Chapter 8: Development of a fuzzy logic model for the prediction of "total" grape quality from multiple must attributes

SECTION 1: A REVIEW OF LITERATURE - The "Quality" question

The relative availability of yield monitors compared with quality monitors has resulted in PA to date being driven primarily by improvements in management with respect to quantity. The absence of quality monitors is not due to the lesser importance of the management versus quality issue. Rather it is due to the need for more complex sensor technologies to measure quality coupled with an ambiguity in what is quality and the best way to measure it. The issue of improved quality is as siginificant or even more so in some crops than improved quantity. Almost without exception there is a pricing gradient in all agricultural produce based on indicative quality measurements. For example, wheat is graded according to protein content and disease content, lucerne hay according to nutritional status and weed seed status, cotton according to fibre length and strength, winegrapes according to the sugar content, pH and titratable acidity of the must and fruit according to flavour and appearance. If profitability is a function of product quality then quality information should form an important data layer in any site-specific production system.

There are several aspects to the "quality" question in relation to PA and PV. Firstly what is meant by "quality"? Secondly are current measurements of "quality" applicable to PA or is the development of new or alternative methodologies required? Thirdly are these measurement systems compatible with and robust enough for real-time monitoring? Finally how can the quality data be analysed and interpreted to identify best management practices from the information received?

8a.1 The Meaning of Quality

The dictionary definition of quality (Collins Australian Pocket Dictionary (1981)) indicates that quality has a variety of meanings including

- A characteristic attribute
- A degree of excellence

When applied to agricultural systems these definitions are somewhat vague and thus inadequate. Giomo *et al.* (1996) have proposed some alternative definitions for agriculture. The first is a production definition and the second an economic definition.

Definition 1: "Quality is the whole of those properties and characteristics of a product and/or a service which combine to meet the consumers requirement".

Definition 2: "Quality is not only a property but also a cost, which can be a burden on the production and consumption".

In general a producer is attempting to maximise the value of the produce by tailoring it to consumer requirements, after all the "consumer is always right". Thus traditional management practices during production are geared towards producing quality as defined by Definition 1 above. From a business perspective the second definition is sensible as it identifies that the quality of the produce is linked to the quality of the production system. Thus an improvement in end-product to fit consumer demands is not necessarily an improvement in quality if the production system is degraded in the process. As environmental auditing becomes more and more common, if not law, this economic definition will take on more importance. The economic value of the "quality" of the production system is already being shown in the premium offered for "organic" foodstuffs in western countries. For the continued development of the Australian wine export market, particularly in European markets, the demonstrability of high-quality production systems i.e. clean green vineyards, should be a major goal for the industry as a whole (Reedman, 2001). The failure to be proactive in this area could lead to a serious loss of market share overseas (Reedman, 2001).

For this research chapter (Part B) the production definition is used with an emphasis on how grape properties combine to meet consumer expectations.

8a.2 The Determination of Quality (Quantifying Quality)

Having established how to define quality there is a need to be able to measure it. Traditionally the quality of a product has been performed on a representative sample due to the fact that it is often difficult to test all of the product, especially in broadacre crops which have a low value per single unit. In crops where the value of a single discrete unit is relatively high and inexpensive measurements techniques have been developed, the testing of individual product is more commonplace for example NIR analysis of sugar content in temperate fruits at a rate of 3 pieces per second (Kawano, 1994). In vineyards quality is currently measured on composite samples from within a block or vineyard (so results are averaged across blocks). This approach is necessitated by the cost and particularly time needed for current grape quality analyses.

Using the definitions of Giomo *et al.,* (1996) "quality" is a very holistic concept encompassing a wide variety of product and production attributes. As mentioned previously little attention is currently afforded to the qualtiy of the production system in agriculture and this review will focus on the quality of the product. As quality is often a function of a multitude of product characteristics generally indicator variables are used. There are a variety of reasons why this may occur;

1) a quality attribute(s) is dominant
2) it is cost prohibitive or too difficult to analyse all potential quality attributes
3) the dominant quality variable(s) is difficult or expensive to measure and a correlated property is cheaper/easier.

The use of an indicator variable relies on a calibration between variables and/or with consumer preference. These calibrations may not be robust enough to encompass all varieties and all production systems, thus disadvantaging some and advantaging others. In particular the ability to link consumer preferences with quality measurements is vital to understanding how production can be altered to improve quality. Research to data indicates that the robustness of generic grape quality models, particularly between varieties but also regions, may be problematic (Esler *et al.*, 2001)

8a.2.1 Quality indices of grapes/wine

It is current practice in vineyards to measure three quality indices to help viticulturists to determine the optimum time for harvest. These are must pH, titratable acidity (TA) and soluble sugar content. These three characteristics have been chosen over time due to their ease of measurement in the vineyard and correlations with wine quality espescially in cooler climate production (Creasy, 2000). However Jackson and Lombard (1993) identify seven key grape/must characteristics that contribute to wine quality. These are discussed below with reference to current measurements methods.

1. Soluble Sugar Content (SSC). This is measured traditionally using a hydrometer to determine sugar content from the density of the must. Nowadays must SSC is more commonly measured using a handheld digital refractometer. There are several different scales used for the measurement of SSC. The three most common being Brix°, Baume and Oesche. SSC is an indication of the potential alcohol percentage and residual sugars (sweetness) of the final wine (Jackson and Lombard, 1993)

2. pH. Wine pH is considered to be limiting if it is >3.6. Lower pH tends to create a more chemically and biologically stable wine with lower microbial activity producing a more even and controllable sugar and malate fermentation. Higher pH leads to decreased colour intensity in reds and often more 'browning' in white varieties. As pH increases so does microbial activity producing unwanted fermentations that may affect the colour and/or flavour of the wine. As well higher pH binds and inhibits the bacterioant SO_2 further increasing microbial activity (Jackson and Lombard, 1993).

3. Titratable Acidity. This is another measure of the content of acids in the must and is considered to be best between 6-10g/L. Problems with TA can be corrected in the vinification process through acidification/deacidification. Low TA is often associated with high alcohol content and a burnt bitter and coarse after taste (Marais, 1987). The two dominant acids are tartaric and malic which can be independently measured enzymically, or with HPLC (Jackson and Lombard, 1993)

4. Monoterpenes. These are the dominant flavour compounds in wine. There are two types, free volatile terpenes (FVT) and potential volatile terpenes (PVT). FVT are the terpenes that can be immediately detected by taste and smell whilst PVT are considered to be a flavour reservoir and become detectable with the aging process (Reynolds 1997). Terpene content is usually measured using gas chromatography/mass spectroscopy (Pollnitz *et al.*, 2001).

5. Potassium. This is important as it tends to bind tartaric acid into potassium tartarate thus reducing the TA of the must (Jackson and Lombard, 1993). High K levels have also been associated with poor colour in red wines (Somers, 1975) Potassium has traditionally been mesured using an Atomic Absorption Spectrometer (Gillespie, 2003) however recent studies have shown that K can also be measured in plant tissue using NIR spectrospy (Ciavarella and Batten, 1998).

6. Anthocyanins. Anthocyanins are found predominantly in the skin of the fruit. They are especially important in red wines as they are the primary colouring compounds in the must. The diglucosides of malvidin, petunidin and cyanidin are predominantly responsible for the red colour in wine (Ballinger *et al.*, 1974). They are measured using HPLC or the wet chemistry method of Willams (1985).

7. Phenolics. These are derived from the skin, seed and rachis rather than the flesh of the fruit and are more important in red wines. They are flavour determinants and like anthocyanins can be measured using HPLC (Jackson and Lombard, 1993) or optical fibre evanescent field absorbance (FIFA) (Lye *et al.,* 2004).

As well as these individual characteristics some research has been done on ratios between individual characteristics. Coombe *et al.* (1980) developed a ripeness ratio that links berry pH and sugar content while more recently Ilane *et al.* (1996) derived the glycosyl-glucose (G-G) assay which provides an indication of the ratio between influential and non-influential flavour compounds in the must. The G-G assay is now commonly used in Australian viticulture (Gishen *et al.*, 2001). Mixed approaches have also been reported where measurement techniques are used conjointly to improve quality prediction. Moio and Etievant (1995) have used gas chromatography to separate volatile components prior to an olfactory rating by an expert sniffer.

8a.2.2 Quality and the Consumer

For viticulture the relationship between the consumer (winery) and producer (vineyard) is fairly strong with the winery often contracting grapes with specific quality attributes. The grower then either meets these specifications to gain the best price or is penalised with reduced prices. It is the connection of these specifications with the end consumer's requirements that is more difficult (Gishen *et al.* , 2001). The relationship betwen wine quality and the consumer is fairly unique within agriculture. Consumer preferences for wine tend to be dynamic thus wine and therefore grape quality can also be dynamic. Wine quality is subjective and often relates to the tasters frame of view and personal preferences. Consumers of wine also range enormously in their experience and perceptiveness which influences their rating. The influence of marketing, expert opinions and wine competitions also tends to shape consumer preferences (Gishen *et al.,* 2001). Consumer sensory preferences can be determined statistically (Lesschaeve *et al.,* 2001), however this is rarely done with vigenerons often producing wine to their preference rather then seeing if their product meets market requirements (Gishen *et al.*, 2001). The rise of "brand" wines for export market will place new emphasis on understanding consumer tastes as companies will not only be looking to produce a consistent quality of product but also ensuring that this quality adapts to changing consumer preferences (Reedman, 2001).

8a.3 Real-time sensing of Quality

The methods of analysis outline above are generally not viable for measurement of on-the-go grape quality, for example, the use of a hydrometer for determination of sugar content, gas chromatography/ mass spectroscopy for terpenes. However there are other ways of measuring these characteristics, such as Near-Infrared Spectroscopy (NIRS), which have potential for real-time sensing. In most agricultural commodities there exists a challenge to develop quality sensors that are applicable for site-specific mapping either pre–harvest or at harvest. This may take time as many quality tests are industry standard and change is often hard to implement. Despite this the fairly rapid adoption of new technology, particularly NIRS, in the grains and wine industry indicates that change is possible. At the moment such technology is applied only on representative samples at collection depots (e.g. siloes or wineries) however the ability to map quality should expedite the movement towards the use of such technology in on-the-go real-time sensors.

The ideal situation is to real-time sense quality at the same time as yield. Thus on-the-go quality sensors need to be robust enough to be attached to harvesting equipment. Alternatively quality can be sensed just prior to harvest either as point data or continuously. The resultant quality map can be incorporated into the harvesting system to segregate yield. Perhaps, until the development of reliable real-time quality sensors, this may be the preferred option. This approach using prior information, rather than on-the-go data, has already been shown to be viable for selective harvesting (Johnstone *et al.,* 1998, Penn 1999, Carothers 2000, Bramley *et al.*, 2003)

The development of quality sensors will necessitate the development of decision support systems (DSS) that are able to segregate yield according to the information obtained from the sensors. The incorporation of a quality sensor(s) with yield monitor produces new challenges involving how the data from multiple sensors is fused and interpreted. The first part of this section looks at possible sensor technology and the second at the issue of multi-data fusion.

8a.3.1 Types of Sensors

There are a wide variety of techniques that can be used to objectively measure the chemical and physical attributes of grapes or must. The difficulty in designing sensors lies in a) the development of robust calibration curves that work well outside of the laboratory environment and b) the engineering problem of sensor mounting and sample presentation sensor. Currently the wine industry is focusing on NIRS and the development of calibration curves (Gishen and Holdstock, 2000, Gishen *et al.,* 2001) for use in wineries rather than vineyards. It is expected that the knowledge gained from the winery will be adapted for the vineyard at a later stage. The following section highlights some of the potential approaches that could be taken for sensor development with an emphasis on the current NIRS approach.

Light refraction – Refractometry has already become the industry standard for measurement of SSC in must with several commercial types of digital refractometers available on the market. Unfortunately refractometry requires a debris and bubble free solution to accurately measure SSC thus sample preparation and delivery o the sensor is of utmost importance. If these problems are overcome then refractometry is capable of producing accurate results. Inhouse research by Pellenc Ltd indicates that an on-the-go refractometer SSC sensor is viable (Bruno Tisseyre, ENSAM, Montpellier *pers. comm.*).

ISFET/ENFET – Ionselective Field Effect Transistors (ISFETs) and Enzyme Field Effect Transistors (ENFETS) have been around for several decades but are now becoming more popular as the possibilities for their use are becoming better understood and more feasible. ISFET/ENFET sensors are able to detect a large range of both inorganic and organic compounds depending on the particular detector reagent or enzyme used. Work on an ISFET (Seo *et al.,* 1996) and ENFET (Shul'ga *et al.,* 1994) Glucose sensor shows the possibility for the use of these sensors in detecting must sugar content. ISFETs also exist for the detection of potassium and pH in solution and are commercially available. Robust ISFET pH sensors have also been designed for the direct measurement of grape pH (Sentron Inc, 2001) in the field however no applications have been tried in real-time situations.

Electronic noses - There are a wide variety of chemosensor technologies that have been developed for use as electronic noses. These include conductometric chemosensors (metal oxide semiconductors and conducting polymers), chemocapacitors, potentiometric chemosensors (e.g. Metal Oxide

Semiconductor Field Effect Transistor), gravimetric chemosensors (Quartz Crystal Microbalances), optical chemosensors (fluorescent sensors), calorimetric sensors, and amperometric sensors (Pearce *et al.*, 2002). Electronic noses are designed to detect complex aromas using sensor arrays. They are of great potential as the organoleptic (aroma) properties of the must is the most sensitive indicator of final wine quality (Scienza *et al.,* 1996).

Of the chemosensors mentioned above the Metal Oxide Semiconductor Field Effect Transistors (MOSFETs) and Quartz Crystal Microbalances (QCM) sensors have been trialled as non-invasive in-line monitors. MOSFETs have been used for process monitoring of *E. coli* fermentations (Haugen and Bachinger in Pearce *et al.,* 2002), for the classification of fruit juices (Winquist *et al.*, 1999) and assessment of the sensory appeal of coffee (Pardo and Sberveglieri, submitted) while QCM sensors have been used for food and beverage quality assurance in fresh fish (Natalle in Pearce *et al.*, 2002). All of these trials have produced encouraging results. However observe that results are improved when the sensor output is coupled with that of an artificial tongue. The use of sensor arrays produces a problem of multi-sensor data fusion and this will be discussed further below. While no research was found during this literature review on winegrapes, the development of the technology in other areas should facilitate adoption in viticulture/oenology.

Near-Infra Red Spectroscopy – This is potentially the most useful tool as the NIR spectra may be able to measure multiple quality characteristics simultaneously. Currently most work is being aimed at the measurement of SSC using NIR transmission spectroscopy. Literature exists on the measurement of SSC in many fruits, for example, peaches (Peiris *et al.,* 1998), tomatoes (Peiris *et al.*, 1998), pineapple and mango (Guthrie and Walsh 1997), pawpaw (Greenshill and Newman, 1999) and nashi (Tanaka and Kojima 1996). Most of this work has been able to predict SSC with r^2 values greater than 0.70. Studies by Huxsoll *et al.* (1995) have shown that NIR transmission spectroscopy has shown highly positive relationships between measured and NIR predicted values of bulk density, visual grade and moisture content in raisins. This work has recently been extended into winegrapes (Gishen and Holdstock, 2000).

In particular extensive progress has been made recently in the use of spectroscopy for quality determination at the winery. The advantage of spectroscopic analysis is that only the one sensor, recording at different wavelengths, is needed to measure a multitude of properties. Instruments such as the Foss WineScan FT120 have been developed to test a variety of must and wine quality factors. NIRS calibration curves have been established for ethanol, total acid, pH, volatile acidity, reducing sugars, tartaric, malic and lactic acids, red grape colour and G_G assay with good correlations for all properties (Gishen and Holdstock, 2000, Gishen *et al.*, 2001 and Kupin and Shrikhande, 2001) except the organic acids (Kupina and Shrikhande, 2001). Calibrations for pH, total anthocyanins and SSC have been developed for different varieties and different regions within Australia as well as a generic calibration for all varieties pan-Australia (Esler *et al.*, 2001).

NIRS research to date has focused on the use of transmission spectroscopy where the sample beam is passed through the sample before being analyzed. This requires a constant sample preparation which is suited to laboratory analysis but not to field measurement. An alternative form of spectroscopy is diffuse reflectance spectroscopy. This method intercepts and analyses the reflected radiation from the surface of the object. Thus the opportunity exists to derive information on the content of a substance e.g. must or grapes by scanning the surface of the substance. This will minimize or negate the need for any sample preparation prior to analysis.

Some problems with the use of this methodology have been identified in the literature. The principle concern outlined by Peiris *et al.,* (1999) is the spatial variability of sugar within the fruit and the inability of NIR spectroscopy account for this variability. Thus a standard point of measurement or multiple scans are needed to allow comparisons between fruit. The small size of grapes compared to other fruit measured, e.g. apples and peaches, may negate this effect.

For repeatable accurate field results, either the sample must be delivered in a homogeneous manner to the sensor or the calibration must be robust enough to account for variability in the scans. Given the inherent high variability between vines and even within bunches (Dunn and Martin, 2000) a statistically valid sampling protocol is require to account for this variability. The number of measurements required for a significant representative sample will depend on the rate of scanning (i.e. the number of wavelengths) as well on the area scanned. Error sources and intrinsic non-linearities such as debris (dust and leaf litter), fluctuating lighting, variable nature of the sample, disease/pest artifacts etc need to be overcome (Sanchez *et al.*, 2000). Some of these errors can be overcome through engineering solutions and others through statistical manipulation of the data (e.g. PLS, Genetic Inside Neural Networks analysis) (Sanchez *et al.*, 2000).

Guthrie *et al.* (1998) found that the NIR calibration procedure was not robust enough to be used between summer and winter crops of pineapple and between varieties. This may have a significant influence in grapes due to the large number of varieties harvested and in particular the difference between white and red grapes. Research from the AWRI (Esler *et al.,* 2001, Gishen *et al.,* 2001) indicates that this may not hold true for winegrapes however varietal and regional calibration models are being developed. These calibrations have been shown to be robust when transfered between similar standardised spectrometers. However the simultaneous standardisation of multiple spectrometers from different manufactors has been identify as a potential problem to the successful use of the technology (Gishen *et al.*, 2001)

8a.4 Multiple quality indicators and multi-data fusion

The ability to measure and geo-reference crop information is just one step of a site-specific management system. As discussed in Chapter 1, Precision agriculture is not just data collection, it is a holistic, cyclical approach involving measurement (data collection), analysis (data manipulation), interpretation (decision support) and action (variable rate input/management) which is repeated every production cycle (see Figure 1.2). As indicated earlier grape/wine quality is multiparametrical thus the collection of multiple individual quality indicators may not and usually does not provide an actual “total” quality estimate. Data must be analyzed and interpreted to achieve a true quality measurement. From this literature search there is a general lack of understanding and research in agronomic disciplines into how to analyse and interpret multi-sensor data. However research into multi-sensor data-fusion is progressing elsewhere particularly in the area of robotics and mechatronics. (For examples in the field of robotics readers are directed to the Proceedings of the NATO Advanced Study Institute on Multisensor Data Fusion, Hyder and Waltz (2002)). For many crops the issue of multisensor data fusion is minor as there is one dominant quality indicator e.g. protein in grains. For viticulture, quality is a much more complex problem. Not only is quality a function of a variety of different quality characteristics that may be uncorrelated (Creasy, 2000) but the relative weight (importance) of each characteristic to the overall quality may differ between varieties as well as within varieties depending on the end use of the grapes.

The short history of Precision Agriculture has already shown that the main impediment to uptake is a lack of decision support for the technology (Searcy, 1995). Given the successful development of an on-the-go grape quality sensor(s) a decision support mechanism needs to be in place to facilitate the adoption of the technology.

At the winery a decision must be made, based on field measurements, field tasting and winery analysis, on the fate of grapes and the potential quality of the resultant wine. Whilst maturity and to a lesser extent quality is determined analytically through Brix°, pH, titratable acidity measurements and asociated indices (Creasy, 2000), the decision on the final quality is still strongly influenced by traditional heuristic expert systems (e.g. a taster tasting in the vineyard, or traditional response from a block) (Guilbaud-Oulton *pers comm.*, 2001). Such undeterministic human expert systems may be highly effective in selecting premium quality wines but from a scientific point of view they are flawed. Measurements are subjective to the training and preference of the taster and no measurement of imprecision is obtained thus risk assessment is difficult to determine (Russo and Rampani, 1994).

The first step in the building of a Decision Support System (DSS) often requires data manipulation and/or reduction. It is likely that the output from the sensor(s) is either too large, in the wrong format or at the wrong scale to be used as a variable in a decision making model, e.g. a raw NIR spectra, or that each sensor has differing performance charactersitics which need to be corrected (Chicolea and Dickstein, 2000). A wide variety of signal processing and statistical techniques exists for data reduction including principal components analysis (PCA), discriminant function analysis (DFA), partial least squares (PLS), multiple linear regression (MLR), cluster analysis (CA), nearest neighbour analysis (NN) and Genetic Inside neural Network (GINN) (Pearce *et al.,* 2002). Chicolea and Dickstein (2000) have also published a list of rules and criteria for data fusion, especially in relation to non-destructive testing. It is not my intention here to describe these methods but to identify that data manipulation/reduction is a principal step in a DSS.

The second step is to create a model that accepts the sensor data and is able to produce a decision. Examples of multi-sensor models already exist in agriculture e.g. the three stage fuzzy logic model of Verma (1996) for prediction of the optimum sell date for tomatoes and the land-cover classification of Solaiman (1999). Zadeh (1994) champions the idea of soft computing, instead of just fuzzy logic, in modelling human perceptions. Soft computing is a term used for the amalgamation of techniques that are used in differing ways and combinations to simulate human thinking. It is an attempt to exploit the tolerance for imprecision, uncertainty and partial truth of information to achieve tractable, robust and a low cost solution. This is a process that humans perform everyday when making decisions. This concept can be illustrated through the process of parking a car (Zadeh 1994). Car parking is generally easy as the final position of the car is imprecise. The more precisely we specify the final position the harder it becomes to park. The increase in precision however does not really improve the final outcome. Zadeh (1994) has proposed three basic components to the soft computing approach - fuzzy logic, neural networks and probabilistic reasoning. Since the publishing of that paper the study of biologically motivated systems has become wide spread and other techniques e.g. self-organising maps (SOM), radial basis function (RBF), genetic algorithms (GA), wavelets, neuro-fuzzy systems (NFS) and adaptive resonance theory (ART) have been developed and expanded (Pearce *et al.*, 2002). These technologies for pattern analysis are especially attractive as they have the potential to perform incremental learning and offer self-organizing and self–stabilizing potential. (Pearce *et al.*, 2002)

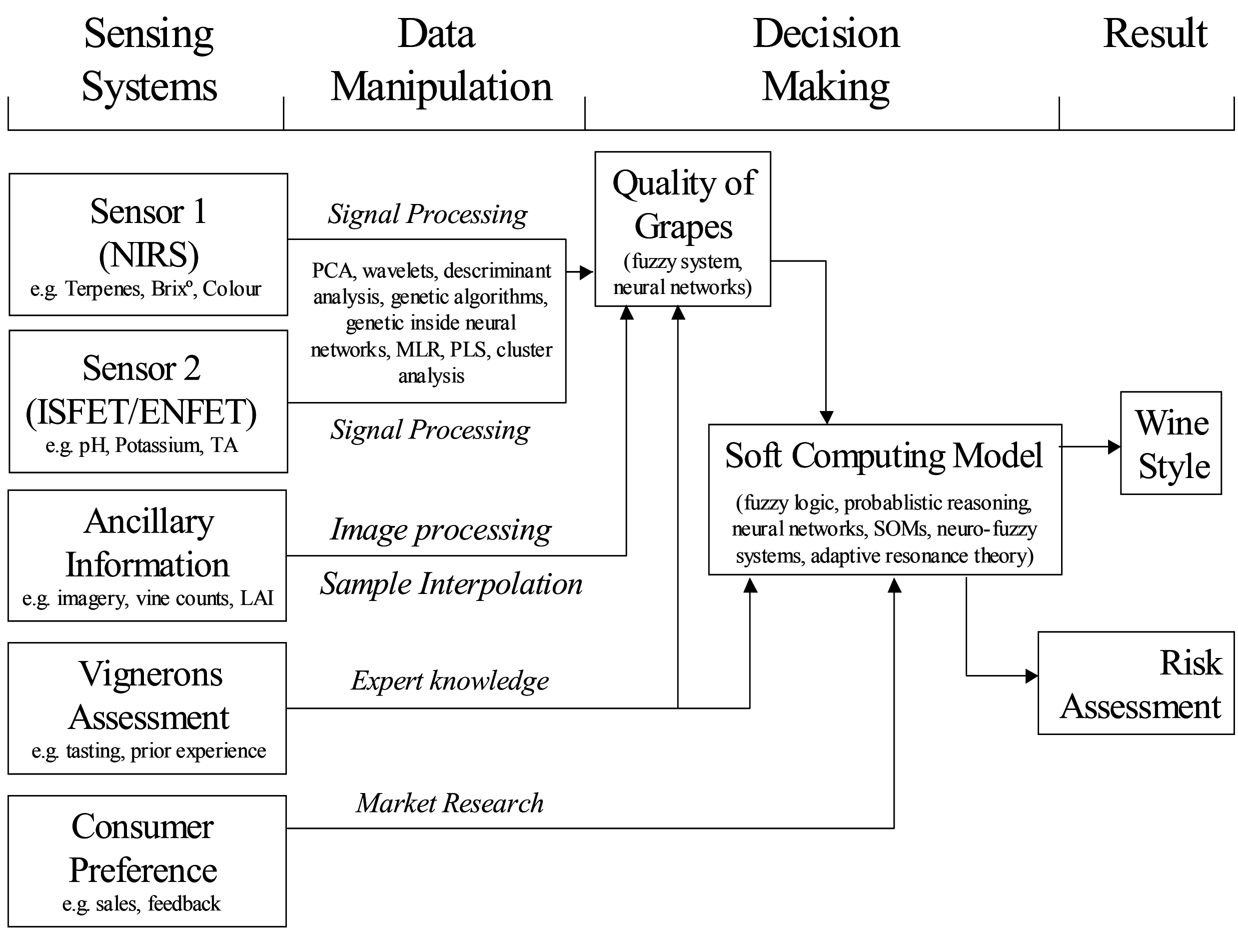

Figure 8a.1: Diagrammatic representation of the process of multi data fusion and decision making of winegrapes.

SECTION 2: **RESEARCH PAPER**

8b.1 Introduction

A large percentage of the Australian crush is now bottled as "brand" wines rather than vineyard specific wines. This changes the emphasis of production from a unique identifiable "vineyard" vintage to a vintage of repeatable quality. The rise of "brand" wines is much more conducive to the use of scientific research/methods in more extensive viticultural production systems. "Brand" wines are often not premium thus it is economically unfeasible to exhaustively sample and categorize blocks using expert tasters. The increased research into and adoption of NIRS analysis by the industry provides the opportunity to quickly determine multiple quality characteristics. These data could be used to construct a hard deterministic model of quality. However decision making in wine production is not a hard science and usually relies on human expertise (often described by heuristic rules) to interpret both hard (e.g. pH, Brix°) and soft data sources (e.g. tasters assessment). For situations such as this, traditional deterministic and probabilistic models fail to account for the adaptive and subjective human component in the decision (Ren and Sheridan, 1995). In the past 30 years a variety of soft modelling techniques have been developed to overcome this limitation e.g. fuzzy systems, artificial neural networks, probabilistic reasoning (Zadeh, 1994) and more recently self-organizing maps (SOM), radial basis function (RBF), genetic algorithms (GA), wavelets, neuro-fuzzy systems (NFS) and adaptive resonance theory (ART) (Pearce *et al.,* 2002).

Deciding the potential of grapes is really a two-pronged question. Firstly a decision on the quality of the grapes must be made and secondly a decision on the potential of the wine and the effort and care required for vinification. These questions require different approaches. Attempts to model grape quality are probably best served by fuzzy systems. While both fuzzy systems and neural networks are applicable, the use of fuzzy systems (e.g. fuzzy logic, fuzzy decision trees) is generally preferred when there is not an extensive training set or there is a strong reliance on "intuitive" or "expert" knowledge (Janikow, 1998). Fuzzy systems try to mirror human thinking by recording expert knowledge as linguistic variables within the model. Linguistic variables allow expert knowledge to be incorporated quickly and easily and tend to provide the operator with a clearer understanding of the model operation (Russo and Rampani 1994, Janikow 1998). A detailed model has been developed for the prediction of sale date and quality in tomatoes (Verma, 1996) and a preliminary investigation into the prediction of grape quality using fuzzy sets has already been carried out in France (Tisseyre and Mazzoni, 2001).

The existing fuzzy viticulture model of Tisseyre *et al.* (2001) is currently applied retrospectively post-harvest. It is based on grape sugar content, maturity and vine vigour. The model does not need the development of appropriate real-time on-the-go sensors to be effective. The methodology and theory of these multi-sensor data-fusion models is constant regardless of whether the data is real-time or laboratory sensed. Thus development of these models will aid growers now and also in the future. With the successful development of robust calibrations and on-the-go quality sensors then, with the further refinement of the existing model(s), a real-time decision support system can be quickly developed and mounted with the sensor to record and manage the crop. If relationships between proximal- and remote-sensed imagery and quality or quantity indicators can be reliably proven then such data may also be incorporated into the model(s). Correctly sampled geo-referenced information on crop parameters, e.g. bud/bunch counts, crop load etc, may also be included. Forward thinking at this stage will facilitate the adoption of the technology and correct interpretation of the resultant information. Integrated models will allow for vertically orientated quality predictions where models may be run repeatedly throughout the growing season as new information comes to hand. Thus growers will have an indication of quality potential and spatial variability from early in the season allowing them to perform differential management to improve overall quality. As the season progresses the model output should reflect the effect of with-in season management.

The second question of what sort of wine to produce is a soft computing problem that may involve a variety of techniques. Given that quality is a variable parameter dependent on consumer preferences any model of the potential value of wine requires a learning capability. Thus as consumer preferences and markets change the model is able to adapt to select the best fate of the grapes. Fruit quality information needs to be combined with information on production costs, consumer preferences, market forces to determine the potential profitability of the wine and the risks associated with it.

Of principal concern for this chapter is the development a model for the the prediction of overall grape quality from quality indicators. Model development is not dependent on sensor development. Laboratory and field measurements can be used as data sources to develop and test various models prior to sensor development. The final version of the model will require some co-operation with those developing the sensor system to ensure that the model mirrors the potential output of the sensor.

8b.2 Methods

8b.2.1 Site and sample selection

The study was carried out at the Orlando Wyndham's Pokolbin Vineyard (latitude 32º 43' south, longitude 151º 14' east) in the Hunter Valley, NSW (approximately 180km North-West of Sydney). Sample sites were determined using the stratified randomised design as described by Webster and Oliver (1990). The strata were ' potential management zones' and were obtained as follows. An aerial photograph of the survey area was digitised using a Umax Mirage IIse scanner. The red, green and blue bands of the digital image were clustered in *JMP*® using hard k-means clustering (Hartigan and Wong, 1979). Assigning two clusters produced two distinct, fairly contiguous zones (Figure 8b.1). The 100 samples were then divided between the two zones based on percentage area.

Of these 100 samples, a further 10 sites were chosen randomly. At these 10 sites nested transects (Pettitt and McBratney, 1993) were used to ensure that the variogram was accurately represented at short lag distances. Samples were taken from the middle vine of the panel, the adjacent vine, the middle vine of the next panel and the middle vine of the 4th panel along from the original sample (Figure 8b.2). This produced a total of 130 vines. Vine location was recorded by block number/row number/panel number/vine number and direction from which row was entered (E or W). Vine sites were geo-referenced with a Garmin 1200XL GPS averaged for 1 min at each location and converted to Eastings and Northings (UTM GDA) using the GEOD transformation program (LPI, 2001) The area of the study was 11.7 ha.

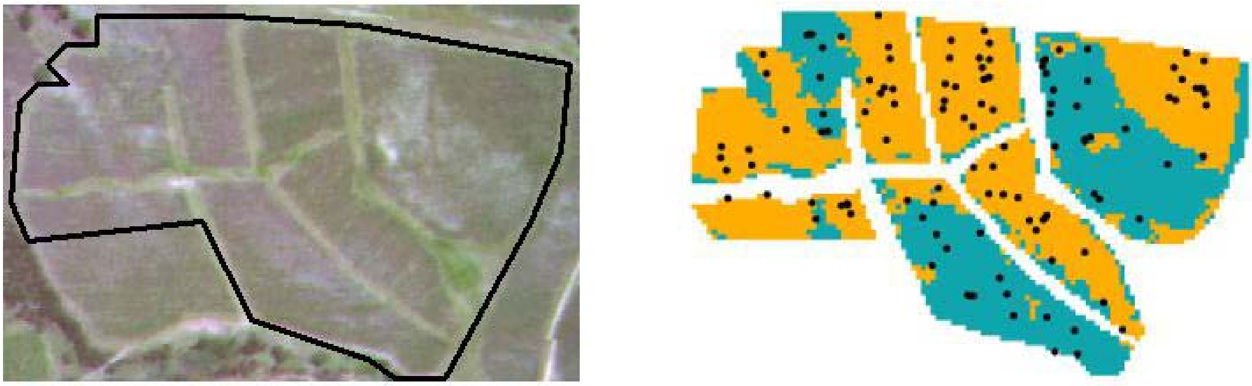

Figure 8b.1: Aerial image of the survey area and result of the 2-cluster analysis showing winegrape sample sites.

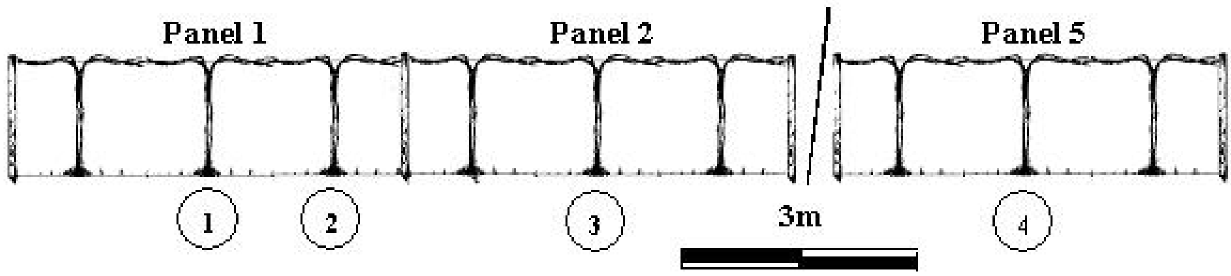

Figure 8b.2: Diagrammatic representation of a nested transect sampling scheme. Numbers indicate vines being sampled

8b.2.2 Sample preparation and analysis

Three bunches were picked from the fruit zone of each selected vine. Bunches high or low in the canopy were not taken. Bunches were crushed in a mortar and pestle and strained through a 2mm sieve to remove coarse grape debris. Samples were frozen immediately after crushing and analysed in May, three months later. Three analyses were performed, pH, TA and Brix°. The must pH was determined using a Radiometer analytical pH meter with a combined electrode. Brix° was determined using an Atago digital handheld refractometer. Titratable acidity (mg/l equivalent of tartaric acid) was determined using 0.1M NaOH to an end point of pH 8.2 (as per the standard method used by Orlando-Wyndham (Deed *pers. comm.* 2001). The mean of the samples was adjusted to the mean value of the blocks, as recorded at harvest, to negate any effect of the freezing process on the must. An analysis of variance was performed on the data to see if the clustering approach had any effect on the grape quality attributes.

8b.2.3 Fuzzy logic quality model.

The fuzzy logic model of grape quality was developed using the fuzzy toolbox extension of MATLAB (Roger Jang and Gulley 1995). The model utilises Mamdani's fuzzy inference method (Mamdani, 1975) with three inputs, pH, TA and Brix°. The fuzzy set for each input was defined by a membership function (MF), denoting low, optimal or high input values. The threshold values for each input were obtained from James Manners, a winemaker at Orlando-Wyndham, are shown in Table 8b.1. Various functions were tried to define the three MFs including (a) trapezoidal, (b) triangular and (c) gaussian (Appendix 8.1). Five potential grades of fruit quality were identified – bulk, commercial, semi-premium, premium and super-premium. The three input fuzzy sets with three levels of membership produced 27 if-then rules (Appendix 8.2). The if-then rules were also formulated in consultation with the winemaker. For shiraz grapes in this region pH is considered the most important must property. The if-then rules reflect this by weighting pH above Brix° and TA. The fuzzy output from the model was defuzzified into a crisp number using the centroid value of the fuzzy inference system.

The potential distribution of output from the models was tested by running different permutations for pH, TA and Brix° values. Values of pH were tested at increments of 0.025 for a range of 3.4 - 3.7, Brix° at increments of 0.25 between 19 - 26 and TA at 0.25 increments for a range from 4 - 8 g/L. A random subset of 50 samples was used to compare output from the models to the opinion of the expert system (winemaker). The distribution of the model output and the correlation of the sample set with the expert system (winemaker) was used to identify the best performed model.

Quality Attribute	**MF**	**Range**
pH	Low	<3.5
	Optimal	3.5-3.6
	High	>3.6
Sugar (Brix°)	Low	<22.5%
	Optimal	22.5-24.4%
	High	>24.4%
Titratable Acidity	Low	<5.5 g/L
	Optimal	5.5-6.5 g/L
	High	>6.5 g/L

Table 8b.1: Range of values for individual must quality attributes.

8b.2.4 Prediction and interpolation of grape quality and gross margin of production

Having identified and refined the best model, the sample data were used as inputs into the model. The resultant output was then interpolated using punctual kriging, based on a global variogram, onto

Quality	**Price per Mg (AUD$)**	**Quality score**
Bulk	325	0 – 25
Commercial	750	25 – 45
Semi-premium	1250	45 – 65
Premium	1600	65 – 80
Super Premium	2000	80 – 100

Table 8b.2: Quality grades and respective price and model output range.

a 3m grid using Vesper (Minasny *et al.,* 2002). The must properties were also interpolated with the same method. Maps of individual must properties are shown in Figure 8b.6. The results of the interpolation of the model output were mapped with a continuous numerical legend (Figure 8b.7) and with a linguistic quality legend, shown in the inset, according to the quality definitions in Table 8b.2. All maps were produced using ArcView® (Esri, 2001).

The gross margin was calculated (Equation 8.1) based on the average yield, as no yield maps were available, with site-specific variable quality. Inputs and cost of production were considered uniform for all parts of the production system. Cost of production was estimated at \$5500/ha by the vineyard viticulturists and value of resultant grapes is according to Table 8b.2. Average yield for the vintage was 4.3 Mg /ha.

$$GM = (Yield * Price) - Cost\ of\ production \qquad \text{Equation 8.1}$$

where price is dependent on quality grade (Table 8b.2)
cost of production includes both fixed and variable costs

8b.3 Results and Discussion

8b.3.1. Results of Must analysis

Table 8b.3 shows the summary statistics for pH, Titratable Acidity (TA) and Brix° analysis of the 130 samples. The pH and TA values are above optimum and the Brix° below optimum. The high TA and low Brix° was expected as the grapes were picked before they reached optimum maturity. As berries maturity TA will fall as malic acid is metabolised and the concentration of tartaric acid declines with increased berry water uptake (Jackson and Lombard 1993). Conversely Brix° tends to increase as the berry becomes the preferred sink for photosynthate (Jackson and Lombard 1993). Grape must pH also tends to increase with maturity especially in warmer climates (Jackson and Lombard 1993) however the relatively high pH in the grapes is unexpected given the ripeness of the grapes. The elevated pH may be due to the unique combination of climatic conditions for the season or due to an external influence e.g. elevated potassium concentration in the grapes (Gladstones, 1994).

Statistic	pH	Brix°	TA
Mean	3.81	19.08	7.30
Std Dev	0.14	1.37	0.35
Median	3.81	19.08	7.30
Maximum	4.17	22.63	8.32
Minimum	3.39	15.4	6.39
Range	0.76	7.23	1.93
N	130	130	130

Table 8b.3: Summary statistics of the grape must analyses

In the Hunter Valley in 2001 the period from veraison to maturity was characterized by below average temperatures and above average rainfall. Fruit from this part of the vineyard was picked before full maturity to avoid further loss from predicted poor weather, the potential onset of fungal disease and a further increase in grape must pH. The combination of bad weather and an early harvest produced low quality grapes.

8b.3.2 Significance of Clustering

The grape sampling design was based on a randomized stratified design derived from cluster analysis of an existing colour aerial photo. Traditionally yield (vigour) and quality have been considered to be inversely related to each other (Creasy, 2000). However recent site-specific studies have shown that quality attributes may not be statistically different between areas of different yield/vigour (Bramley, 2001, Ortega and Esser, 2003). The validity of using this random stratified sampling system was tested by ANOVA of the measured grape charateristics and the total quality prediction between the predicted clusters. The comparison of the spread of the data, mean and standard deviation is shown in Figure 8b.3 and the cluster means and probability statistics from the ANOVA is given in Table 8b.4.

	pH	Brix°	TA	Total Quality	N
Cluster 1	3.828	19.329	7.285	22.479	52
Cluster 2	3.795	18.910	7.312	22.504	78
Prob > F	0.194	*0.086*	0.664	0.9916	

Table 8b.4: Cluster means and summary of the ANOVA of winegrape attributes and total quality between the two clusters. (Italics indicate significance at the 0.1 level)

All three grape characteristics and the predicted total quality were not sifgnificantly different between the two clusters at the 0.05 level. Brix° was significantly different at the 0.1 level. The lack of significance reinforces the results from concurrent studies that yield and quality do not show any strong constant relationship. Given these results randomized stratified sampling based on plant vigour imagery may not be suitable for studies of winegrape quality. Despite these findings the use of plant vigour imagery has been shown to be effective for selective harvesting (Johnston *et al.,* 1998,

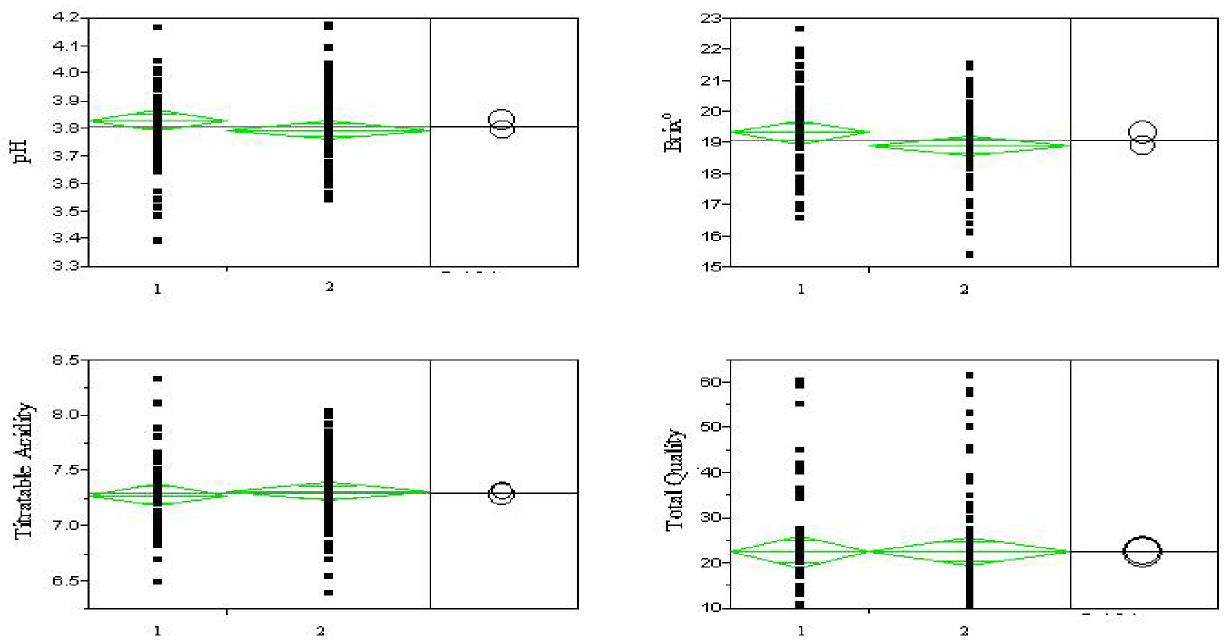

Figure 8b.3: Graphical results of ANOVA of winegrape properties and toral quality showing spread of the data, cluster means and Students t-test comparison.

Bramley *et al.,* 2003, Carothers, 2000, Penn, 1999).

8b.3.3 Test of the model

Figure 8b.4 shows the distribution of output from the hypothetical permutations of must properties for each model. The models with triangular and trapezoidal MFs ranged from 10 to 90 and the gaussian MF model from 8 to 84. The gaussian MF model had very few permutations that produced total grape quality higher than 75 and was discarded. The trapezoidal model produced a more even spread of outcomes than the triangular model. This is consistent with previous work (Pedrycz, 1994) who found that triangular and traezoidal models produced the best estimation of the possibility distribution when modelling an "expert" based system.

Figure 8b.5 shows the output from the three models versus the validation set from the winemaker . The triangular and trapezoidal models produced a better fit (r^2=0.58) than the gaussian model (r^2=0.45) (N.B. the linear regressions are fitted with the line passing through the origin). The trapezoidal model was chosen as the best model based on a more even spread of output from the permutation set.

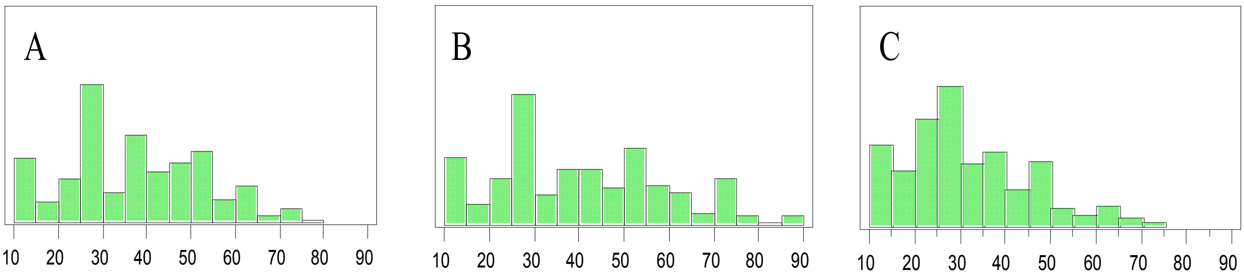

Figure 8b.4: Distribution of permutation output from the three models ((A) triangular, (B) trapezoidal and (C) gaussian.

8b.3.4 Determining site-specific quality

Individual must properties are displayed in Figure 8b. 6 ((a) pH, (b) Brix°, and (c) Titratable acidity (TA)). The correlation matrix between the quality predictions and individual must properties for the 130 sample points are given in Table 8b.5.

When applied to the 130 sample points the trapezoidal MF model returned quality scores ranging from 10.6 to 61.3 with a mean of 22.5. This value places the fruit in the bulk category (Table 8b.2).

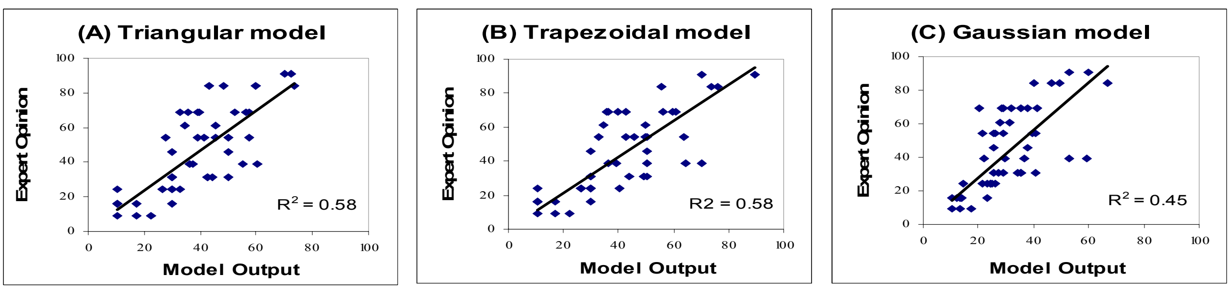

Figure 8b.5: Comparison of output from the fuzzy models vs. expert opinion

However only 73% of points were located in this grading with 19% graded as commercial and 8% as semi-premium.

The corelation matrix shows that all three attributes are negatively correlated with final quality. pH and TA show the strongest correlations with quality which is expected as the model is weighted towards these properties. A negative correlation is generally expected for pH and TA. A high must pH tends to produce unstable wines with higher microbial activity and weaker colour (Jackson and Lombard 1993). Titrable acidity tends to be excessive following veraison and decreases with maturity (REF). Brix° however is generally positively correlated with total quality (Gladstones, 1992).

While pH and TA are both negatively correlated to total quality they exhibit no relationship with each other. The results show that Brix° is positively correlated with pH which is expected as they both tend to increase during maturity (Jackson and Lombard, 1993). This positive correlation coupled with the emphasis on pH and TA in the model, the unusual season and the poor development of grape sugar probably explains the anomolous correlation between Brix° and Quality in Table 8b.5.

	pH	**Brix°**	**TA**	**Quality**
pH	1.00	0.55	0.03	-0.56
Brix°		1.00	0.02	-0.24
TA			1.00	-0.44
Quality				1.00

Table 8b.5: Correlation matrix for individual must characteristics and overall predicted quality (from model).

The absence of strong relationships between must properties e.g. TA and pH or TA and Brix° in this study, is not uncommon in winegrapes (Reynolds 1997, Bramley, 2001, Creasy, 2000) and highlights the reasons why multiple "quality" indicators are required. The reason for this lack of relationship is due to the wide range of external factors that can affect the physiology of the berry – either directly or indirectly by influencing vine-growth parameters (Jackson and Lombard, 1993).

8b.3.5 Mapping of fruit quality

The quality map resulting from the interpolation is shown in Figure 8b.7. This has been simplified in the inset as a map of grape grade (using values from Table 8b.2). After interpolation the mean quality value is 23 however 71% of the vineyards shiraz was considered to be of bulk quality and 29% of commercial or greater.

Visually the difference between the quality map and the individual must property maps highlights the need for a picture of overall quality when considering differential harvesting. The maps visualize the differences observed in the correlation matrix (Table 8b.5).

This analysis however has not considered the taster's opinion of the blocks. Taste is the best indicator of quality however it is a subjective variable and difficult to quantify hence the reliance on quantifiable properties such as pH, Brix° or TA. Prior to harvest, winemakers physically visit vineyards to taste and grade individual blocks. While it is not feasible to do this site-specifically a general knowledge of the mean "taste" of the block will aid in any quality model. Grapes with different taste grades but

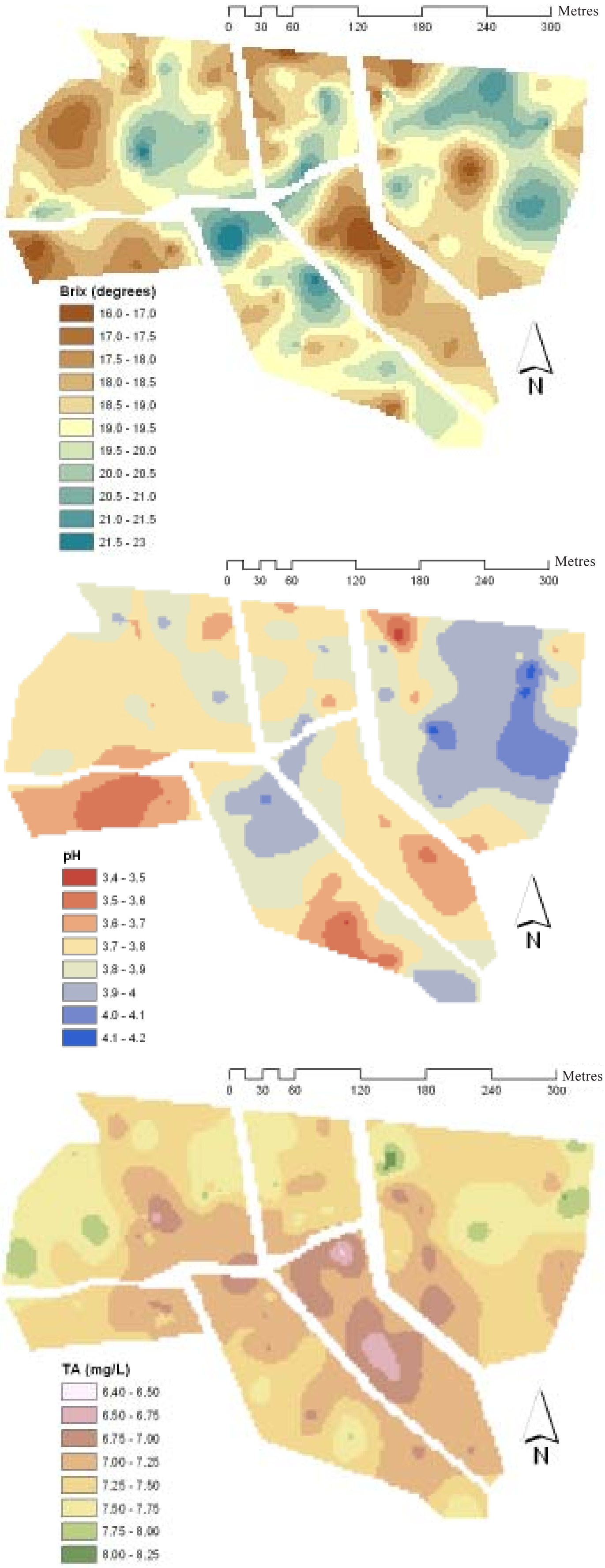

Figure 8b.6: Interpolated maps of individual must properties.

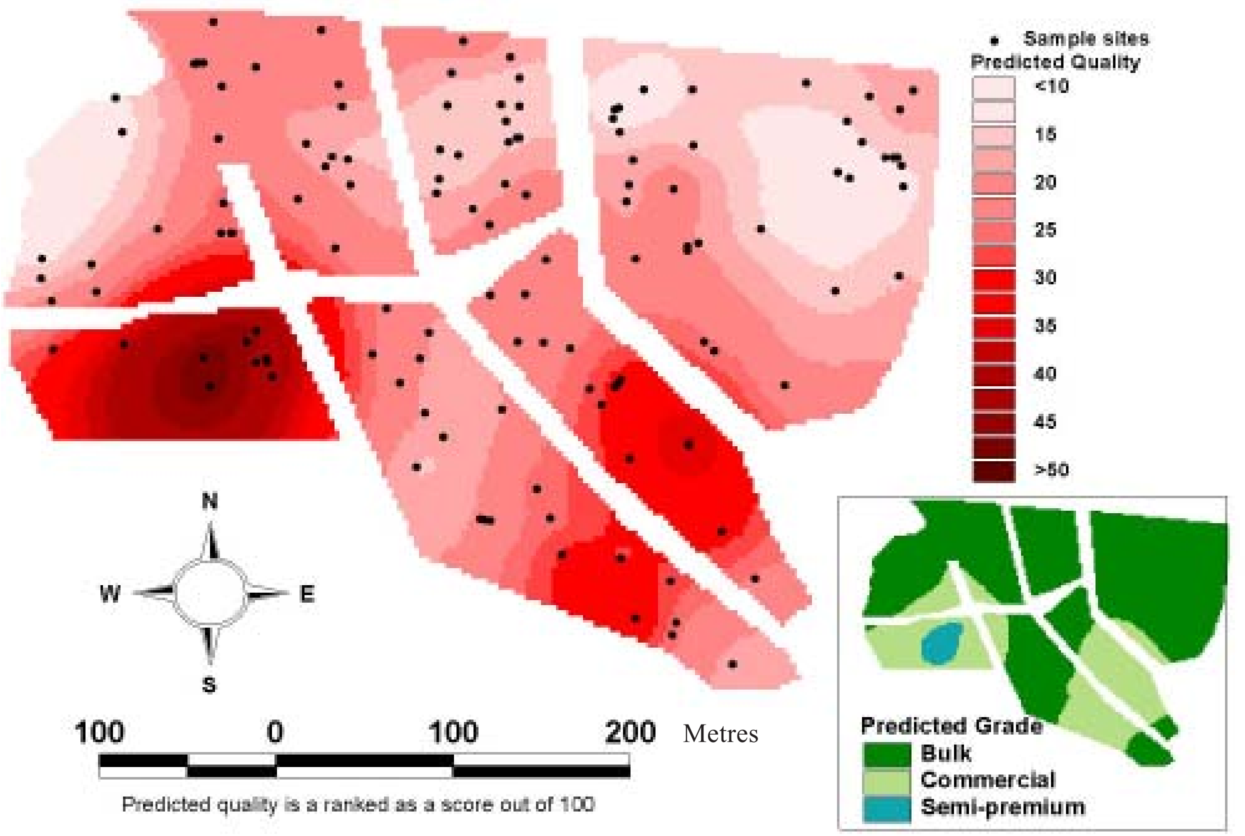

Figure 8b.7: Interpolated map of overall quality prediction from the fuzzy trapezoidal MF model (showing simplified inset of wine grades).

identical pH, Brix° and TA will have a different quality grade.

Without this additional information on "taste" the output from the model is incomplete. According to the output from the model the grapes produced were predominantly of bulk grade. The blocks however had a good taste and despite the early harvest and poor season still produced primarily commercial fruit. The next step in the development of the fuzzy model proposed here is the inclusion of the taster's opinion into the model.

8b.3.6 Gross-margin analysis

The mean quality of the blocks indicates bulk quality grapes. However with over a quarter of the vineyard able to be graded to a higher category it is obvious that there is an opportunity for differential harvesting to improve profitability. The potential for differential harvesting is also helped by the large discrete areas of higher quality grapes that minimizes the cost of differential harvesting (re inset of Figure 8b.7). The area of semi-premium grapes is considered to be too small for differential harvesting and recatergorised into the commercial grade.

The gross margin analysis for uniform harvesting shows a loss of \$4,102.5 ha^{-1}. Differential harvesting into bulk and commercial lines (according to the inset in Figure 3) shows a loss of \$4,102.5 ha^{-1} in the bulk grade areas, \$2,275 ha^{-1} in the commercial grade areas and \$3,571 ha^{-1} overall. This figure does not account for the increased cost of differential harvesting however an average saving of ~\$600 ha^{-}

[1] will easily offset this additional cost. The potential savings associated with differential harvesting in this study are similar to those reported elsewhere (Bramley *et al.*, 2003, Carothers, 2000, Penn, 1999).

8b.4 Conclusions

The aim of this chapter was to develop a model to help grapegrowers and winemakers to understand the interaction of individual quality parameters on "total" quality and the spatial variation of individual and toatl quality. This information should help improve the winemaking decision support system The use of trapezoidal and triangular membership functions produced the best fuzzy models for the prediction of overall grape quality. All models will benefit from the inclusion of additional information especially the score given pre-harvest by an expert taster. The models represent a step towards a decision support system for grape quality. Further research needs to be conducted to verify the output from the model e.g. micro-vinification.

The output from the fuzzy model produced a map of overall quality that was different to the individual quality parameters. The vineyard produced predominantly bulk grade grapes. A gross margin analysis for uniform versus differential harvesting showed a saving of ~AUD$600 per hectare for differential harvesting.

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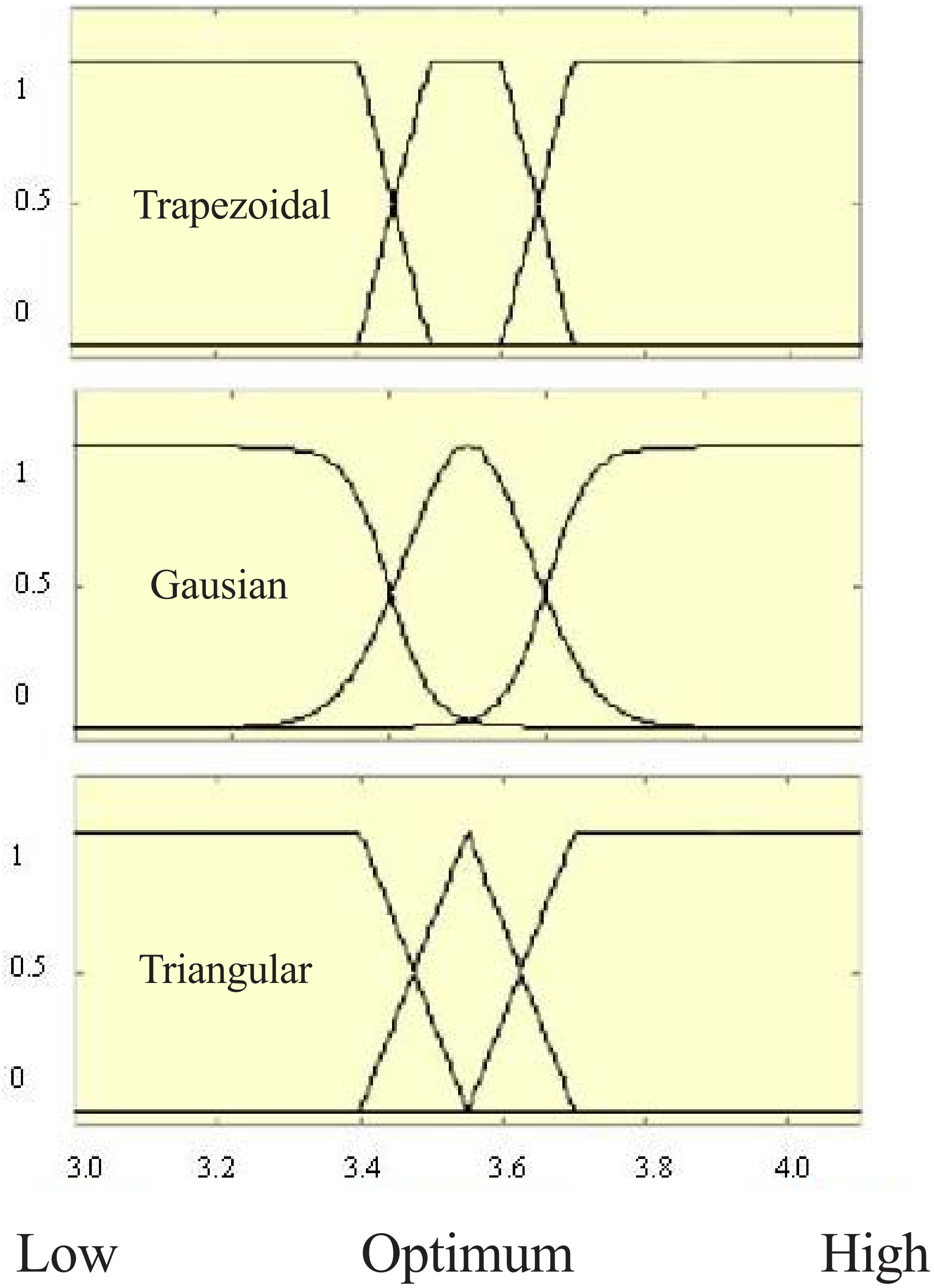
Appendix 8.1 - Membership Functions for pH



Appendix 8.2 - If-then rules for fuzzy grape quality model

Antecedent	Consequent
If (pH is low) and (Brix° is low) and (TA is low)	Then (grade is bulk)
If (pH is low) and (Brix° is low) and (TA is high)	Then (grade is bulk)
If (pH is low) and (Brix° is high) and (TA is low)	Then (grade is bulk)
If (pH is low) and (Brix° is high) and (TA is high)	Then (grade is bulk)
If (pH is high) and (Brix° is low) and (TA is low)	Then (grade is bulk)
If (pH is high) and (Brix° is low) and (TA is high)	Then (grade is bulk)
If (pH is high) and (Brix° is high) and (TA is low)	Then (grade is bulk)
If (pH is high) and (Brix° is high) and (TA is high)	Then (grade is bulk)
If (pH is low) and (Brix° is optimum) and (TA is low)	Then (grade is commercial)
If (pH is low) and (Brix° is optimum) and (TA is high)	Then (grade is commercial)
If (pH is low) and (Brix° is low) and (TA is optimum)	Then (grade is commercial)
If (pH is low) and (Brix° is high) and (TA is optimum)	Then (grade is commercial)
If (pH is high) and (Brix° is optimum) and (TA is low)	Then (grade is commercial)
If (pH is high) and (Brix° is optimum) and (TA is high)	Then (grade is commercial)
If (pH is high) and (Brix° is low) and (TA is optimum)	Then (grade is commercial)
If (pH is high) and (Brix° is high) and (TA is optimum)	Then (grade is commercial)
If (pH is optimum) and (Brix° is low) and (TA is low)	Then (grade is semi-premium)
If (pH is optimum) and (Brix° is low) and (TA is high)	Then (grade is semi-premium)
If (pH is optimum) and (Brix° is high) and (TA is low)	Then (grade is semi-premium)
If (pH is optimum) and (Brix° is high) and (TA is high)	Then (grade is semi-premium)
If (pH is optimum) and (Brix° is optimum) and (TA is low)	Then (grade is premium)
If (pH is optimum) and (Brix° is optimum) and (TA is high)	Then (grade is premium)
If (pH is optimum) and (Brix° is low) and (TA is optimum)	Then (grade is premium)
If (pH is optimum) and (Brix° is high) and (TA is optimum)	Then (grade is premium)
If (pH is optimum) and (Brix° is optimum) and (TA is optimum)	Then (grade is superpremium)
If (pH is low) and (Brix° is optimum) and (TA is optimum)	Then (grade is semi-premium)
If (pH is high) and (Brix° is optimum) and (TA is optimum)	Then (grade is semi-premium)