Predicting California Grape Cultivation Conditions in the Era of Climate Change and Wildfires

Avalon Vinella, Margaret Capetz, Siyan Zhao
Department of Computer Science
UCLA
{avinella, mcapetz17, siyanz}@g.ucla.edu

Abstract

The U.S. wine industry, significantly centered in California, is under threat from changing climate conditions and increasing wildfires. These changes, which influence the quality and yield of grape harvests, have economic implications for an industry contributing $170.5 billion to the U.S. economy. Recognizing the multifaceted challenges, we introduce a novel predictive method that combines agricultural metrics with extreme weather insights, particularly focusing on wildfires. By finetuning the foundational ClimaX model, we offer a comprehensive evaluation of grape cultivation conditions in California, shedding light on both current predicaments and future scenarios while addressing previously overlooked wildfire impacts. We implement a heuristic evaluation strategy to determine the suitability of growing seasons for California-specific grape varietals, contributing to viticultural methodologies and the broader field of agriculture.

Access to our code here.

1 Introduction

Climate change poses a significant threat to various agricultural industries, especially those that hinge on specific weather conditions for optimal yield. Among these, the wine industry is particularly vulnerable. Grapes, which are the primary raw material for wine, are highly sensitive to their growth conditions, including variations in rainfall, sunlight, and temperature.

The wine industry holds significant importance with a substantial economic footprint. In the U.S., it contributes $170.5 billion and provides employment opportunities for approximately 1.1 million individuals [Win, 2022]. California stands at the forefront, producing roughly 81% of the nation's total wine, with a well-known global reputation [eco, 2022].

In recent years, however, hotter and drier growing seasons and frequent extreme weather events have driven many Californian winemakers out of state, as their vineyards have become difficult to manage [Pezzetti, 2023]. A grape's phenological qualities are very sensitive to its growing conditions, and such adversities have long-lasting implications on soil and vine health [Dell'Aquila et al., 2023]. The vines need the right amount of moisture to encourage growth, but not too much as to invite fungal disease. At more complex levels, the sugar content and acidity of the grapes are affected by the amount of sun exposure, the diurnal shifts of day and night temperature, and the amount of time they have to grow in a certain temperature range. As climate change pushes weather conditions to extremes, California vineyards will struggle to maintain suitable growing conditions, leading to a lower output of quality grapes. Wildfires, which have occurred at large scales in California wine country nearly yearly since 2016, pose a more destructive risk for winemakers. Not only can the grapevines be destroyed in the fire, but the lasting effects of scorched soil and smokey air will heavily affect the flavor of the current and future years' crops.

In light of these multifaceted challenges, there is a need for a predictive tool that can assist winemakers in forecasting meteorological aspects crucial for grape cultivation to be able to best manage their vineyards among changing climate conditions. In this work, we introduce a novel approach that integrates viticulturally relevant climate data with extreme weather conditions to offer a holistic evaluation of grape cultivation conditions specific to California, addressing a gap in previous research that overlooked the wildfire dimension. Toward this goal, we fine-tune an existing foundational climate model, ClimaX [Nguyen et al., 2023], integrating it with agricultural meteorological data and wildfire susceptibility, aiming to provide a comprehensive analysis of grape cultivation conditions for both present and future seasons. We evaluated the results with comparisons to heuristic ranges and thresholds based on related work, which are illustrated in threshold heatmap plots. We utilized fine-tuning of ClimaX with a customized data loader, modified model architecture, and experimentation with LoRA. Overall, we provide a tool and evaluation pipeline for adapting viticultural practices to the evolving climate landscape.

2 Preliminaries and Problem Statement

The shifts in global climate patterns, marked by intensifying extreme weather events and wildfires, are challenging weather-dependent industries like the wine industry. The primary objective of this study is to fine-tune the foundational ClimaX model to the specialized downstream task of assessing grape cultivation conditions.

ClimaX [Nguyen et al., 2023] is a state-of-the-art deep learning model tailored for weather and climate science, uniquely adaptable across heterogeneous datasets with varying variables, spatio-temporal extents, and physical foundations. The model accepts an input format of $\mathbf{V} \times \mathbf{H} \times \mathbf{W}$, where $\mathbf{V}$ represents input variables such as geopotential, temperature, and climate forcing factors like CO2 and SO2. The spatial resolution, denoted by $\mathbf{H}$ and $\mathbf{W}$, hinges on the granularity of global gridding, with two primary resolutions: 5.625° (32 $\times$ 64 grid points) and 1.40625° (128 $\times$ 256 grid points). Architecturally, ClimaX builds upon the Vision Transformer (ViT) and integrates two pivotal changes: variable tokenization and variable aggregation. This model undergoes pre-training using a self-supervised learning objective on datasets sourced from CMIP6, which allows it to subsequently fine-tune for a diverse range of climate and weather-related tasks, even those involving unseen atmospheric variables and spatio-temporal scales.

The climate parameters influencing vine and grape growth can vary among global wine regions and grape varieties. To ensure a focused selection of these parameters, we examine the state of California, as it is home to the US's most prominent growing regions, and also because the Californian wine industry has already felt drastic effects of climate change with a particularly high risk for wildfires. We will accordingly be using the ClimaX model at its higher spatial resolution to isolate this region.

3 Related Work

With the interest in leveraging computational methods in the wine industry, many works have started to introduce numerical analysis and machine learning for climate-centric applications. Notably, the inclusion of wildfire risk remains untouched in prior works.

ClimaX [Nguyen et al., 2023] offers a novel foundation model built on vision transformers that excels in weather forecasting, climate downscaling, and climate projections tasks. In contrast to conventional climate models that rely on physics-driven differential equations and typical machine learning models tailored for specific tasks, foundation models engage in extensive, unsupervised pre-training and are subsequently fine-tuned for diverse downstream applications. This approach makes it feasible to train on agriculturally and wildfire-focused variables, consequently delivering robust results.

Prapas et al. [2022] introduces a comprehensive dataset tailored for predicting wildfires via deep learning, covering atmospheric, climatological, vegetation, and socioeconomic factors, drawing data from ERA5, Copernicus Emergency Management Service (CEMS), and others. It offers a global spatial coverage with a temporal span from 2001 to 2021. The spatial resolution is $0.25° \times 0.25°$ and it updates every 8 days, providing around 900 time steps. In total, there are 54 discrete variables including climate variables, vegetation, historical data on wildfire emissions, and burn areas. The size of this dataset 15.6 TB. A performance baseline using a UNet++ encoder-decoder is also provided for a gloabl-scale prediction. In this project, the datacube provided by this work will be used for fine-tuning our ClimaX model.

Dell'Aquila et al. [2023] collaborated with wine industry experts from Portugal's Douro region to determine the most crucial weather variables in grape growing, and subsequently devise a tool that can assess the quality of current and future growing seasons. They also determined the overall wine quality of past years in order to build a correlation between growing conditions and wine quality. They leveraged existing classical seasonal and climate forecasting services and bias correction methods to provide predictions. We adopt some of their justified climate variables in our model.

Jones et al. [2005] performed a numerical analysis of global temperature and yearly vintage quality using linear regression. The effect of the warming growing seasons was found to be fairly small in North America during the years of 1950-1999, but future climate predictions using the HadCM3 climate model indicate more extreme warming that is anticipated to have a much greater impact on grape viticulture. Their dataset is limited to the 20th century and only investigates air temperature during the growing season.

Bai et al. [2022] establishes a dataset containing the growing conditions, harvest data, and phenology data from California over the years of 1911-2018. During their trend analysis, they noted that red wines had increased levels of sugar content over the last century, while white wines are now harvested earlier and have lower sugar content. These trends may suggest how different grape varieties have responded to notable increases in temperature and shifts in the growing season.

4 Data

4.1 Climate Factors

We use the Global Wildfire Dataset provided in Dell'Aquila et al. [2023](access link). This wildfire dataset motivates the use of deep learning for burned area forecasting, thus we can utilize the curated analysis-ready datacube for the downstream task of making predictions for the wine industry.

The wine industry's nuanced response to climate dynamics necessitates a rigorous analysis of pivotal climate factors. We emphasize the following, which can be broken up into daily variables that can be measured at a daily frequency, and seasonal measurements that describe aggregations of daily variables. These variables were identified as impactful to viticulture based on Dell'Aquila et al. [2023] and cms [2019].

- **Daily Variables**
  1. **Total Precipitation:** Rain is essential to vine and berry growth, but excessive moisture can introduce fungal disease.
  2. **Solar Radiation:** Sunlight heavily determines the amount of vine and grape growth and will affect the sugar content, which will in turn influence the wine's alcohol content after fermentation.
  3. **Diurnal Shifts:** The difference between the maximum and minimum daily temperatures, which corresponds to the difference between daytime and nighttime temperatures. Cooler weather during the night allows the grapes to slow maturation to balance their sugar and acid contents.
  4. **Degree Days:** The difference between the mean temperature and 50°F, which is determined to be a threshold for suitable growing temperatures for typical California climate and grape varieties [deg, 2020].
- **Seasonal Measurements**
  1. **Spring Total Precipitation (STP):** Quantifying the precipitation from April to June, this metric evaluates the primary berry growth phase. Varying precipitation levels influence vine growth, grape development, and disease susceptibility. A dry spring will result in less vine and grape growth, while a wet spring will encourage cultivation but may also increase the risk for fungal diseases that will lower yield and quality.
  2. **Harvest Total Precipitation (HTP):** This represents the precipitation from August to October. An ideal harvest season will have minimal rainfall. Excessive moisture will dilute the contents of the grapes or invite fungal diseases, and heavy precipitation may even damage or knock grapes off the vine.
  3. **Growing Season Temperature (GST):** A growing season can broadly be bounded by the beginning of April through the end of October in the Northern Hemisphere. GST would then be the average temperature during this period. Grape varieties can be sorted in GST classes that represent their ideal growing temperatures.

4. **Total Degree Days (TDD):** Aggregates the degree days over the entire season. Certain ranges of TDD mark suitable regions for specific varieties.

We additionally incorporate novel variables elucidating wildfire susceptibility, specifically fire weather indices, which reports fire risk, and other weather and climate variables that are associated with wildfire development. In total, we train our model on 9 variables: total precipitation; surface solar radiation downwards; the min/max/mean temperature at 2 meters; fire weather index max/mean; relative humidity; and wind speed at 10 meters.

5 Methods

5.1 Data Preparation

The SeasFire datacube is provided as an xarray Dataset, which we access specific slices from before feeding into the model as tensors. A major concern in our pipeline is memory; given the size of the dataset, we identify specific useful spatial and temporal regions as soon as possible to avoid loading unused data. We crop the the spatial range to the latitude and longitude bounds of our region of interest, which is California. Our model also allows for the input of several time steps instead of just one, so we additionally use a sliding window to extract the "time history" of each input. For long-range time histories, we sample the data in strides. The target data contains each variable's value at one time step at some lead time away from the last inputted time step. We use lead times in units of 8 days for consistency with the dataset. We form a 80-10-10 train/validation/test split over time and use mean-normalization, replacing any missing values with the mean. As another mechanism to save memory, we externally cache commonly used datasets as tensors after they have been preprocessed.

5.2 ClimaX

ClimaX's default configuration is already very suitable for our task. Our main change to the architecture is the inclusion of multiple input time steps, meaning that our input shape is $B \times T \times Vi \times H \times W$, adding an additional dimension that ClimaX does not account for. We aggregate all time steps in our forward embedding such that it reduces the dimensions appropriately. Additionally, our model patches based on regional bounds, which is useful for data that has not been pre-cropped to the desired region. We use weights from ClimaX's CMIP16 pretraining at 1.40625° and train each of our models for an additional 50 epochs on 1 T4 GPU with a learning rate of 3e-4.

5.3 Baselines

In our evaluation, we will employ a standard decoder-based transformer as a baseline to compare the performance of our wildfire prediction ability with ClimaX. The transformer has the following hyperparameters: two attention heads, an embedding dimension of 512, three decoder layers, and a feedforward network dimension of 512.

6 Results and Discussion

In order to best understand and evaluate the effect of our input parameters, we first compare models that vary in the following dimensions:

1. **Lead Time:** Given that predictions of the upcoming and future growing seasons should be made with ample time to make viticultural and management decisions, our model must support large lead times that will cover the season. We experiment with training for lead times of 3 months (a calendar season length), half a year, and a full year.
2. **Time History:** We experiment with using varying amounts of historical data as part of the input, such that region specific data can be emphasized. We train models with time histories of 3 months, half a year, and a full year.
3. **Region Size:** Even with a 0.25° resolution data set, the state of California is very small, resulting in a 20x29 image. We compare our regional model to one trained on the entire continental US, which is size 100x232. Given memory constraints, however, we had to significantly reduce the overall dataset size to about 100 samples, and we used a time history of 3 and lead time of 1.

This comparison is solely to examine the effect of region size, as an evaluation of the entirety of North America as a viticultural region would be insignificant, since wine production in the US is concentrated on the west coast and in New York state [cms, 2019].

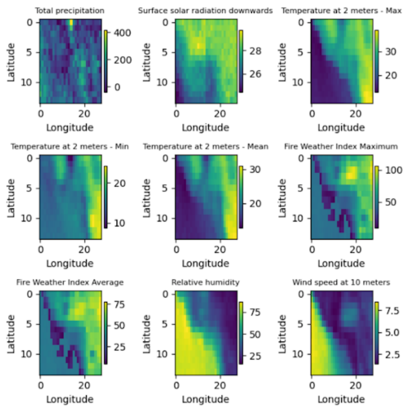

Figure 1: Our model's prediction

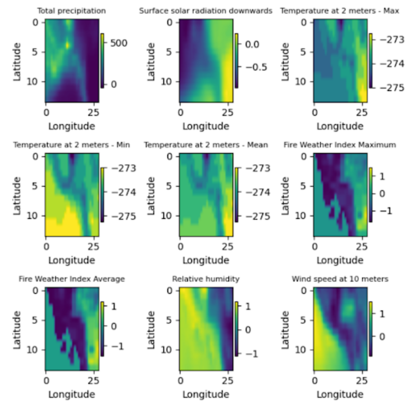

Figure 2: Ground truth prediction

6.1 Quantitative Results

Effect of different time history and lead time prediction: Table 2 showcases the validation loss, measured as Mean Squared Error (MSE), for predictions made over different lead times. Two forecasting periods are considered: one season ahead, which corresponds to 11 timesteps in our dataset, and half a year ahead, equivalent to 22 timesteps in our dataset. The predictions based on the past half-year data yield the lowest validation loss across both periods. However, this was balanced against the trade-offs of data requirements and the implications of using a strided step size, which was necessary to fit memory constraints but resulted in poorer performance for past 1 year history. All models were trained over 50 epochs on a single T4 GPU on Google Colab for around 1 hour each.

Figure 1 shows predictions of our best model on a test sample, and Table 1 shows the MSE on the validation set.

tp	ssrd	t2m_min	t2m_mean	t2m_max	fwi_max	fwi_mean	rel_hum	ws10
0.776	0.070	0.090	0.089	0.092	0.225	0.195	0.213	0.178

Table 1: Validation MSE of our model with a half year time history and one season lead time.

Forecasting Period	Past 1 year	Past half year	Past season
One season ahead (11 timesteps = 90 days)	0.5369	**0.1879**	0.2469
Half-year ahead (22 timesteps)	0.5476	0.2323	0.2356

Table 2: Validation Loss (MSE) for Time History and Lead Time Predictions

Extend to North America model: Figure 3 shows a test prediction of our model that has been trained on data in the North America region. The patching is much more visible than in the limited California region, but the overall shape and trends of the continent are still visible. It achieved a validation MSE of 0.2166, which is comparable to our California trained models that use up to a half year of time history. Table 3 shows the MSE of the variables predicted. It shows higher error for variables that are higher for localized regions, such as fire weather index.

Comparison to baseline transformer: We have conducted a performance evaluation between two models: the standard decoder-based Transformer Baseline and our fine-tuned ClimaX model. The goal was to determine their predictive accuracy for a season ahead, relying on data from the past season. As illustrated in Table 4, the fine-tuned ClimaX model significantly outperformed the Transformer Baseline, achieving a lower mean squared error (MSE) of 0.2469 compared to the

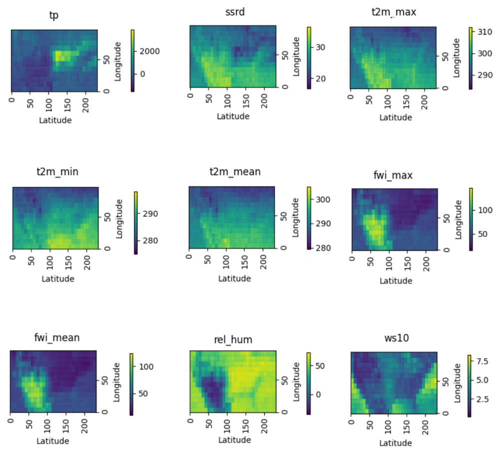

Figure 3: Model predictions for the North America region

tp	ssrd	t2m_min	t2m_mean	t2m_max	fwi_max	fwi_mean	rel_hum	ws10
0.746	0.186	0.091	0.059	0.058	0.250	0.237	0.299	0.240

Table 3: MSE of the North America model on a test sample

baseline's 0.7685. This improvement underscores the effectiveness of the fine-tuning process applied to the ClimaX model, which seems to capture the seasonal trends more accurately than the baseline model, suggesting a more robust prediction capability for time-sensitive agricultural planning and forecasting.

Setup	Transformer Baseline	Fine-tuned ClimaX
Past season predict, lead time = season ahead	0.7685	0.2469

Table 4: Performance comparison between the fine-tuned ClimaX and Transformer Baseline models for predicting a season ahead.

Attempt for LoRA efficient finetuning: We attempt to integrate LoRA Hu et al. [2021] as a method of improving the efficiency of fine-tuning. However, LoRA does not work well in our setup, even though we train the layers in the head and time aggregation, as well as attention layers in the middle with LoRA, resulting in trainable parameters of 14.4% of total parameters. This increased the training speed from 10.1 iterations per second to 23.2 iterations per second. Nevertheless, the application of LoRA was not successful. The limited transfer of pre-trained weights to our model due to size mismatch, coupled with a domain shift between the pre-trained ClimaX data and our wildfire dataset, contributed to the ineffectiveness of LoRA in our context.

6.2 Heuristic Evaluation

Without concrete ground truth labels to define ideal grape-growing conditions, we turn to a heuristic evaluation method to determine the appropriateness of yearly growing seasons for specific grape varieties in California as identified in cms [2019]. This approach leverages information from relevant articles and reports to assess the potential of different periods for viticulture.

Variable Threshold Heatmap Plots: Our heat maps color-coded in red mark the thresholds beyond the suitable ranges for each variable, providing a clear visual representation of the regions falling outside the desired conditions for grape cultivation. Firstly, for the Fire Weather Index, values below 50 are deemed reasonable for viticulture, as illustrated in the heat map in Figure 7, with any value above 50, highlighted in red, indicating potential fire weather that negatively impacts grape growth ucd [2023]. The Diurnal Shift, as shown in Figure 6, we plot a threshold identified with an optimal range of 10-20 degrees, which is vital for maintaining the balance between acidity and sugar levels in grapes caw [2020]. In terms of Growing Season Temperature win [2012], as plotted in Figure 4, an average temperature range of 14 to 16 degrees Celsius is categorized as a Cool climate, ideal for cultivating grape varieties such as Chardonnay, Pinot Noir, and Sauvignon Blanc, while a Temperate climate, ranging from 16 to 18.5 degrees Celsius, is suited for Cabernet Sauvignon. For Total Degree Days cal [2023], which measures the cumulative heat over the season and is critical for the grapes to reach full maturity, we classify Region I as having below 2,500 degree days, suitable for Chardonnay and Pinot Noir, as seen in Figure 5. Region II, ranging from 2,500 to 3,000 degree days, supports Cabernet Sauvignon and Merlot. Region III, with 3,000 to 3,500 degree days, is favorable for Zinfandel C. Liles [2020]. Regarding wind speed pri [2014], moderate levels are beneficial for vineyard cooling and grape maturation, while excessive wind, particularly exceeding 20 mph, can hinder the vines' metabolic processes, as shown in Figure 6.

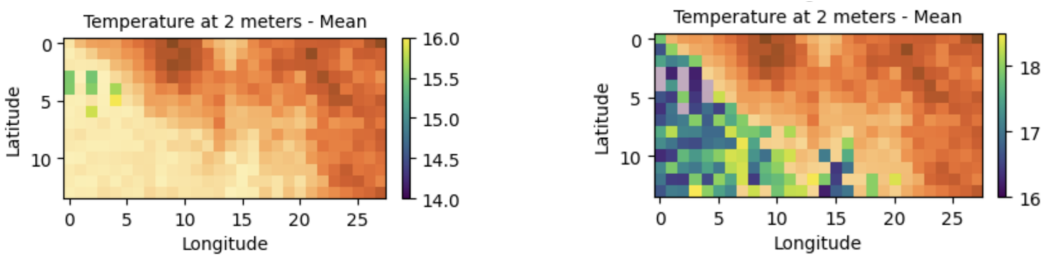

Figure 4: Threshold heat map plot for GST comparison, type I and type II from left to right.

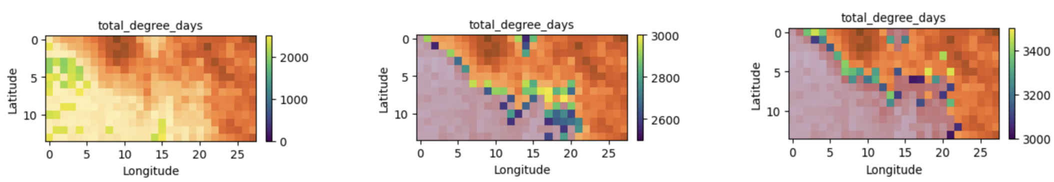

Figure 5: Threshold heat map plot for total degree days for different regions I, II, III from left to right.

Figure 6: Threshold heat map plot for wind speed and diurnal shift

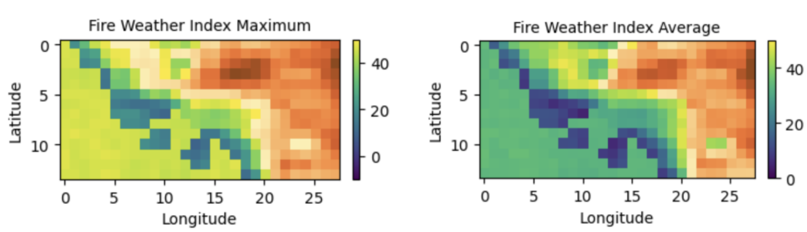

Figure 7: Fire Weather Index heat map indicating regions with potential wildfire risks, highlighted in red, that could adversely affect grape production.

Example of comparing to actual cultivation location: In our analysis, we focused on the Zinfandel grape variety, which thrives within a total degree day range of 3,000 to 3,500. Our heat map visualization, represented in the left of Figure 8, highlights suitable areas for Zinfandel cultivation with green markers. A notable comparison was drawn with San Joaquin County in California, a prominent Zinfandel growing region. The county's location overlaps with the green areas identified by our model, confirming the model's effectiveness in recognizing viable cultivation zones for this grape variety.

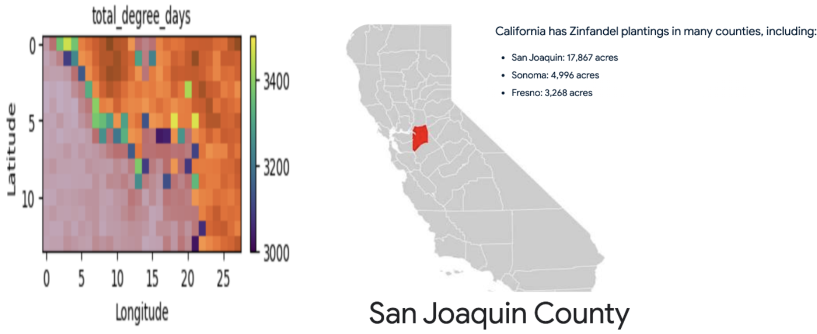

Figure 8: Overlay of Zinfandel cultivation areas on the Total Degree Days heat map, with San Joaquin County highlighted, validating our model's predictive accuracy.

7 Limitations

For evaluation, it was difficult to find accurate thresholds from related academic work. In addition, extrapolation error led to incorrect predictions for large lead time. This was further exacerbated by memory limitations, as the use of strided step size to fit the memory constraint for past 1 year data. This led to poor performance in predictions. We also found that spatial resolution was a limitation, resulting in poor predictions. Finally, California is very small, thus this proved to be a limitation as data was constrained to this region.

8 Future Work

First, this model can be applied to other regions worldwide, and given fine-resolution data, to more localized wine regions. Most wine-producing countries have wine laws that indicate approved regions for commercial wine production. Second, we can directly predict seasonal measurements, rather than aggregrating intermediate ones to save both memory and compute by reducing the required input data size for this task. Moreover, the formulation of a dataset containing grape phenology and vintage quality data would facilitate an end-to-end prediction of the wine quality resulting from a certain growing season. Lastly, we hope to incentivise further work on the integration of natural disasters in agricultural predictions, which has high stakes outside of the wine sector.

9 Conclusion

The California wine industry is impacted significantly by climate change, thus we address this by predicting California grape cultivation conditions using agricultural and wildfire data. We evaluated the results with comparisons to heuristic ranges and thresholds based on related work. To carry out our predictions, we utilized fine-tuning of ClimaX with a customized data loader, modified model architecture, and experimentation with LoRA. Overall, we provide a starting point for future work not only on prediction of grape cultivation conditions, but also for future interdisciplinary agricultural and climate work.

A Author Contributions

The workload of this project was split up in the following manner:

Avalon: ClimaX fine-tuning pipeline, data preparation, model training
Margaret: Data preparation, evaluation, model training
Siyan: Evaluation, efficiency improvement, LoRA experiment, baseline training, model training

References

Growing season temperature data, 2012. URL `https://www.winewisdom.com/articles/facts-and-figures/growing-season-temperature/`.

Petaluma gap: Cooling wind is the recipe for fine wine, 2014. URL `https://www.princeofpinot.com/article/1597/`.

Introductory Sommelier Course: 2019 Workbook. Court of Master Sommeliers Americas, 2019.

Why is diurnal spread important to wine quality?, 2020. URL `https://www.cawineclub.com/blog/ask-a-winemaker-why-is-diurnal-spread-important-to-wine-quality/#:~:text=The%20best%20tasting%20wine%20needs,spread%20of%20about%2020%20degrees`.

Uc davis heat summation scale, 2020. URL `https://www.calwineries.com/learn/grape-growing/climate/heat-summation-scale#:~:text=The%20whole%20system%20rests%20on,minimum%20temperature%20for%20grape%20growing.`

California wines pour jobs and dollars into economy, 2022. URL `https://wineinstitute.org/press-releases/california-wines-pour-jobs-and-dollars-into-economy/`.

California and us wine production, 2022. URL `https://wineinstitute.org/our-industry/statistics/california-us-wine-production/#:~:text=California%20produces%20an%20average%20of%2081%20percent%20of%20total%20U.S.%20wine%20production.`

Heat summation scale in grape growing, 2023. URL `https://www.calwineries.com/learn/grape-growing/climate/heat-summation-scale#:~:text=The%20whole%20system%20rests%20on,minimum%20temperature%20for%20grape%20growing`.

Wildfire impact on california grapes, 2023. URL `https://wineserver.ucdavis.edu/industry-info/viticulture-resources/wildfire-impact-ca-grapes`.

H. Bai, G. A. Gambetta, Y. Wang, J. Kong, Q. Long, P. Fan, W. Duan, Z. Liang, and Z. Dai. Historical long-term cultivar$\times$ climate suitability data to inform viticultural adaptation to climate change. *Scientific Data*, 9(1):271, 2022.

D. V.-K. C. Liles. Refining the growing season temperature parameter for use in winegrape suitability analysis. *Australian Journal of Grape and Wine Research*, 2020. doi: 10.1111/ajgw.12447. URL `https://onlinelibrary.wiley.com/doi/full/10.1111/ajgw.12447`.

A. Dell'Aquila, A. Graça, M. Teixeira, N. Fontes, N. Gonzalez-Reviriego, R. Marcos-Matamoros, C. Chou, M. Terrado, C. Giannakopoulos, K. V. Varotsos, F. Caboni, R. Locci, M. Nanu, S. Porru, G. Argiolas, M. Bruno Soares, and M. Sanderson. Monitoring climate related risk and opportunities for the wine sector: The med-gold pilot service. *Climate Services*, 30:100346, 2023. ISSN 2405-8807. doi: https://doi.org/10.1016/j.cliser.2023.100346. URL `https://www.sciencedirect.com/science/article/pii/S2405880723000079`.

E. J. Hu, P. Wallis, Z. Allen-Zhu, Y. Li, S. Wang, L. Wang, W. Chen, et al. Lora: Low-rank adaptation of large language models. In *International Conference on Learning Representations*, 2021.

G. V. Jones, M. A. White, O. R. Cooper, and K. Storchmann. Climate change and global wine quality. *Climatic change*, 73(3):319–343, 2005.

T. Nguyen, J. Brandstetter, A. Kapoor, J. K. Gupta, and A. Grover. Climax: A foundation model for weather and climate. *arXiv preprint arXiv:2301.10343*, 2023.

L. Pezzetti. Winemakers head to the pacific northwest amid changing climate, environmental factors, September 2023. URL `https://www.king5.com/article/tech/science/climate-science/washington-pacific-northwest-haven-of-opportunity-for-winemakers-wineries/281-1bb9ad7f-bef2-42a4-a235-658a6d6b7694`.

I. Prapas, A. Ahuja, S. Kondylatos, I. Karasante, E. Panagiotou, L. Alonso, C. Davalas, D. Michail, N. Carvalhais, and I. Papoutsis. Deep learning for global wildfire forecasting. *arXiv preprint arXiv:2211.00534*, 2022.