

Modelling the effects of daily extreme weather on grapevine and wine quality

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Abstract: Modelling the effects of climate change on vegetation and agriculture is arguably one of the most challenging issues the scientific community has to deal with in recent times. Grapevine being among the world's old and most expensive cultivated crops with winemaking consisting of a rich history of centuries-old traditions makes contemporary research into modelling climate effects on viticulture of significant interest. Novel approaches are explored for gaining more scientific knowledge on the phenomenon climate change, in particular its potential impact on grapevine growth stages, phenological events and wine quality. In this context, the paper looks at literature on recent χ^2 analysis based approach to establishing associations between daily extreme weather conditions and some perennial crop yield at larger spatiotemporal scales, i.e., yield comparisons among wine regions/ national annual yield of apples, walnuts, oranges, almonds and avocados with three decade old data. Consequently, recent novel approaches investigated at the Geoinformatics Research Centre (GRC) to studying the effects of daily maximum temperature on grapevine yield using data at a different spatiotemporal scale along with results obtained are outlined. The paper then details on extending the approaches to other daily extreme weather data; minimum air and soil (grass) temperatures with a) a single vineyard's yield over a period of 12 years (1997-2009) and b) weather conditions, recorded at a nearby weather monitoring station belonging to the National Institute of Water and Atmosphere (NIWA), extracted via NIWA's web portal. The results show interesting nexuses between daily extreme weather conditions, the independent variables and grapevine yield, the dependent variable at spatiotemporal scales not previously ascertained i.e., at a vineyard (micro scale) but using macro climate data. The approach provides a means to gaining precise information relating to climate effects on viticulture, useful for training grapevines appropriately and thereby improving the quality of grapevine yield/vintage.

Keywords: daily air maximum, minimum and soil (grass minimum) temperature.

1. CLIMATE EFFECTS ON VITICULTURE

Climate change, especially its impact on vegetation and agriculture, is seen as one of the world's most argued thorny issues. Climatologists worked on the issues now ponder upon the accuracy of the climate data initially used in the analysis which led to the conclusion that the recent climate warming as most likely to be "predominantly man-made". Meanwhile, the debate on whether the "Medieval Warm Period was warmer than the current period..." still continues as stated by Jones, [2010:1]. In this context, research into analysing the climate effects on viticulture with different climate prediction models, draws significant interest. The research results of Jones [2007] suggest that the effects of potential climate change on vegetation and agriculture to be inconsistent across the globe and hence on the world's famous wine growing regions too. The effects are predicted to be severe in Mediterranean wine regions, where even over 1°C increase in temperature is predicted to change grapevine phenological events and growth stages dramatically that would in turn make the continued production of premium quality wines produced from these regions impossible as they are already at their peak in ripening ideal grapes for the varieties cultivated. In the southern hemisphere, within Australia, viticulturists are advised to prepare themselves for replanting their vineyards with new varieties that would suit the

country's changing climatic conditions, which is an expensive exercise this again has led to further controversies as discussed by Webb [2006].

1.1 Introduction

Viticulture has its origins dating back to as much as medieval times. Present day world famous wine regions could be distinguished with narrow climatic and geographical niche conditions that most suit different grapevine varieties. Some centuries old manual records in particular, at a prominent Château in France, records belonging to sixtieth century, evidence how these wine regions have developed into what they are today identified with fine wine labels as detailed in a study by Jones, et al., [2000]. However, scientific understanding on climate effects in this regard is still rather limited. But the situation is changing, since the last decade, research into unravelling some old traditional practices and concepts, such as the Mediterranean "*Terroir x clutiva*", relating to environmental and crop varietal factors that influence grapevine growth stages, phenological events (budburst, *floraison* and *veraison*), berry ripening process and wine quality from a regional perspective appears to be more focused and valuable for viticulturists. The research results provide beneficial insights into the way independent factors impinge upon grapevine growth, response and yield useful for improving viticulture practices (i.e., buds/ shoots to retain at pruning, irrigation) that best suit the region's base and local year-to-year variability in climatic conditions thereby enhancing the berry ripening process. Gaining additional knowledge in the regard could further help viticulturists to estimate target yields (grapes tons/ ha) in quantity and quality achievable and also economically feasible.

1.2 Previous research on modelling the effects daily extreme weather on viticulture/ horticulture

The section briefly outlines recent research in modelling the effects of daily extreme weather conditions i.e., daily maximum temperature, on selected perennial crop production (annual) that is considered to be significant and relevant to this work.

In the original research, the influence of daily extreme weather conditions (maximum/ minimum temperatures and precipitation) on annual apple production was modelled using iterative χ^2 statistical method. The approach was successful in that it enabled analysts to establish the measures of association between the weather (independent) and yield (dependent) variables analysed. For this, apple annual production data was initially separated into quartiles by the level of production and then both "upper" and "lower" quartiles were analysed separately against combined "mid" two quartiles. Meanwhile, data on the daily extreme weather conditions was converted into matrices of occurrences (frequencies in number of days) recorded at consecutive 3°C interval classes (for temperature) over moving three week windows within a stipulated period of time prior to harvest. Iterative χ^2 analysis was run for high-low and low-high for all independent variables in search of any deviation in the χ^2 rates generated between each extreme and the combined mid-quartiles. A deviation was identified with the "critical" (cardinal or turning) point in each weather interval. The approach enabled the analysts to find not only the significant associations but the degree of those existed between the climate and annual apple high/ low yield data as well over the 72-year (1920–1991) time span.

An Australian research by Soar [2008] used a similar iterative χ^2 analysis approach to modelling the influence of daily extreme weather conditions on grapevine phenology and wine quality in four major wine regions within that country. This Australian research looked at ways and means to quantify what was described by the authors as "qualitative and fragmented knowledge" on the nexuses between key weather variables and berry ripening/ wine quality using the approach. This study was carried out using data from Australia's four major wine regions, namely, Hunter Valley, Margaret River, Coonawara and the Barossa Valley. The regional wine ratings were used in the study as surrogate for wine quality for a comparative analysis between the frequency of defined weather conditions and the "high" (top 25%) and "poor" (bottom 25%) vintages. The results of this study produced the exact maximum (and minimum) temperatures associated with better quality wine in the different regions, such as temperatures above 34°C throughout most of ripening in the Hunter, below 28°C in early January in the Margaret River, 28-33.9°C towards harvest in Coonawarra, and below 21.9°C in late January and early February and

28–30.9°C towards harvest in the Barossa. It was concluded that the approach provided a means for a quantitative assessment that allowed for establishing the timing and magnitude of weather influences on wine quality on a regional scale with data covering at least three decades.

In a similar study, Jones and Davis [2000] compiled grapevine phenology of *floraison*, *veraison*, and harvest dates for Bordeaux region in France. In this study, authors used reference vineyards' data from 1952 to 1997 and calculated the average dates (averaged between châteaux and variety). They also established budburst dates with the use of simple models based on an observation that in most viticulture regions, on average, budburst starts to occur when the mean daily temperature exceeds 10°C for five consecutive days or six after a cold spell.

Meanwhile, vintage ratings for the whole time span (1940-1995) were compiled using data from a wide variety of sources stating that any qualitative assessment of a vintage would be a generalisation, ratings being commonly seen as serving as the industry-wide benchmark for comparing vintages. The overall vintage quality ratings for the reference vineyards used in the study were scaled from 1 to 7 with 1 being a terrible year and 7 an exceptional year. Even though quality ratings were considered to be inherently subjective, it was presumed that variations in quality among the individual châteaux would not be contributory to the final ratings due to the relativity in measure and therefore, when tabulated in a consistent manner, the rating method was considered to produce a reliable measure for an assessment against general climatic influences.

For the climate data, the authors used meteorological recordings from a Bordeaux station for 1949 to 1997 obtained from METEO-France weather station, the only reason for selecting this station was that this had not been relocated over this period. This data consisted of daily observations of maximum temperature (Tmax), minimum temperature (Tmin), hours of insolation, and precipitation. Based on these general climate parameters other variables commonly used in viticulture studies for the region, such as The Sum of Average Temperatures ($SAT = (Tmax + Tmin)/2$), Estimated Potential evapotranspiration ($PET = SAT - precipitation$) and the number of days with extreme cold were derived. The extreme cold days were stipulated with two variables, the numbers of days with minimum temperatures less than -2.5°C and less than -10°C, two variables were used for the assessment of both moderate and extreme cold events respectively. Similarly, the numbers of days with maximum temperatures greater than 25°C as well as 30°C were derived for the assessment of both moderate and extreme warm events respectively.

Finally, the associations between the viticulture data (on phenology, production, must composition, and vintage ratings) discussed above (or the dependent variables) and the climate (or the independent variables) in this case (summed by phenological interval), were then analysed with multiple regression procedures.

In a study by Caprio and Quamme [1998], authors modelled the response in yield to temperature and precipitation changes in some perennial crops with statistical models developed from 1980-2003 records of state-wide yield and variations in monthly average temperature (minimum and maximum) and rainfall data. In another study, the same authors Caprio and Quamme [2002] used an exploratory data analysis and then multiple regressions to develop a suitable model to predict the annual yield for different crops, namely, Grapes (wine & table), Lettuce, Almonds, Strawberries, Hay, Oranges, Cotton, Tomatoes (processing), Walnuts, Avocados and Pistachios. The initial exploratory analysis was performed to select appropriate predictor climate variables. Of these predictors derived, two most important climate averages (daily/ monthly) were later used in the multiple regressions to develop best fit models with three climate variables for each of the crops analysed.

2. DATA AND THE METHODOLOGY

The section outlines the data used, pre-processing methods adopted to create matrices on the weather variables and finally the different approaches explored to model the associations between the dependent (grapevine yield) and independent (daily extreme weather) variables analysed in this research.

2.1 Grapevine yield and daily weather data

The grapevine yield data and classification used in a previous research by Shanmuganathan, et al., [2010], is used in this research as well along with the daily minimum of air and soil (grass) temperatures extracted from NIWA's web portal. The yield data (grapes in tons/ hectare, Brix, acid and pH) for 12 years (1997-2009) is classified into *low*, *average* and *high* years based on winemaker observations.

The NIWA's daily extreme weather variables logged at Henderson River Pk, (36.85539S, 174.62383E) agent no. 1423(A64863), and disseminated via NIWA's web portal [2009] is used to create matrices of numbers of days recorded in each of the continuous classes (at 3°C interval) within moving 3 week windows, each window in succession adding a new week and dropping the first week as the window advanced. Time span of each matrix is 45 weeks prior to harvest date and separate matrices were created for daily extreme air and soil (grass) minimum temperature data obtained from NIWA. The 12 year vineyard harvest yield data consists of 3 years of each *low*, *average* and *high* rating. Daily extreme maximum temperature data has been already studied against the vineyard's yield and for further details on this work please refer to (Shanmuganathan, et al., 2010).

2.2 The methodology

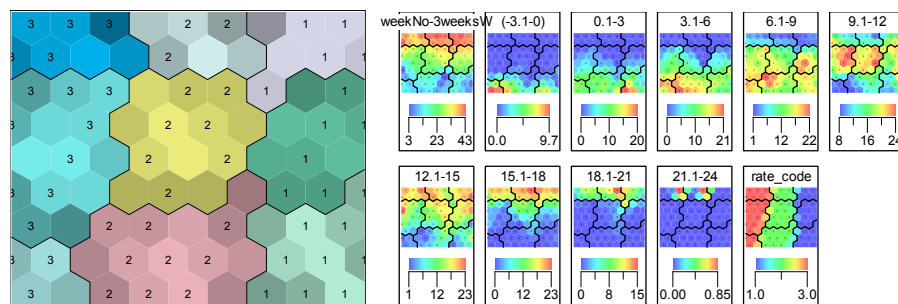
The weather data converted into frequencies of daily minimum temperature (air and soil) at 3°C intervals (between the maximum and minimum of the variable in consideration) during moving week windows over a period of 45 weeks prior to harvest of each yield year was analysed to find out any associations between yield classes (low, average and high) and extreme weather frequencies. The yield data from this vineyard covers only 12 years hence, insufficient for any meaningful analysis with conventional methods, in this case with iterative χ^2 analysis approach alone in a similar manner to that of examples explained in section 2. Therefore, an explorative data mining approach with Kohonen's self-organising map (SOM)¹ was applied to the data initially to look for any correlations between the weather frequencies and yield, the independent and dependent variables.

3. THE RESULTS

The results of both, SOM technique based data mining and iterative χ^2 analysis give details on the daily extreme minimum (air and soil) temperature range/s and frequencies at which they affect the yield and are illustrated in this section.

3.1 Data mining results

SOMs were created with daily extreme minimum (air and soil (or grass)) temperature frequencies at 3°C intervals within -3.1 to 24°C and -5.1-22°C respectively for the weather variables being analysed in this paper.



¹ Self-organising maps (SOMs) are single layered, feed forward artificial neural networks (ANNs) that use an unsupervised algorithmic training developed by Tuedo Kohonen based on late twentieth century understanding on the functioning of the cortex cells of the human brain. SOM techniques are considered to be excellent tools for exploratory data analysis as trained SOMs produce low dimensional displays of complex multi dimensional data sets, in which correlations between the vectors in the raw data could be easily visualised and studied,

Figures 1 a & b. SOM and components of daily minimum frequencies (within moving three week windows) over the 45 weeks prior to harvest date. Grapevine yield years (rate_code) and week nos are given higher priority to enhance clustering based on these factors.

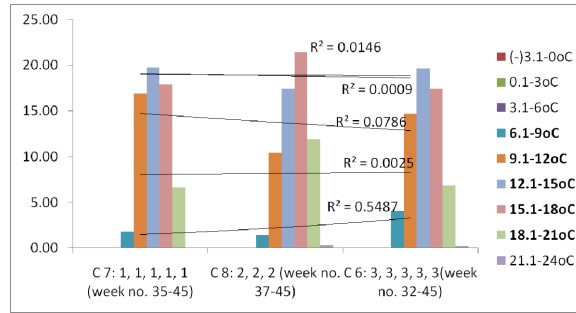


Figure 2. Graph of C7, C8 and C6 SOM cluster profiles showing the temperature frequencies in daily minimum during week 32-45 (moving three week window) prior to harvest, for yield year rated low (1), average (2) and high (3). Frequencies at 6.1-9°C and 18.1-21°C show notable difference between low and high yield years.

A SOM was created with all the air minimum temperature frequencies along with week no. (with priority 2) and rate code (with priority 4) to favour clustering based on the latter two variables. In this SOM (Figures 1 a & b) of air minimum temperature frequencies, 6.1-9, 9.1-12, 12.1-15 and 15.1-18 °C show marked differences within the low, average and high yield years. More importantly, 6.1-9, 9.1-12 and 18.1-21°C are the intervals that show different frequencies between the low (cluster 7 rate code 1) and high (cluster 6 rate code 3) ratings. Similarly, a SOM (figure 3) was created for minimum soil temperature frequencies and -5.1-2, 2.1-1, 1.1-4, 4.1-7, 7.1-10, 10.1-13, 13.1-16, 16.1-19 and 19.1-22°C along with week no. (with priority 2) and rate code (with priority 4), the priorities being given more for the two variables to favour clustering based on them.

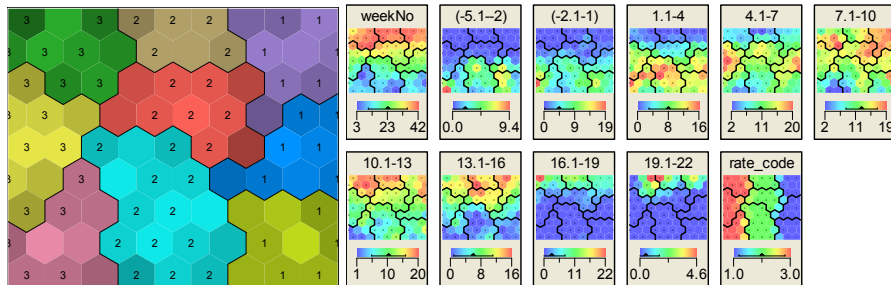


Figure 3. SOM and its components of soil minimum temperature frequencies, rate code and moving three week show the associations between temperature interval ranges, frequencies and yield classes.

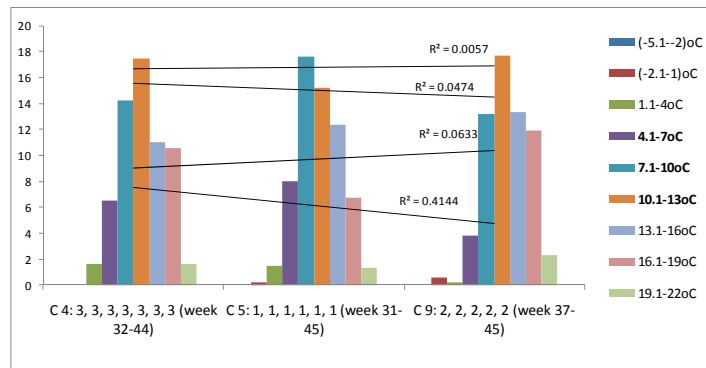


Figure 4. SOM cluster profiles of low, average and high yield years for soil (grass) minimum temperature frequencies at continuous 3 °C intervals within -5.1-22°C. The histograms show the difference in frequencies for low (C 5) and high (C 4) yield year temperature intervals 4.1-7°C, 7.1-10°C and 10.1-13 °C intervals during week 31-45.

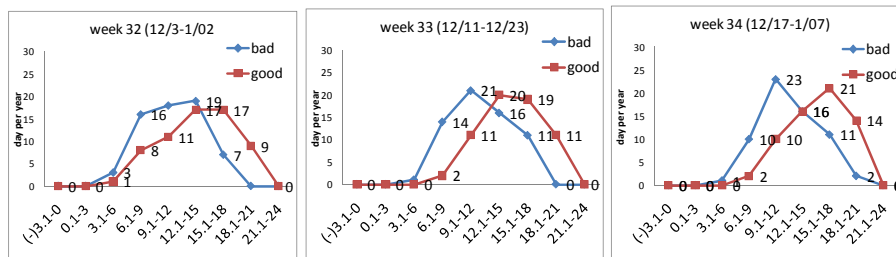
3.2 χ^2 analysis method results

Iterative χ^2 analysis was carried out for the 30-45 moving week temperature frequencies of low and high yield years to find out the exact minimum temperature ranges (air and soil) and the frequencies (figures 5 - 8) that show associations between yield classes and weather conditions. In both temperate frequency matrices, very low and high ranges were added up to remove the zeros in them. For example, below 9°C intervals of soil minimum (-3.1-0, 0.1-3, 3.1-6 and 6.1-9) were added to form <9 °C. Similarly, above >15°C intervals (15.1-18, 18.1-21 and 21.1-24) were added to form >15 °C. The time span as well had to be reduced to 30-45 week period to remove any zero frequency in preparation of the data set to run the χ^2 analysis.

The iterative χ^2 rates for daily minimum temperature during week 32-34 i.e., late November to early January (*veraison*/ change in grape berry colour) show that >15°C at higher frequencies to be associated with high yield years and <9°C at higher frequencies associated with that of low years. In the meantime, an opposite effect is reflected during the ripening season, late February to early March higher frequencies of <9 °C is associated with high yield and higher frequencies of >15 °C with low yield years (figures 5 & 6). These findings seem to reflect that of the daily soil (grass) minimum temperature and are illustrated.

week	time	<9°C	9.1-12°C	12.1-15°C	>15°C	χ^2 rate	p-value
32	11/30-12/21	3.00	3.67	5.67	8.67	10.94	0.001
33	12/07-12/28	0.67	3.67	6.67	10.00	8.81	0.003
<i>33</i>	12/13-01/03	<i>5.00</i>	7.00	5.33	3.67	9.94	0.002
34	12/14-01/04	0.67	3.33	5.33	11.67	10.08	0.001
<i>34</i>	12/20-01/10	<i>3.67</i>	<u>7.67</u>	5.33	4.33	6.23	<i>0.013</i>
						<u>5.12</u>	<i>0.024</i>
<i>40</i>	01/31-02/21	<i>0.33</i>	7.00	7.33	6.33	3.90	<i>0.048</i>
44	02/22-03/14	2.67	6.33	6.67	5.33	5.44	0.020
45	02/29-03/21	4.00	9.00	4.67	3.33	9.31	0.002
<i>45</i>	03/07-03/28	<i>0.33</i>	5.00	6.00	9.67	9.26	<i>0.002</i>

Figure 5: Table showing the details of χ^2 analysis for minimum air temperature frequencies that are associated with high (in bold) and low (in italics) yield years.



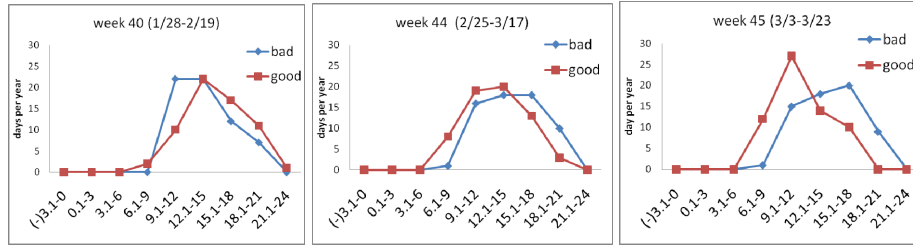


Figure 6: Graphs showing the daily minimum air temperature range, week and frequency distribution that are associated with high and low yield years at a vineyard in north of Auckland. Week 32-34 early - late December and week 40-45 late February to early March are related to *veraison* and ripening of grapes respectively in northern New Zealand.

week	time	<7°C	7.1-10°C	10.1-13°C	13.1-16°C	>16°C	χ^2 rate	p-value
31	11/23-12/14	8.67	3.67	4.00	2.00	2.67	5.444	0.020
32	11/30-12/21	5.00	2.00	5.00	1.33	7.67	20.167	0.000
<i>32</i>	12/06-12/27	8.00	5.33	4.00	3.33	0.33	4.555	0.033
33	11/30-12/21	2.00	2.67	6.33	2.33	7.67	17.640	0.000
<i>33</i>	12/13-01/03	6.67	5.33	4.00	4.33	0.67	7.538	0.006
34	12/07-12/28	1.67	3.00	5.00	2.67	8.67	10.939	0.001
<i>34</i>	12/20-01/10	<u>5.00</u>	6.67	3.67	3.33	2.33	<u>5.000</u>	<u>0.025</u>
							4.172	0.033
42	02/08-02/29	1.00	7.33	7.00	4.00	1.67	4.571	0.033
44	02/22-03/14	6.33	5.00	5.00	3.67	1.00	4.481	0.034
44	02/28-03/20	2.67	5.33	3.33	6.00	3.67	6.259	0.012
45	02/29-03/21	8.67	6.00	3.67	2.33	0.33	12.500	0.000
<i>45</i>	03/07-03/28	2.00	5.67	3.33	<u>6.67</u>	3.33	<u>4.571</u>	<u>0.001</u>
							7.364	0.003

Figure 7: Table showing details of χ^2 tests for minimum soil (grass) temperature frequencies that are associated with high (in bold) and low (in italics) yield years.

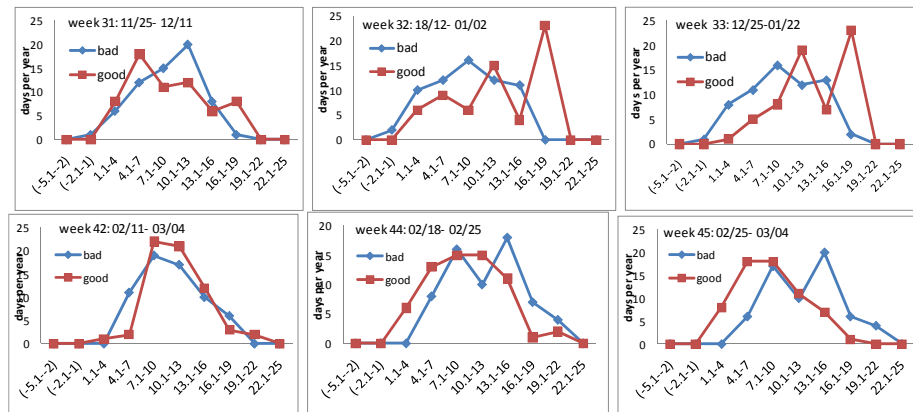


Figure 8: Graphs showing the daily soil (grass) minimum temperature frequency distribution that show associations with high and low yield years at two critical phenological stages (*veraison* and ripening of grapes) in a vineyard in north of Auckland.

Iterative χ^2 analysis method conducted on soil (grass) minimum as well produced precise details of the associations between the temperature ranges and frequencies (number of days) with high and low yield years of the vineyard (figures 7 and 8). During week 31-34 late November to early January, here again the time relates to fruit *veraison* and >16°C daily minimum soil temperature, at higher frequencies 2.67, 7.67, 7.67 and 8.67 respectively, are associated with high yield years. Meanwhile, <7°C at frequencies 6.67 and 5.00 during week 33 and 34 respectively are associated with low yield years. Before harvest time, weeks 42, 44 and 45 (at frequencies 1.00, 6.33 and 8.67 respectively), late February to early March, ripening of grapes season temperature ranges <7 °C at higher

frequencies show associations with high yield years. This is reinforced by the higher frequency 6.00 and 6.67 at 13.1-16 °C during week 44 and 45 respectively being associated with low yield years.

4. CONCLUSIONS

The results of both data mining and χ^2 analysis method based approach support the anecdotal evidence provided by the winemaker relating to climate effects on grapevine phenology and yield. At this particular vineyard, higher frequencies of >15°C in daily extreme weather conditions (in maximum, minimum (air and soil) temperatures) during grapevine *veraison* (late November to mid December) as expected are seen to be associated with high yield years. During near harvest i.e., mid February to early March, which is the grape ripening season, higher frequencies of <9 °C temperatures again are seen to be associated with high years. Similarly, higher frequencies in daily extreme weather conditions <9 °C during *veraison* and >15°C before harvest show associations with low and high yield years respectively. Hence, with these quantified information on temperature ranges, frequencies and their associations with high and low yield years, it is now possible to estimate target yield for the vineyard / wine region that could be economically viable as well achievable under current weather conditions (that could be captured *in situ* using wireless sensors) and then to adopt cultivation practices accordingly in order to achieve the set target yield/s.

5. FUTURE WORK

The GRC team is working on building yield prediction models to use along with these models to estimate the yield achievable under current weather conditions that is economically feasible as well.

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