Is Climate Change Transforming the UK into a Thriving Wine Producer?

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1 Abstract

This report attempts to predict future grape yields in the UK using quantitative models that utilise the different measured climate variables experienced by grapevines during their growth cycle. Different machine learning (ML) methods were explored to fit climate variables to UK grapevine yields. Linear regression was used as a robust baseline model, gradient-boosted trees (XGBoost) were used as a non-linear ML model, and symbolic regression (PySR) was used as an attempt at obtaining an interpretable equation. Whilst it is found that climate change is likely to have a positive impact on grape yields, numerical estimates for growth depend heavily on the type of model used for predictions. One of the main challenges faced in model training was the lack of data available for validation of the model architecture. This is reflected in the fact that predictions vary greatly between models. We also identify several areas for improvement in future research. These include different ways to expand the limited grape yield dataset and the application of more detailed climate predictions.

2 Introduction

Although the United Kingdom's cool and damp climate has limited its suitability for large-scale viticulture, domestic wine production dates back to the Roman period[1]. Climate change, however, is altering agricultural systems worldwide, and UK wine production has emerged as one of the most notable beneficiaries[2]. These changes coincide with a rapid expansion of the local industry. Vineyard area, the number of wineries, and global recognition have all increased, with particular attention focusing on sparkling wine produced using traditional Champagne grapes and methods. Wine production in the UK has surged in recent years, and the industry has seen significant investment, including from the renowned French Champagne house Taittinger[3].

However, despite comments that the UK is becoming an important wine-producing region due to climate change, there has been little quantitative research to examine this relationship. The motivation for this report was to address this unexplored area. Understanding the change to the UK's wine industry is important for several reasons. Viticulture is among the most climate-sensitive agricultural systems and is indicative of broader change. There are direct economic implications for the UK's agricultural output, with policy decisions, including land-use planning, likely to be affected.

There are several quantitative reports [4, 5, 6] that investigate the relationship between climate and viticulture. The most notable is by Ashenfelter, Ashmore, and Lalonde[7], which looks at the relationship between the price of different vintages of Bordeaux wines and weather variables using linear regression. However, there are no reports specific to the UK, nor that attempt to utilise more advanced modelling techniques.

This report aims to analyse how climate affects annual grape yields and, from this, develop models that assess whether climate change may be contributing to the UK's emergence as a more prominent wine-producing region. The modelling techniques used are linear, gradient-boosted tree (XGBoost), and symbolic regression (PySR) architectures. These will be examined in more depth later. Datasets are utilised from satellite observations and industry surveys to examine how climate variables at different times of the year, such as temperature, precipitation, and sunshine, impact grape yields. By forecasting how these variables will change, future grape yields for the UK can be predicted. The report shows that whilst there is likely to be a relationship between climate and grape yield, modelling this is difficult due to limited data and the many additional variables, such as changes in grape variety, for which data was insufficient to model. Despite this, the results indicate that a positive effect of climate change on grape yields in the UK is plausible. The report also highlights areas where further research could focus.

3 Background

The growth of grapevines is inherently a biological process, and to fully understand the relationship between production and climate in the UK and the model parameters and outputs, we must relate them to these processes. It is also important to consider impactful non-climate factors that are not included in the models due to the lack of numerical data, as this provides further context.

UK wine production has surged in recent years, with the number of wineries and grape production areas all increasing (see Appendix A.1 for numerical data on these changes). Further, wine consumption per person in the UK is increasing despite a general reduction in alcohol consumption, further reinforcing the commercial case for continued growth of the sector. The majority of UK wine is consumed locally; however, exports have been increasing and comprised 9% in 2024 (compared with 4% in 2021)[8], with Norway, Japan and the USA as the top importers.

There has also been a notable change in the variety of grapes grown, with Pinot noir, Chardonnay, Bacchus, and Meunier comprising the vast majority of production, compared to the cooler weather German varieties that dominated in the late 1980's. This shift has given rise to the premium 'English sparkling wine', produced with the same varieties and methods (and even grown on similar chalk soil) as Champagne from France. At higher prices, these wines aim to compete directly with Champagne and provide producers with a commercially viable product despite lower yields.

3.1 Viticulture Background

To better inform our interpretation of the climate variables used, it is important to understand the grapevine's growth cycle. Months in which the stages occur are given for the northern hemisphere in Fig. 1; however, there is significant variation depending on the local climate. We summarise the key growth cycle properties in the following, and further detail can be found in Ref. [9].

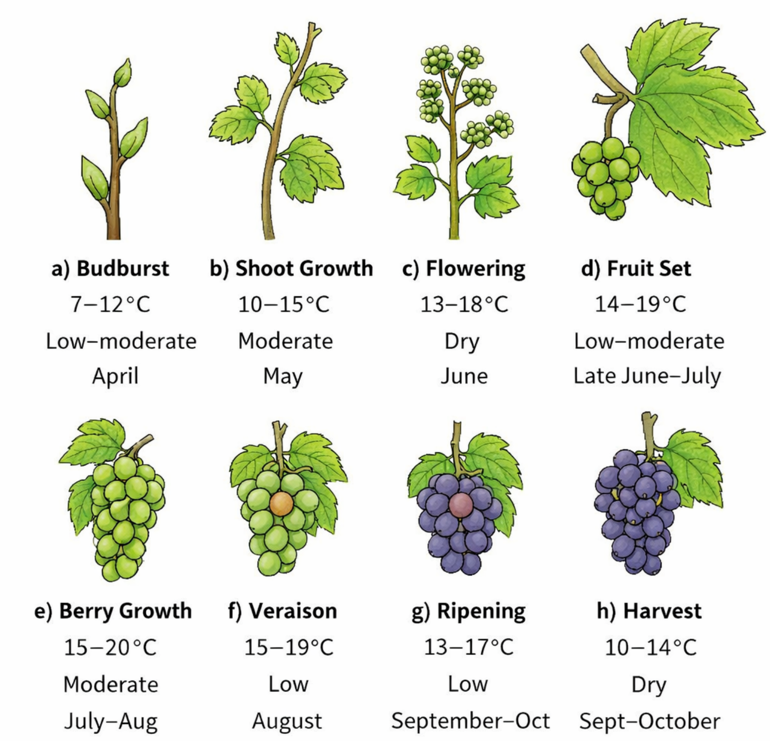

Figure 1: Stages of the annual grapevine growth cycle with optimum temperature, precipitation and months of occurrence

Dormancy occurs during the winter months of December to March, and no growth occurs during this time.

The yearly growth cycle starts with bud break in March-April. As the soil warms, osmotic forces push water through the vines and cause the buds to swell. Each bud contains three small shoots from the previous summer. Using carbohydrate stores, the shoots sprout leaves, beginning the process of photosynthesis and accelerating growth. In warmer climates, early-budding varieties can be at risk of premature bud break, leaving shoots vulnerable to frost if temperatures drop.

Approximately 40-80 days after bud break, flowering begins. Average daily temperatures between 15 and 20°C are required. Small flower clusters initially appear and grow in size. Once individual flowers are observable, pollination takes place.

Fruit set immediately follows flowering, and is when the fertilised flower begins to develop the seed and grape berry. This stage is important for determining yield. Low humidity, high temperatures, and water stress can reduce the proportion of fertilised flowers, with unfertilised flowers eventually falling off the vine.

The ripening process begins with Veraison, when the berries grow in size, gain sugar, lose acidity, and take on colour in the skin depending on the variety. Simultaneously, the vine cane ripens, and energy is diverted into carbohydrate reserves for the following growth cycle.

The time of harvest can vary due to the subjective nature of ripeness, the threat of adverse weather conditions, and vine diseases; the winemaker must assess these factors to determine the optimum time to harvest. After harvest, the vines continue to photosynthesise and build carbohydrate reserves. Once this is completed, the chlorophyll in the leaves starts to break down, changing the colour to yellow, and eventually falling.

The next period of dormancy begins, and the cycle repeats in the following year.

3.2 UK Climate Background

Over the past several decades, the UK has experienced significant changes in climate, particularly in variables that are important for agriculture and viticulture. Mean growing season temperatures have increased significantly (Fig. 2), with the strongest warming in the south and south-east of the UK. Temperature extremes have also changed, with a reduction in spring frost days (good for the early stages of vine growth) and an increase in hot summer days (good for ripening).

Precipitation patterns have changed less uniformly. Whilst total precipitation during the growing season shows no uniform national trend, there is increased variability with a greater number of intense rainfall events in several wine-growing regions. This will require more nuanced changes in vineyard management to combat shifts in soil moisture patterns and increased disease pressure.

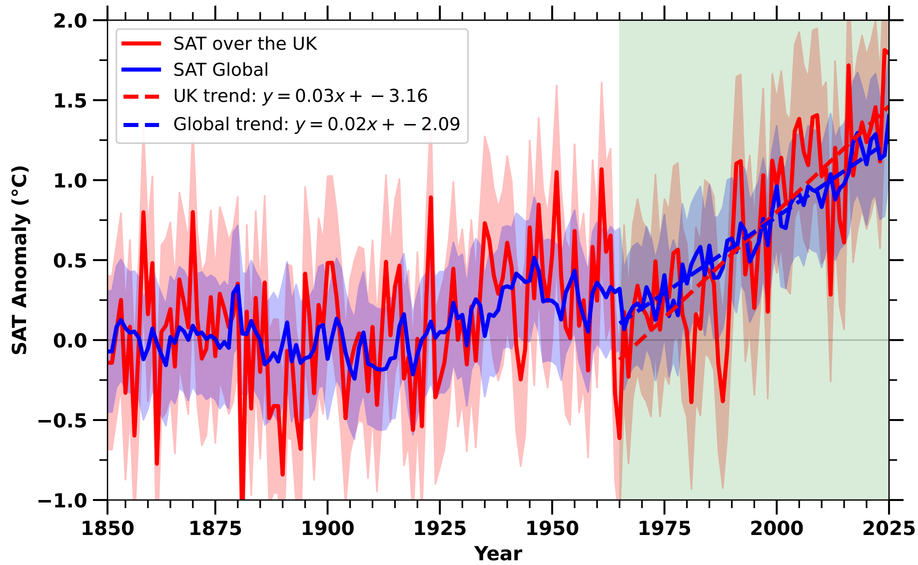

Figure 2: UK Surface Air Temperature (SAT) Anomaly
(Difference between observed temperature and long-term average, showing the change to climate in the UK)

4 Methods

4.1 Model Suitability

The target variable for the models to predict is grape yield in hectolitres per hectare (hl/ha). Reporting grape yields has been compulsory for producers since 1989, and so we have a good source of production figures provided by the Wine Standards branch of the Food Standards Agency, both through Wine GB[8] and Stephen Skelton MW[10]. Detailed UK historic climate data is available from the Centre for Environmental Data Analysis[11]. This discretises the climate within the UK into grid cells, with the output data for a grid cell being the spatial average of the climate within. Monthly average data is available for 10 climate variables at various grid resolutions and is normalised before processing to facilitate comparison of variable importance later. The 25 km grid size data was used due to its comparable size to the wine-growing regions where production data is available. The Sussex cell is highlighted in blue in Fig. 3 because of its prominence as a wine-producing region of the UK and its location in the centre of the main grape production area in the south-east of the UK. Definitions of the climate variables are provided in Appendix A.2.

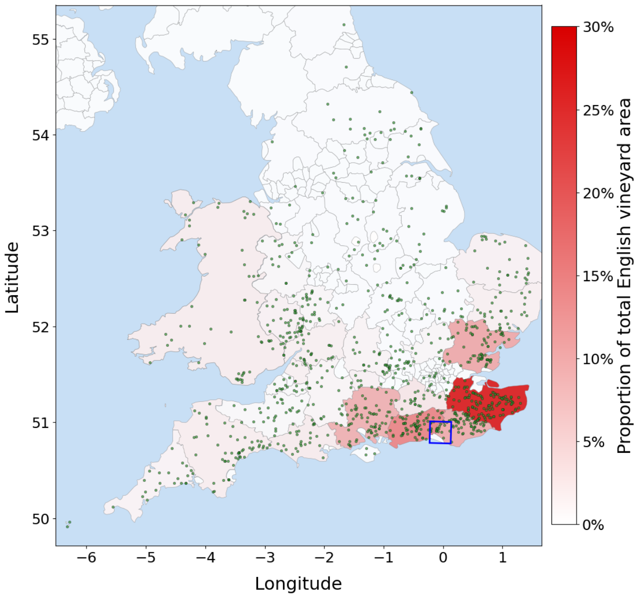

Figure 3: Vineyard locations in the UK with proportion of total UK vineyard area in each county. The Sussex grid cell is highlighted in blue, vineyards locations are shown as green dots.

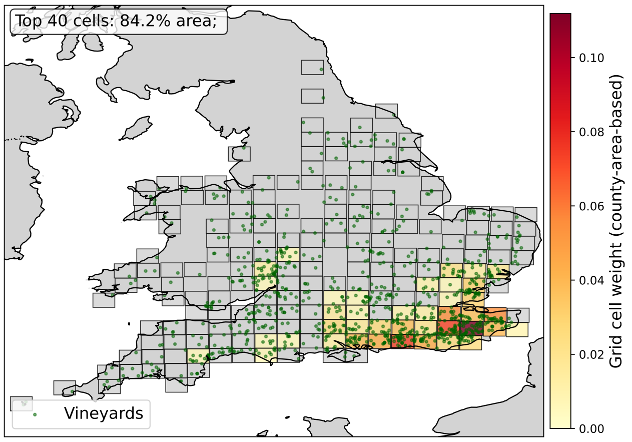

Figure 4: Vineyard distribution and contributing climate grid cells for the weighted average climate data. Vineyards locations are shown as green dots.

This report attempts to predict future grape yields in the UK using quantitative models and examines different methods to best achieve this, given the small dataset (only 35 data points).

4.2 Weighted Average Climate Data

Because the average grape yield for the UK is calculated for the UK as a whole rather than just the Sussex grid cell, using a weighted average of climate data across vineyards would be more appropriate for fitting a model to the yield data. To achieve this, data on the proportion of vineyard area for each county is used along with location data for all the vineyards in the UK. Using this, the number of vineyards in each county is calculated, and the average area of each vineyard across counties is therefore calculated. The climate data used has a 25×25km grid size, and so by looking at the different vineyards in each grid square, the proportion of vineyard area for that grid cell is calculated with respect to the total UK vineyard area. From this, a weighted average of the UK's climate variables was produced. The top 40 cells were used to avoid the impact of low-contribution cells, which could be located in counties where the individual proportion of vineyards was not explicitly reported. The reader is referred to Fig. 4 for an illustration of this.

The model was first run on climate data from the Sussex grid cell, and then it was run on the weighted average of the grid cell data. The main variation in the performance of the linear model depended on the number of features in the final model test/train dataset split, and the results were not significantly different between the sets of climate data. This is likely due to the similar climate in the main producing region of the south-east.

4.3 Feature Selection and relation to growth cycle of the grapevine

The climate dataset contains 10 climate variables over 12 months of the year; therefore, there are 120 input features for our model. This is far too many to fit 35 target variable points, as we are not able to obtain a unique set of parameters for the model. Therefore, a feature selection process is required to ensure that the input features for our model have both high correlation with yield and low cross-correlation. This removes redundancies in the free parameters that prevent a unique fitting for the model and increases the interpretability of the parameter weights. To start, the Pearson correlation coefficient between the individual variables and yield is examined. Given that the grape harvest concludes by October, a 'growing year' is defined as starting in November and concluding in October.

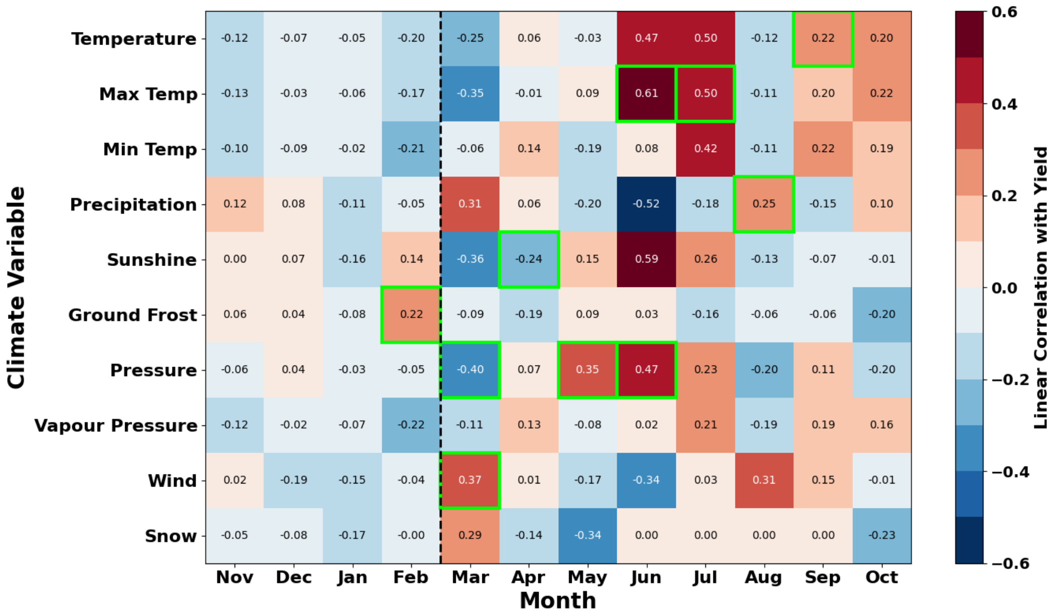

Figure 5: **Correlation between grape yield and climate variables.**

The top 30 variables by correlation coefficient are taken and and the cross-correlation is calculated between variable pairs. Removing one variable from a pair with cross-correlation > 0.4 results in a final list of 10 variables, which are highlighted in green in Fig. 5 (the retained variable from the pair has the higher correlation with yield). By looking at the growth cycle of the grapevine, we can relate the selected climate features to yield.

It is seen that colder temperatures in February, and low pressure and high wind in March, have a positive correlation with yield. This could be linked to the growth cycle by ensuring that bud break does not occur too early in the year through lower temperatures and reduced sunlight, and reduces the risk of cold shocks for fragile buds later on. High wind could help growth through increased transpiration, or could be correlated with adverse conditions, slowing bud break.

In May, June, and July, a positive correlation is seen between pressure and maximum average daily temperature with yield. High pressures generally lead to lower rainfall and higher sunlight, which are advantageous for ripening.

In the UK, recent harvests have taken place in August and September, so the climate after this point in the year cannot affect the yield. Therefore, correlations with variables that occur after this point in the year are only indicative of the general climate of a high-yielding year.

4.4 Model Selection

The data is fitted to three different models: a least-squares linear booster, XGBoost, and PySR symbolic regression.

XGBoost (Extreme Gradient Boosting) [12] is a gradient-boosted tree library. It starts with an initial tree and subsequently adds new trees that predict the residuals of the previous models. It is particularly effective in predicting tabular time series data and is well-suited to the non-linear physical reality of viticulture, as it can model threshold effects (e.g. heat stress) and interaction effects (e.g. rain $\times$ temperature). It is also able to fit a much smaller dataset than a neural network and has built-in regularisation options to reduce over-fitting.

PySR (Python Symbolic Regression Toolkit)[13] provides interpretable equations through a multi-population evolutionary search within a defined space. Allowed operators, equation complexity, and a loss function are defined before the search begins, and multiple different equations of varying complexity and fit are output. This can capture non-linear features depending on the allowed operators, though not to the same extent as XGBoost. This model was an attempt to extract terms that may be physically interpretable.

4.5 Climate Predictions

The models map the current climate to the current grape yield for each year. Therefore, to make predictions of future grape yield, we need predictions of the climate for those years. Due to the lack of availability of detailed climate predictions for all climate variables, linear or modal predictions of average climate are extrapolated from prior data, with errors in the gradients used to form bounds, and the more extreme gradient is used as the 'High' climate scenario. 'Snow' is removed as a climate variable for the model, as there is no clear trend over time for the months with a higher correlation with yield, and so accurate predictions cannot be made. The linear correlations of the different climate variables with time are very low and do not capture the relationship between the variables (e.g. high-pressure weather is normally sunny due to cloud formation being affected). Aside from the low accuracy of these predictions, the lack of interrelation may cause problems, particularly for the XGBoost model, as a yearly average of each of the climate variables may not be conditions we would actually expect to be realised. This is important, as bad conditions early in the year may significantly reduce the yield for that year, even if later conditions are favourable. The training data does not cover this, and so the yield future forecast outputs are unreliable.

4.6 Feature Engineering

By manually constructing expressions using them, climate variables can be used to produce new features that may capture more complex relationships with target yields, thus improving the model. The PySR regression produces an interpretable equation from which individual expressions can be taken as features. Due to the small dataset and lack of variety in the variables used by the PySR expression (1), there is a high risk of over-fitting. Hence, only existing features are used to maintain reliability in the model, with a penalty of a reduced R^2 in fitting to the training and test datasets.

5 Results and Analysis

5.1 Linear Model

The linear model was used as a robust model for a baseline to compare to other models. Results for the model are displayed in Figs. 6 and 7. As can be seen, whilst the performance in fitting is reasonable, the model fails to fully capture peaks and deep troughs in yield. 'Year' was inserted as a variable in the model to see if there is an increase in yield over time that cannot be explained solely by climate. This could be due to changes in the planted grape varieties, grapevine spacing, cropping practices (when unripe berries are trimmed to ensure full ripening and concentration of flavour in the remaining fruit), or practices related to crop protection in extreme weather. Other factors include changing vine age and spacing, and expansion into better sites. Interestingly, the feature importance for the variable 'Year' is very low, indicating that these factors may not cause the expected changes to yield.

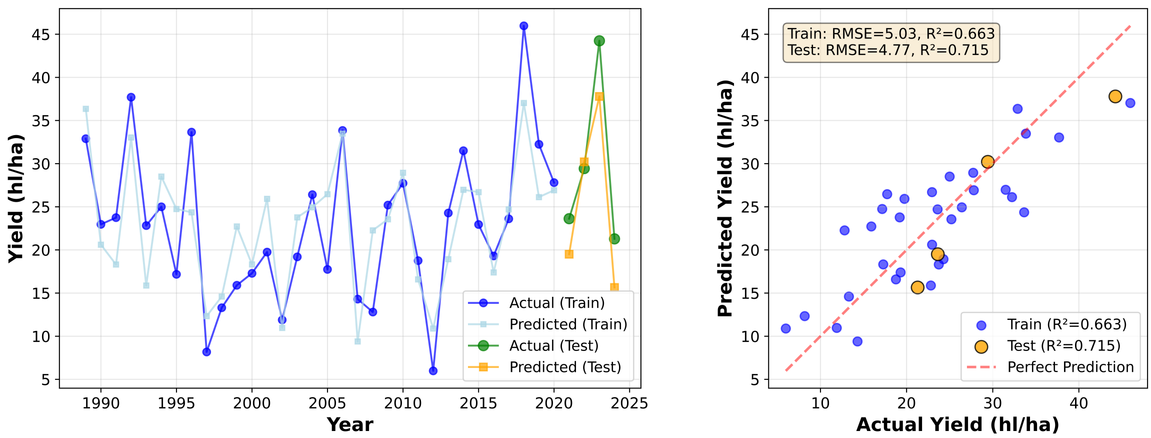

Figure 6: Linear Regressor: Predicted vs Actual Yield

Looking at Fig. 6, R^2 values of 0.66 and 0.72 for the linear model fit to the training and test datasets, respectively, are seen. This demonstrates that the raw climate variables used can produce predictions for yield that outperform simply predicting the mean and that the linear model remains robust over recent years.

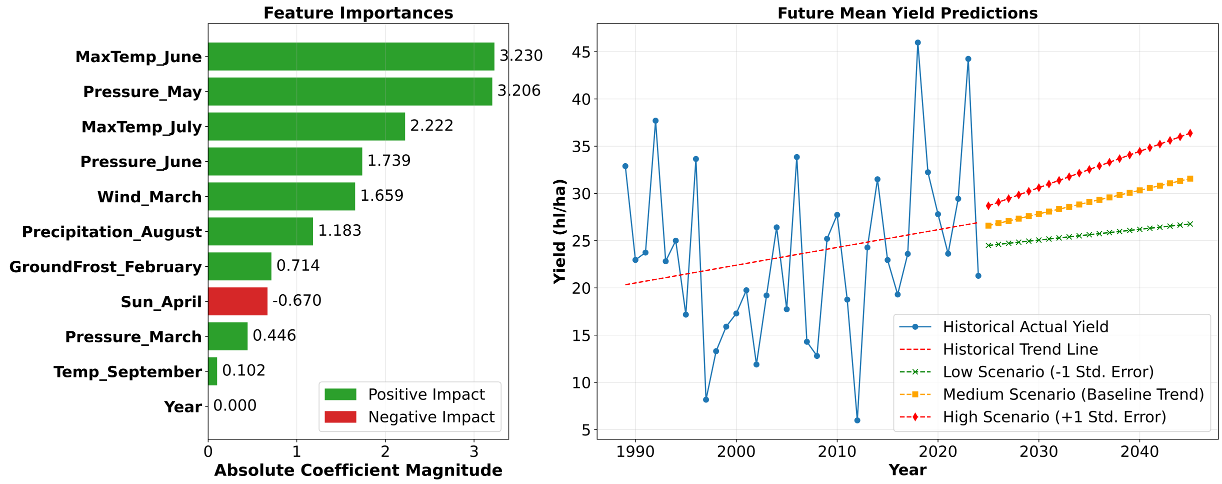

Figure 7: Linear Model Weights and Future Predictions

Fig. 7, shows that the most important climate features in the model occur during the ripening process rather than at earlier stages (e.g. fruit set). Steps can be taken to protect vines at these key stages, such as the use of heaters or blowers to prevent the accumulation of cold air between vines; however, it is more difficult to intervene at later stages to ensure full ripening occurs during poor weather conditions.

The report concludes that despite under-fitting more extreme scenarios, the linear model is a good model to use for predicting grape yields in the UK, due to its interpretability and ability to be trained on a limited dataset, even if the small test set of 4 points makes it difficult to draw more complex conclusions. Using this model, we see a continued linear increase in mean yield, indicating the positive effects of climate change on UK wine production.

5.2 XGBoost Model

The XGBoost model was attempted as an improvement to the linear model by capturing non-linear dependencies on features, and for its good functioning with time-series problems. Following on from the results in the previous section where it was determined that the variable 'Year' had low feature importance, the XGBoost model was trained without 'Year' as a variable.

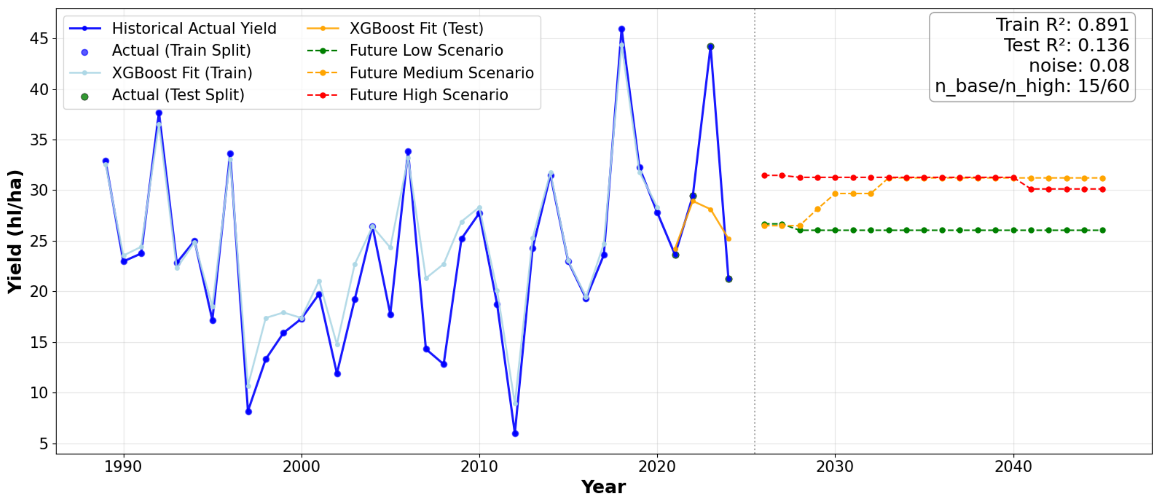

Figure 8: Example XGBoost model with training data and future yield prediction.

Various techniques were applied to reduce over-fitting, such as both L1 and L2 regularisation (adding a penalty term to the cost function of the optimisation) and reduced tree depth. However, the constraints of the small dataset meant that to achieve reasonable performance of the XGBoost model on the test set, there had to be heavy over-fitting of the training data. To reduce this, the training data variables were augmented through repetition with the addition of Gaussian noise. This reduced the fitting to specific data points. Additional replications were performed for the less frequent high-yielding years to further aid the fit.

Despite this, over-fitting was still a consistent issue, with any reasonable performance on the test data showing an overly high fit to the training data. Furthermore, future predictions seem to predict similar values to specific years in the historical yields rather than providing a smooth prediction.

The XGBoost model was trained on the augmented historical climate data whilst climate predictions used a linear model to predict future climate variables. These climate variable predictions were performed in the same way as for the linear yield model for comparability. However, this prediction method takes the climate variable predictions outside of the range of values seen in the model training. This means that when the XGBoost model makes predictions on years with the climate predictions, it struggles to infer. Ideally, the training would be performed on a dataset with a greater range of climate variables to eliminate this issue and provide better future yield predictions.

Fig. 8 shows example outputs of a fit using the XGBoost model, with noise of variance 0.08 added to the training data to reduce over-fitting. n_{base}/n_{high} denotes the number of additional copies with added variance of the training data made for normal and high-yielding years. We see a high Train R^2 and a very low Test R^2 due to high-yielding years being ignored by the model.

5.3 PySR Model

The PySR model fit was an attempt at obtaining an interpretable model where physical meaning can be extracted from the terms that appear. The PySR output, is displayed in equation (1). All climate variables are normalised values for the climate between 1989 and 2024. It can be seen that good weather conditions, such as maximum temperature and high pressure (which lead to clear skies), during the months of ripening have an exponential link and constitute the majority of the change in yield.

$$\begin{aligned}\text{Yield} = {} & \text{Pressure}_{June} + \exp\big(\text{MaxTemp}_{July} + 0.4373559\big) \\ & + \left(\text{MaxTemp}_{June} + 18.01798 - \frac{\text{Pressure}_{June}}{0.23814727}\,\text{Wind}_{March}\right) \\ & + \exp(\text{MaxTemp}_{June} + \text{Wind}_{March})\end{aligned} \tag{1}$$

The variables listed here are normalised dimensionless quantities. This mapping should not be interpreted as a real physical mapping to relate climate variables to grape yield, but rather should be seen as an attempt to improve upon the linear model that seeks to capture some of the non-linear dynamics associated with the system. Therefore, caution should be exercised when looking at values far from the mean.

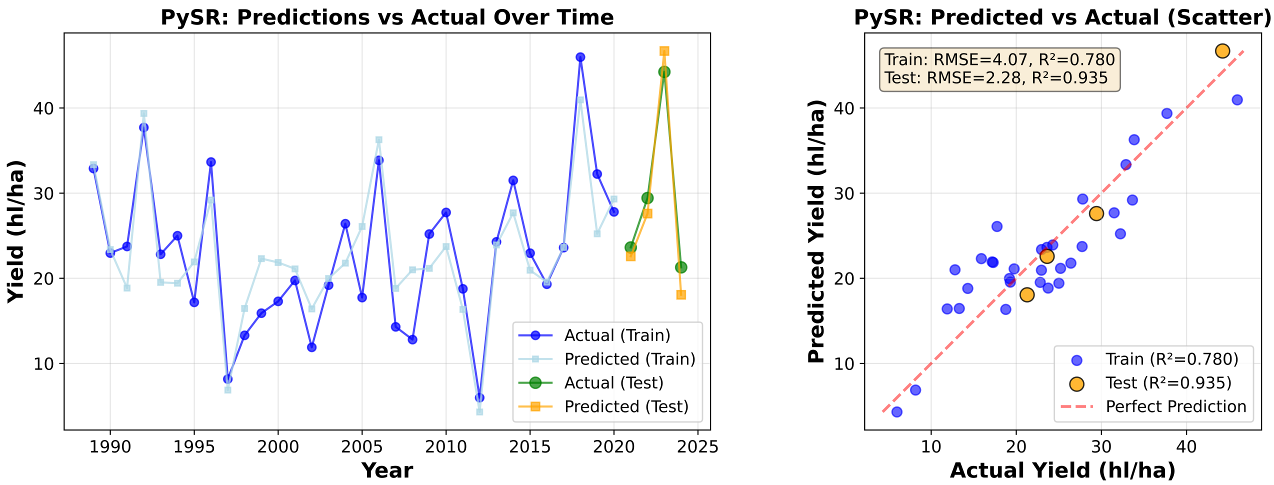

Figure 9: PySR Equation Model: Predicted vs Actual Yield

Looking at Fig. 9, a high R^2 for both the training and test datasets can be seen. It is difficult to evaluate for over-fitting due to the small size. However, the higher R^2 of the model on the test dataset is indicative of a good fit rather than an over-fit. Despite this, features that are difficult to interpret, such as the $Pressure_{June} \times Wind_{March}$ term.

Fig. 10 shows the future mean yield forecasts to 2040 using this equation. The report notes that the historical trend line aligns more closely with the high error bounds of future climate predictions and that this model predicts an exponential increase in mean yield over the coming years for medium to high scenarios.

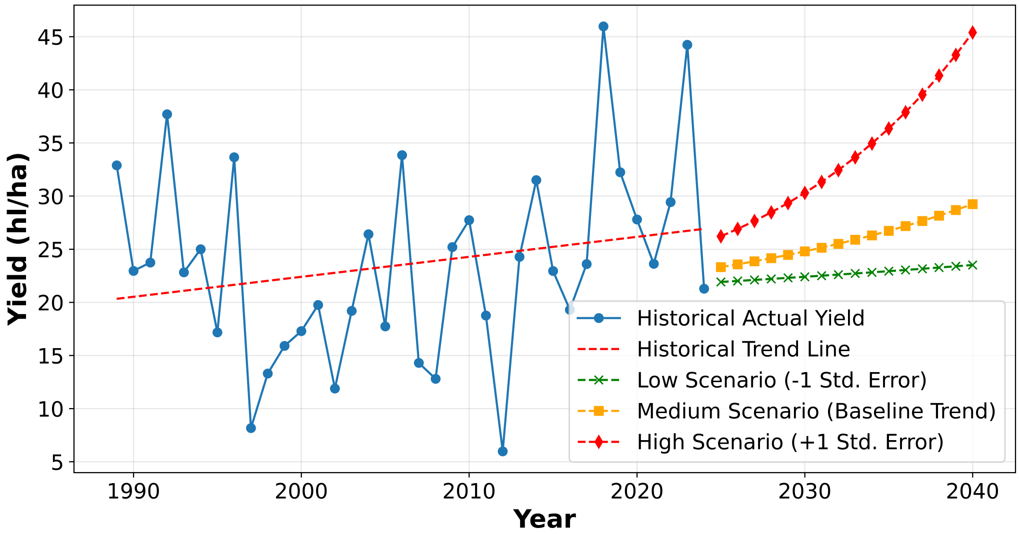

Figure 10: PySR Mean Yield Forecast

For all of the models, due to the lack of data, there were not enough data points for a cross-validation set upon which it would be normal to attempt to obtain the optimal model architecture. Furthermore, it is normal to perform k-fold splitting of the test dataset to ensure there is no anomalous performance on only one-fold, but due to limited data we only had one test set. Therefore, the model could just be performing well on this test set by chance.

5.4 Uncertainty and Expansion of the Dataset

Whilst the models do provide evidence that climate is an important factor for UK grape yield, and it is entirely plausible that a changing climate has been beneficial in recent decades, the quantitative forecast uncertainty is still large. With only around 35 annual data points and a large range of predictions, there is an inevitable risk that the fitted relationships depend rather strongly on modelling choices. Therefore, the predictions themselves must be treated with an appropriate degree of scepticism. The wine data is sparse, which makes it difficult to train a robust predictive model. Expanding the dataset would greatly benefit this area of research and aid in reducing uncertainty. Unfortunately, vineyards are reluctant to publish individual data on yields due to their close link to profits and the operation of the business in comparison to competitors. It is possible, however, that the limited wine-yield dataset could be supplemented indirectly through a related agricultural dataset.

In Champagne, there are annual caps on yields due to the strictures of the Appellation system that aims to control the supply and hence prices of the wine. Thus, the actual yields from the vines are less reflective of the climate conditions under which the grapes were grown in comparison to market demand for the wine. As a result, it was not possible to conduct a similar exercise of analysing the impact of climate on grape yields in Champagne. Instead, the relationship between weather in Champagne and the overall tasting score for the vintage (based on the 100-point scale for rating wines, developed by the wine critic Robert Parker) was examined. Unfortunately, linear correlations between climate variables and score were far lower than between climate and yield in the UK. This reflects the complex nature of flavour in wine, which underpins the tasting score of a vintage. Further problems include how ratings for a particular year change as the vintage evolves through ageing. Creating a mapping between the tasting score in Champagne and yield in the UK to supplement the dataset was therefore not possible.

It may be possible to ask whether there is another crop for which far more extensive yield records exist, and which responds to at least some of the same climatic controls, even if not in an identical biological manner, such as apples [14]. A richer agricultural yield dataset might allow the climate signal to be learned more robustly, after which one could investigate how that information transfers, with appropriate caution, to viticulture. It is beyond the scope of the present work, but it would make a sensible and constructive avenue for further research, alongside the need for more detailed vineyard-level yield, variety, and management data.

6 Conclusion

The quantitative yield predictions of the linear and PySR models support the existing qualitative analysis of the positive effect of climate change on the sector. The most important climate features in terms of their effect on yield occur during the ripening process, with average maximum temperature in June and July of high importance, along with additional features that contribute to adverse conditions for early shoot and flower growth, such as pressure, wind, precipitation, and frost. The linear model forecasts an increase in yield over the coming years, whilst the symbolic PySR equation output (1) predicts an exponential relation between ripening temperatures and yield, and an exponential increase in yield in the future.

Further areas of research should involve expanding the yield dataset by the number of points and including non-climate variables such as the grape varieties planted, vine spacing, fertiliser usage and irrigation. Refining the PySR training would also benefit by ensuring that only terms with a direct link to the biological processes appear in the equation, and a wider variety of climate variables are included. To improve yield predictions, a more rigorous approach to climate forecasts is necessary. This is a matter of ongoing research and is beyond the scope of this paper; however, new techniques in AI training that allow for more localised predictions may be of assistance. While yield prediction errors are large, this report demonstrates the possibility of applying more rigorous modelling methods to viticulture prediction and affirms the positive effect of climate change on the UK's wine industry.

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A Appendix

A.1 UK Wine Production Background

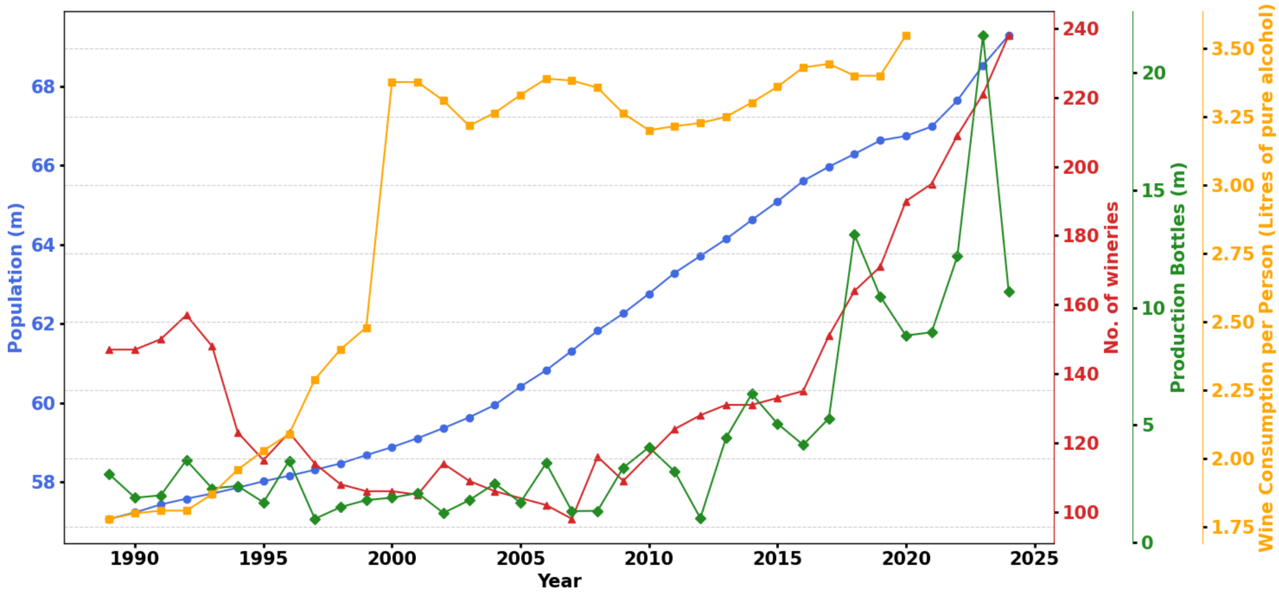

Figure 11: Population, No. of wineries, Production Bottles, and Wine Consumption per Person vs Year for the UK

A.2 Table of Climate Variables and Definitions

Climate Variable	id	Definition
Max Temp	tasmax	Average of daily maximum air temperature over the calendar month, season or year (°C)
Min Temp	tasmin	Average of daily minimum air temperature over the calendar month, season or year (°C)
Temperature	tas	Average of daily mean air temperature over the calendar month, season or year (°C)
Precipitation	rainfall	Total precipitation amount over the calendar month, season or year (mm)
Sunshine	sun	Duration of bright sunshine during the month, season or year (hours)
Wind	sfcWind	Average of hourly mean wind speed at a height of 10 m above ground level over the month, season or year (knots)
Pressure	psl	Average of hourly (or 3-hourly) mean sea level pressure over the month, season or year (hPa)
Vapour Pressure	pv	Average of hourly (or 3-hourly) vapour pressure over the month, season or year (hPa)
Ground frost	groundfrost	Count of days when the grass minimum temperature is below 0°C (days)
Snow	snowLying	Count of days with greater than 50% of the ground covered by snow at 0900 UTC (days)

Table 1: Climate variables and definitions [11]