World Automation Congress © 2010 TSI Press.

MICRO-CLIMATE VARIATIONS RELATED TO VINEYARD CROP QUALITY

PHILIP SALLIS*, SUBANA SHANMUGANATHAN*AND AJIT NARAYANAN**
**Geoinformatics Research Centre, (www.geo-informatics.org)*
***School of Computing and Mathematical Sciences*
Auckland University of Technology, New Zealand.

ABSTRACT- The influences of daily weather extremes such as maximum-minimum temperatures, humidity and precipitation are observed in relation to grapevine phenology. The quality of a vintage is produced when the skill of the winemaker is combined with crop quality factors such as grape berry component ratios for sugar, aroma, flavour and colour pro-phenols. With reference to previous published work in climate influences on crop yield and quality, this paper describes a data mining approach used for data association modelling to depict dependency relationships between daily weather extremes, grapevine phenology, crop yield and wine quality indicators. This method is applied to sample data from a vineyard in northern New Zealand. The sample data was classified into two sub-sets reflecting *high* and *low* years. The classification parameters for membership of either set were defined in a min-max spectrum for *crop yield* (grapes harvested in tons/hectare) with values for a 12 year period. Climate data with values for daily weather extremes logged at a nearby meteorology station was pre-processed into a matrix of occurrence frequencies at continuous 3^{o}C intervals within the lowest and highest of maximum temperature recorded in a moving three week window for 45 weeks prior to every harvest date during the 12 year period (1997-2009). The processed weather occurrence frequency and wine quality data sets were analysed for quantifying any new and already known associations between the two major sets of variables. An artificial neural network algorithm was used to classify the data associations and a chi-square statistical test was used to establish the degree of independence between the related variable values. Focussing on temperature variation for this study, the results show that temperatures <23^{o}C in mid November-early December and >26 ^{o}C in late February-March led to *low* yield years while conversely 23-26^{o}C (so slightly cooler) and <23^{o}C (so slightly warmer) in the respective time periods led to *high* years in this particular vineyard. This is practically an inverse ratio where apparently minor temperature variations are significant.

Key Words: daily climate extreme recordings, grape wine, self-organising maps (SOM)

1. INTRODUCTION

Viticultural and oenological research has shown that variability in daily extreme weather conditions such as maximum and minimum temperatures, wind velocity, humidity and precipitation can influence plant physiology and growth stages significantly. These influences can ultimately result in substantial grapevine phenology shifts in growth events such as budburst, flowering, *Veraison* and harvest (1). The changes in grapevine phonology in turn typically lead to changes in berry sugar content and the composition of other major components, such as the proteins (pro-compounds) responsible for wine colour, aroma and flavour phenols. These are the ingredients that determine the quality of vintage produced from the grapes despite the best efforts made by the winemaker. The quality of any vintage related to its wine style depends fundamentally on the grapes used but they are in turn influenced particularly by the weather conditions that ripened the grapes. The final and very significant influence comes from the wine maker's experience and talent. Our previous data mining work with wine quality classification methods (2) (3) illustrates this point.

The centuries-old traditional *Terroir x Cultiva* (4) concept is used by contemporary viticulturists who continue to adapt ways and means to compensate for seasonal daily weather variations. An example of this is irrigation control. This is in order to optimise grapevine growth, which is seen to be very common during the berry ripening processes to ensure that the best kind of grapes for refining the vintage within the wine appellation are produced from the vineyard. Climate variation and climate change trends are considered as significant influences on grape growth and crop yield. We demonstrate this in our previous work relating to the modelling of climate variations for vineyards (5) (6).

The next section of this paper reviews published work in modelling daily recordings of selected extreme weather conditions and their effects on different crops in addition to grapevine and wine quality. The methodology section follows, which describes data sources, element pre-processing and data analysis methods used in this research such as the Kohonen unsupervised artificial neural network self-organising map (SOM) algorithm (7). This algorithm is used for the data mining phase of the sample pre-processing and was selected because of the data relationship clusters it generates, which provides a classification of the element values for the next phase of statistical analysis. The statistical analysis of the data is then explained with its results, describing the potential of the methodology for use in gaining greater insights to the intuitive proposition that grapevine yield and vintage quality are influenced by daily weather extremes. This means that enhanced indicative precision can be gained in the context of anticipated results and leads to the notion of predictability when using these methods. A χ^2 test is used to produce these results. A geo-statistical analysis of these results using a kriging algorithm(8) illustrates the potential for visualising a two-state extreme weather pattern across a temporal distribution, in this case 12 years. Because of the two-state classification, a fractal depiction is also possible using a geometric bifurcation algorithm (9). For yield data in the two categories (*high* and *low*) an inverse temperature distribution can be seen, which provides a near symmetrical image of this crop quality indictor.

2. PREVIOUS RESEARCH INTO WEATHER INFLUENCES ON GRAPEVINES

Based on an innovative approach using the χ^2 test method described elsewhere (10) (11), an Australian study (12) described research that modelled the varying influence of daily extreme weather data on grapevine phonology and wine quality in four major wine regions. In the original study, the influence of daily temperature and precipitation on annual apple production was modelled with frequencies of daily weather variability. Each separately consisted of a matrix of days with values in each of the continuous classes (at 2^o F intervals) within a period of a moving 3 week window. Each window in succession added a new week and dropped the first week as the window advanced, for testing with an iterative χ^2 test approach. For this annual apple production data was initially separated into quartiles by level of production and then each *upper* and *lower* quartiles were tested with a combined *mid* two quartile values to find the *critical* (cardinal or turning) point in each climate variable. The χ^2 test was run for high-low and low-high scans to see any deviation in test values generated for the extreme quartiles from that of the combined mid-quartiles, an increase followed by a decrease (or a turning point) in a given scan being referred to as the *cardinal value* of the respective climate variable. These test results concluded that a significant association existed between the climate variables analysed and annual apple production within the 72-year period 1920–1991. The results and associations established included flower bud initiation in June (30°C) and flower bud development in August (26°C) with poor production in the following year. November, December and February (critical value range, –7°C to –29°C) were found to be months where the main climatic factor limiting the apple production occurred in the data set. These time periods correspond with the occurrence of historical winter injury events. Similarly, Daytime temperatures that influenced apple production adversely as well as favourably with respective *low* and *high* years were established along with some indications and actions, such as early irrigation, for avoiding a potential *low* year. Production favoured by mild temperatures during bloom and adversely affected by both very low temperatures and unseasonably high temperatures were explained to be coinciding with the temperature requirements of pollination and pollen tube growth. Good production years were also associated with a lack of low night time temperature in spring, explained to be associated with frost in low lying areas. Hot, dry weather during August of the harvest year was found to be having a negative impact on apple production possibly because of loss in net photosynthesis, lower fruit size or apple sunburn. Warm weather during harvest favoured production, probably because of improved conditions for harvest operations and low fruit losses from autumn frosts.

The Australian study (*op cit*) looked at quantifying what was been described by the authors as “qualitative and fragmented knowledge” on the links between key weather variables during berry ripening and wine quality using this χ^2 test method in four major wine regions in Australia, the regions being the Hunter Valley, Margaret River, Goonawarra and the Barossa Valley. The regional wine ratings were used in the study as surrogate for wine quality for comparison between the *high* (top 25%) and *poor* (bottom 25%) vintages in relation to the frequency of defined weather conditions. The results of this study showed that with maximum temperature, better quality was associated with 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 quantitative assessment allowing for the timing and magnitude of weather influences on wine quality and that this was possible on a regional basis.

3. THE DATA, ISSUES AND METHODOLOGY

This section examines the formulation of data sets and analytical issues when applying the χ^2 test method to gain further insight to the data dependencies between daily extreme recordings in weather variables, grapevine growth and wine quality as they were described in the research outlined in Section 2.

3.1 Daily weather and wine quality data sets

Daily weather data, namely maximum, minimum and grass minimum temperature, has been obtained from the National Institute of Water and Atmosphere (NIWA) gathered at the nearest meteorology station from April 1997 to March 2009 (13). Each of these weather variables is converted into a matrix of occurrence frequency at continuous 3^{o}C intervals between the maximum and minimum recorded for that variable during a moving 3 week window for 45 weeks prior to the harvest date of each yield year.

Wine quality and grapevine yield data for the same period was obtained from the grape grower. This data consisted of Wine Vintage, Grapes harvested (in Yield tons/hectare, Harvest Date, Brix (dissolved sugar-to-water mass ratio of a liquid), Acid and pH [must]. Of the 12 vintages, 1998-2000 are classified as *moderate*, 2001, 2003, 2005 are as *low* and 2002, 2004 and 2006 as *high* by the winemaker. The two sets of data (climate and grapevine yield) are used in this research to see the links between them and are described in the next section.

3.2 The methodology

Data mining techniques were used to analysis daily extreme weather frequencies within a moving 3 week window over 45 weeks prior to harvest and grapevine yield from a vineyard spanning a 12 year period. The χ^2 method used in the literature referenced in Section 2 was regarded as inadequate as a single test due lack of sufficient data so alternative analytical techniques were used, particularly some connectionist methods using the Kohonen algorithms embodied in self-organising maps (SOMSs) (14)

The 12 year grapes yield data consists of *low* and *high* production (3 years of each) and of the rest the years 1997-2000 are described as *moderate* as indicated by the winemaker. Thus, 2007-2009 can be used for testing the prediction capability of the models being investigated for this purpose. The *high* and *low* years are considered as *upper* and *lower* quartiles respectively for the χ^2 test. However, in the SOM based data mining, *moderate* years as well are included to see the correlations between the dependent (yield data) independent (weather data) variables of this research by analysing the SOM cluster patterns and profiles.

4. THE RESULTS

This section illustrates the results from experiments with the sample data using a Kohonen SOM data mining algorithm together with an analysis of the expected and observed value relationships using the χ^2 statistic test.

4.1 SOM results

A SOM (figure 1) of 100 nodes with a principal plane ratio 100:67 was trained with 8 cycles and a 0.5 tension value under *normal, exact mode* conditions. A 135 data point array was created with 9 temperature calibration intervals together with a rate value (set to priority ratio 4) and week number (priority 2) to favour the clustering based on these variables. The frequencies of daily maximum temperature at 3^{o}C intervals (8.1-11, 11.1-14, 14.1-17, 17.1-20, 20.1-23, 23.1-26, 26.1 29 and 29.1-32) show the associations between week numbers and temperature frequencies for *low, moderate* and *high* yield years in the 45 weeks prior to harvest. The map provides a means of visualising the associations between different temperature frequencies during the weeks as shown in figures 1-4. Table 1 illustrates the results from the SOM clustering and show the temperature intervals and the moving week no. that influence the yield rated as *high, low* and *moderate*.

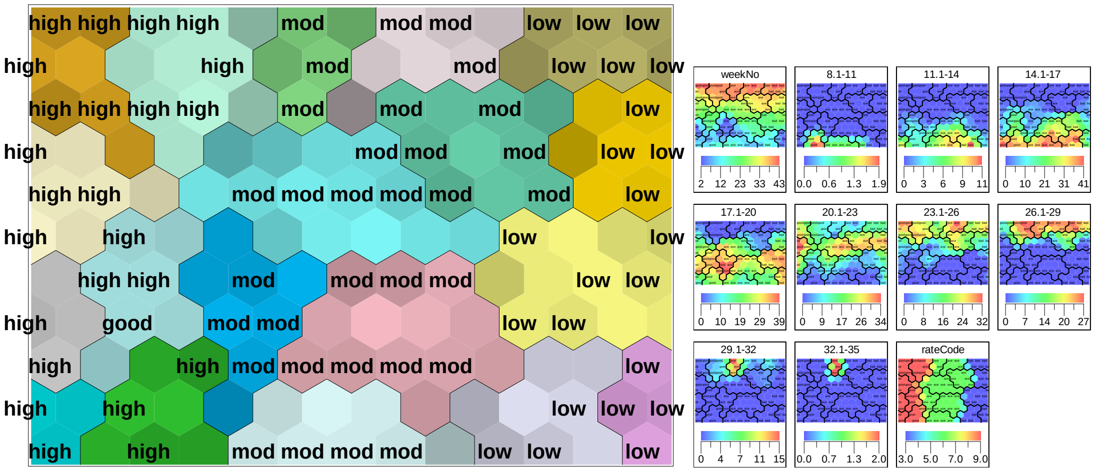

Figure 1 a & b: The SOM (a) and its components (b) used in the analysis for any association between daily maximum temperature frequencies and grapevine yield years rated as *high*, *low*, *moderate*.

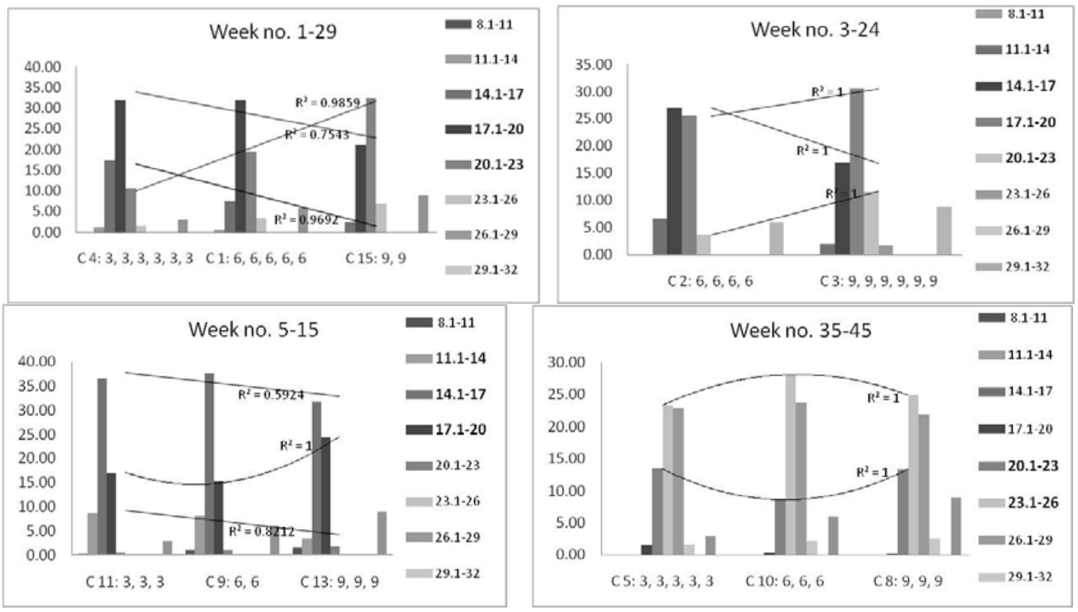

Figure 2: Graphs showing the associations between maximum daily temperature frequencies (in bold) and yield years rated as 3: *low*, 6: *moderate* and 9: *high*, during the specified growth stages (in week no. within the 45 moving weeks prior to harvest dates).

4.2 Geo-statistical results and depiction

Statistical analysis of the data using the χ^2 test outlined below in section 4.3 produced precise results indicating that the sample had two major clusters of temperature range values related to *high* and *low* yield years. In order to visualise this distribution we used a kriging algorithm (op cit) and then generated an isotropic logarithmic based variogram to illustrate the two-state extreme weather pattern across a temporal distribution, in this case 12 years. This two-state classification was confirmed using a fractal geometric bifurcation algorithm (op cit). For yield data in the two categories (*high* and *low*) an inverse temperature distribution can be seen, which provides a near symmetrical image of this crop quality indictor. The visualisations are depicted below in Figures 3 a and b).

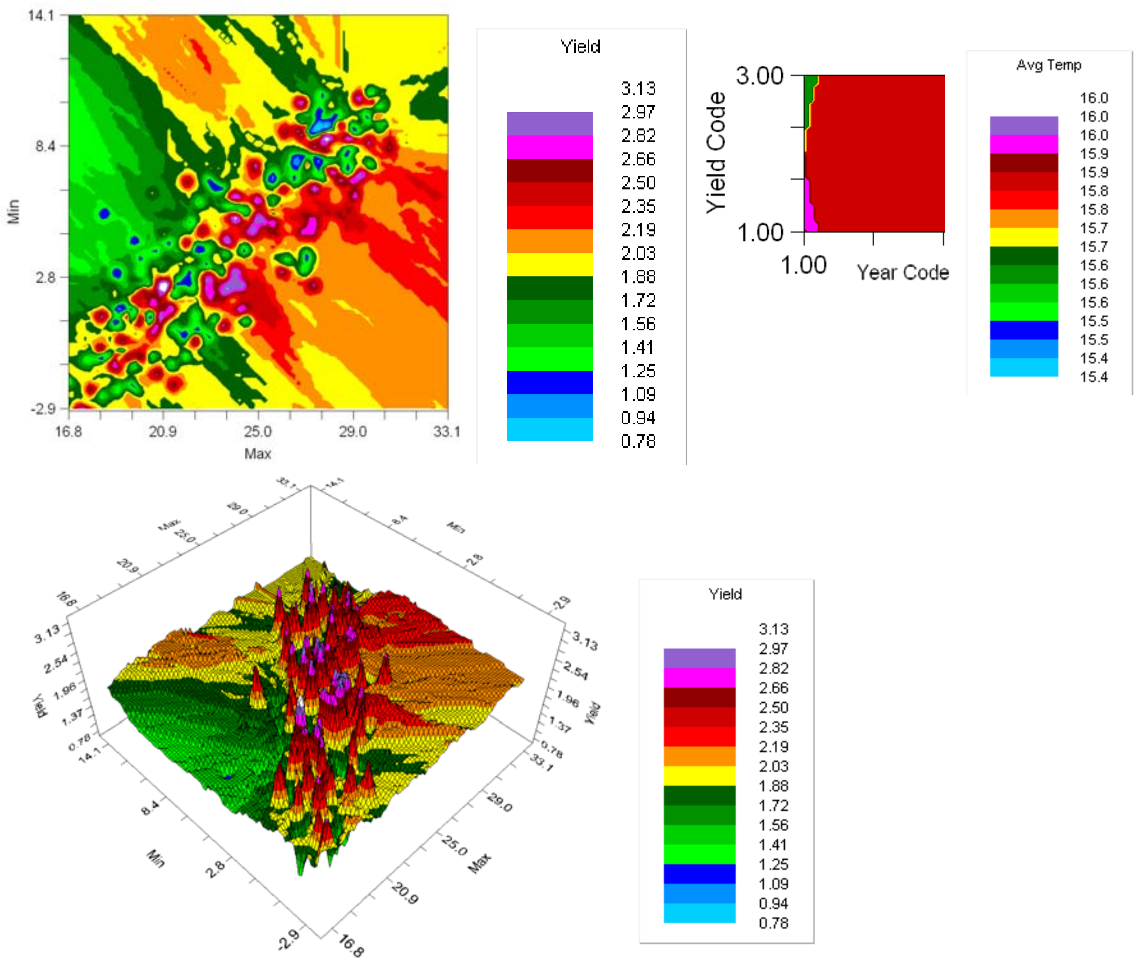

Figure 3 a & b: Variograms (in a: 2D and b: 3D) illustrating the distribution of temperature ranges for *high* and *low* yield years.

4.3 χ^2 test results

Initial results of χ^2 test conducted for moving week numbers 31-45 show the associations between the *high* and *low* rating and the three temperature intervals being analysed in this research (figure 4 and table 1). The temperature intervals have to be reduced to only three classes as χ^2 test cannot be conducted with zero values for frequency hence temperature intervals 8.1-11, 11.1-14, 14.1-17, 17.1-20 and 20.1-23^{o}C intervals were combined and a <23^{o}C temperature class was created. Similarly, 26.1-29 and 29.1-32^{o}C were added to create a >26.1^{o}C. For both classes a moving 3 week window from the period 31-45 weeks were analysed again to overcome the 0 frequencies that makes χ^2 test meaningless which is an issue in this research arising due to lack of sufficient yield data.

week No.	<23	23.1-26	>26	chi square rate	p-value
31	11.67	8.00	1.33	8.000	0.005
32	17.67	3.00	0.33	9.228	0.002
32	8.67	9.00	3.33	7.364	0.007
33	16.00	4.67	0.33	7.247	0.007
33	8.33	8.33	4.33	10.286	0.001
44	5.33	8.00	7.67	6.125	0.013
45	4.33	7.33	9.33	14.235	0.000
45	9.00	10.00	2.00	4.900	0.027

Table 1: Frequency distribution of daily maximum temperature and week numbers found to be associated with *low* (grey) and *high* (brown) yield years along with their χ^2 rate and p-values in a vineyard from northern New Zealand.

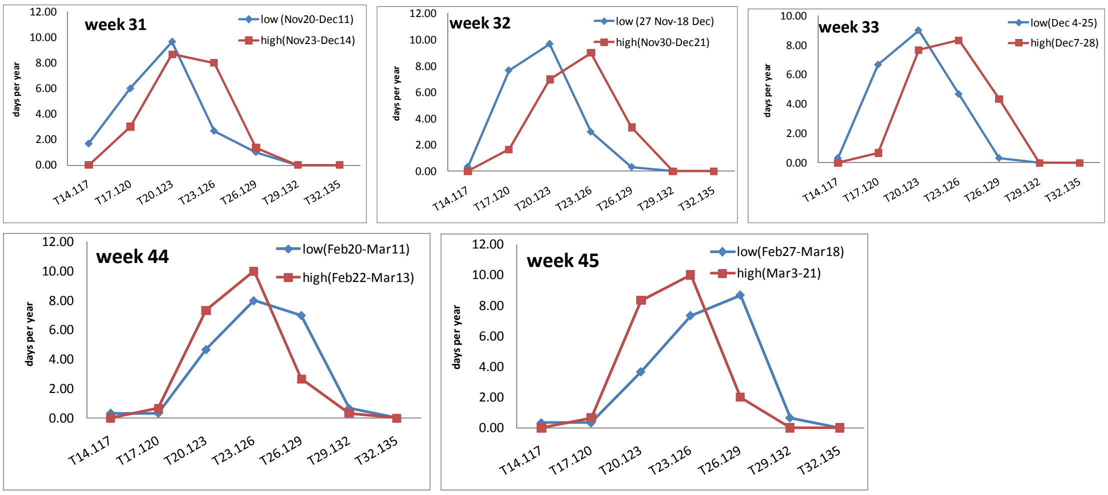

Figure 4: Graphs showing the frequencies of temperature intervals found to be influencing the grape yield *low* and *high* years. For example, in the graph top left, 10 days of temperature interval (frequency) at 20.1-23^{o}C and 2 days 23.1-26^{o}C at during week no 31 (between Nov 20-Dec 11) relate to *low* yield years whereas, 9 days at 20.1-23^{o}C and 8 days 23.1-26^{o}C during (Nov 23-Dec14) relate to *high* yield years. It is also interesting to note that just before harvest 8 days of 26.1-29^{o}C led to *low* yield years.

5. CONCLUSIONS

The paper illustrates a Kohonen SOM based data mining method used to depict the influence of daily extreme weather conditions on grapevine phenology, annual crop yield and wine quality. The initial SOM results of this work show associations between daily maximum temperatures of 14-23C^o (rounded) during weeks 1-29 and >26C^o during weeks 35-45 (ten weeks prior to harvest).

Using only temperature variability data (acknowledging that a more comprehensive set is necessary for continuing work in this research domain), extremes in weather conditions have been observed in relation to crop yield. Temperatures that are <23C^o during weeks 32, 33 and >26C^o during weeks 44-45 are associated with *low* yield. The χ^2 test was used to confirm this expectancy from the observed sample data. Similarly temperatures in the range 23-26 C^o during weeks 31-32 and <23C^o during week 45 have been confirmed as being associated with *low* yield years. This means that temperatures <23C^o in mid November to early December and >26C^o in the period from late February to early March are linked to *low* years in terms of yield. Meanwhile, temperatures 23-26C^o in the period mid-November to early December and late February to early March with <23C^o are associated with *high* years. Further research is underway to establish the associations between daily minimum temperatures (including grass minimum) and other weather variables as they influence grapevine growth and other wine quality indicators. The results are expected to enrich both the impact relationship matrix for crop yield and quality and consequently their visualisations as aids to a better understanding of the stochastic nature of this variable attribute combination.

ACKNOWLEDGEMENTS

The authors wish to thank Kumeu River Winery in New Zealand, Professor Jeffrey Hunter and Mathangi Shanthakumar for their advice during the preparation of this paper.

REFERENCES

1. Jones, G V, and Davis, R E,. (2000) Climate Influences on Grapevine Phenology, Grape Composition, and Wine Production and Quality for Bordeaux, France. Vols. Am. J. Enol. Vitic., Vol. 51, No. 3, 2000 pp249-261.

2. Sallis, P.J., Shanmuganathan, S., Pavesi, L., and Jarur, M. (2008) Kohonen Self-organising maps in the mining data mining of wine taster comments,:, 2008. Data Mining IX, Data Mining, Protection, Detection and other Security Technologies 2008. WIT press, Cadiz, Spain pp. 125-139.

3. Shanmuganathan, S., Sallis, P., and Narayanan, A., 2009 Statistical data analysis incorporating web text mining to establish correlations between grape wine taster comments and wine ratings.. s.l. : Published by IEEE computer society, 2009. In proceeding of the 6th International Conference on Information Information Technology in Asia 2009 (CITA09) "Towards Human-Centered Computing" held in Hilton Kuching Hotel, Sarawak, 6-9 July 2009 pp 258-262

4. Van Leeuwen, C., Friant, P., Choné, X., Tregoat,O., Koundouras,S., and Dubourdieu,D. (2004) Influence of Climate, Soil, and Cultivar on Terroir Am. J. Enol. Vitic. 2004, pp.55:3:207-217

5. Shanmuganathan, S., Sallis, P., and Narayanan, A. (2009) Modelling climate change effects on wine quality based on expert opinions expressed in free-text format: The WEBSOM Approach. M. Kppen et al. (Eds.), Springer-Verlag Berlin Heidelberg 2009. pp. 915-925., 2009. ICONIP 2008, Part I, LNCS 5506.

6. Shanmuganathan, S., Sallis, P., and Narayanan, A. (2009) Unsupervised artificial neural nets for modelling the effects of climate change on New Zealand grape wines. B. Anderssen et al. (eds), 2009. 18th IMACS World Congress - MODSIM09 International Congress 13-17 July 2009, Cairns, Australia. ISBN: 978-0-9758400-7-8. pp. 803-809.

7. Teuvo Kohonen, Self-organizing maps, Springer-Verlag New York, Inc., Secaucus, NJ, 1997

8. Drignei, D. A kriging approach to the analysis of climate model experiments. (2009) Journal of Agricultural, Biological and Environmental Sciences. Springer New York 2009 Vol. 14(1) pp 99-114. ISBN 1085-7117 (Print) 1537-2693 (online).

9. Selyam, A.M. Chaotic Climate Dynamics. Lunivar Press, 2007. ISBN-13 978-1-905986-07-1

10. Caprio, J M, and Quamme H A. (1998) Weather conditions associated with apple production in the Okanagan Valley of British Columbia., Agriculture and Agri-Food Canada Pacific Agri-Food Research Centre, Summerland, British Columbia, Canada, V0H 1Z0 1998, Vol. Contribution no.1075 129-137.

11. Caprio, J M, and Quamme, H A,. (2002) Weather conditions associated with grape production in the Okanagan Valley of British Columbia and potential impact of climate change. Agriculture and Agri-Food Canada, Pacific Agri-Food Research Centre Summerland, British Columbia, Canada V0H 1Z0 : s.n., 2002, Vol. Contribution no. 2139. pp755-763.

12. Soar, C J,, Sadras, V O, and Petrie, P R,. Climate drivers of red wine quality in four contrasting Australian wine regions. 2008, Australian Journal of Grape and Wine Research 14, 78–90, 2008.

13. National Institute of Water & Atmospheric Research. The National Climate Database, National Institute of Water & Atmospheric Research,. http://cliflo.niwa.co.nz/.

14. Viscovery: the modelling software, (2010). http://www.viscovery.net