009; Hall et al., 2011; I. Goodwin, et al., 2009; Kasimati et al., 2022; Oliver et al., 2013; Srivastava and Sadistap, 2018)). There are also further differences when comparing winegrowers to other agricultural industries as they are vertically integrated within the wine industry, tying them to secondary and tertiary industries, such as wine production, packaging, transport and sales. This results in unique issues, where on-the-ground choices are influenced by other wine industry's decisions, such as the use of sustainable practices in vineyards to sell in overseas markets; notably these interactions are further complicated by some winegrowers being totally integrated into wine companies, while others are not (Knight et al., 2019). It is incredibly difficult to attribute external business decisions to produced grape quality but it is important to acknowledge that some growers are contracted to produce grapes of a particular grade; it is difficult to know whether another consumer may have graded the grape quality differently paying more or less for the same grapes given the opportunity to purchase them. It is difficult to untangle the contributing factors to the success of winegrowers and the quality of grapes produced without further specifics of choices made through out a season (Leilei He et al., 2022).

Historically strong demands for Australian wine have helped to create a thriving industry, however recently sharp reductions in exports to mainland China due to significant deposit tariffs have caused a decline of 19Figure 1: The exports of Australian wine over time in Australian Dollars Free On Board, comparing exports between China and the rest of the world. This graphic is taken from the Wine Australia Annual Report of 2020-21(Wine Australia, 2022).

These regions differ greatly in practice and geophysical properties, with the Riverland being a dry warm inland region and Coonawarra being a cooler, wet coastal region. However, they are both similar in operational scales, with vineyards being relatively large compared with other regions. The differences in resources and practices between these regions are also significant, such as the Riverland utilising the river Murray as a water source.

The difference between grape quality is most notable between warm inland regions and coastal regions such as the Riverland and Coonawarra, respectively. Grape quality is only described by a singular variable within this study, however in reality it is driven by market demand and subject to complex forces such as international market pressure, fire, pests and disease (**????????**) The decision trees were able to offer some insights into the factors that influence grape quality and regional contrasts that contribute to different qualities. The most prominent being what readily available resources of each region were, particular the types of water available. Heavy water consumption is often linked to the mass production of grapes, where lower quality grapes are targeted in a quantity over quality strategy. These types of business decisions are unfortunately obfuscated by lack of in-depth data regarding vineyard business plans. Notably the literature shows that there are many complex decisions to be made on the ground depending on many compounding factors that influence both quality and yield (**???????**)

. There are also further differences when comparing winegrowers to other agricultural industries as they are vertically integrated within the wine industry, tying them to secondary and tertiary industries, such as wine production, packaging, transport and sales. This results in unique issues, where on-the-ground choices are influenced by other wine industry's decisions, such as the use of sustainable practices in vineyards to sell in overseas markets; notably these interactions are further complicated by some winegrowers being totally integrated into wine companies, while others are not (Knight et al., 2019). It is incredibly difficult to attribute external business decisions to produced grape quality but it is important to acknowledge that some growers are contracted to produce grapes of a particular grade; it is difficult to know whether another consumer may have graded the grape quality differently paying more or less for the same grapes given the opportunity to purchase them. It is difficult to untangle the contributing factors to the success of winegrowers and the quality of grapes produced without further specifics of choices made through out a season (**?**).

4.5. Model 1 GI Regions

The first Model was used to classify GI regions and resulted in an accuracy of 36.48% across 52 classes. The most prominent features used to classify regions were the types of water resources available (see Figure 1). Two regions, the Riverland and Coonawarra, were the most accurate classes being 92.74% and 96.97% respectively. These regions differ greatly in practice and geophysical properties, with the Riverland being a dry warm inland region and Coonawarra being a cooler, wet coastal region. However, they are both similar in operational scales, with vineyards being relatively large compared with other regions. The differences in resources and practices between these regions are also significant, such as the Riverland utilising the river Murray as a water source. Many of the regions had significantly lower reporting rates, resulting much poorer classification performance. The regions with the most samples performed the best (see Table 1). Notably bordering regions were routinely grouped together and misclassified as the same region, for example the two closest regions to Coonawarra, Padthaway and Wrattonbulley, were misclassified as Coonawarra even though they had 147 and 137 samples respectively. The same case was found for the Murray Darling, with 143 samples, it was misclassified as the Riverland. These misclassifications are likely due to the incredibly similar regional properties and close proximity these regions have with one another. Other misclassifications were most likely due to lower reporting rates with many regions being under represented.

4.6. Climate

Classifying the SWA climatic categorisation of the given regions had better performance than the GI Regions, with 41.66% being classified correctly. These categories were divided into 12 climatic classifications with 3 and 4 separate subsets for rainfall and temperature respectively. The decision tree behaved similarly and over classified climates with higher response rates. The results posed an interesting similarity with grape quality classifier, being influenced predominantly by water and area. The use of fungicide to separate regions that were 'Very dry' and 'Damp' can be considered as indicative of the different practices required due to climatic pressure; fungicides being more prominent in cooler regions with greater rainfall due to the higher risk of disease pressure (**?**). This could also potentially explain the use of contractor tractor use to discern differences in grape quality, where the lack of contractor use to prevent disease could have led to lowered quality of grapes.

4.6.1. Rainfall

The rainfall decision tree showed a greater use of fungicides sprays to discern between damp and very Dry as shown in Figure 4; with the accuracy improving to 62% but was unable to effectively discern between dry and very dry regions (see Table 3).

was again used to differentiate between warm and cool regions, likely being due to disease pressure. The temperature classification tree

4.7. Model 3 Grape Quality

The classification of grape quality through its grade had an accuracy of 55.72% across 5 separate grades. There was a notable issue with the classification of B grade grapes when compared to A and C (see Table 2). The classification tree itself shows similarities to that of classifying regions in Model 1, with the type of water resource used being a prominent determiner. Although not surprising the number of contractor tractor passes is new deciding factor due disease and pests reducing the potential quality of a crop. The prevalence of contractor use is greater in regions such as the Barossa Valley and the McLaren Vale, this could be due to the difference in operational scales, with larger sites being more likely to have ownership of their own equipment for weeding and spraying due to the cost benefit.

5. Conclusion

The type and availability of water resources were a major contributing factor when classifying grape quality and region. This was seen in the two most accurately classified regions, Coonawarra and the Riverland, with the Riverland predominantly utilising river water. Furthermore, the study highlighted the influence of water use, fungicide application, and contractor use in differentiating grape quality, climate and region respectively. These models provide insight into the complex dynamics between regional characteristics, sustainable practices, and grape quality in the Australian winegrowing industry. It is important to acknowledge that grape quality is subject to external influences such as market demands and prior established business arrangements. Further in-depth data and understanding are necessary to fully grasp the nuances of decision-making and the interplay of factors impacting grape quality.

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