Wireless sensors in the Vineyard

Philip Sallis, Subana Shanamuganathan and Akbar Ghobakhlou

[1] Geoinformatics Research Centre, School of Mathematical and Computing Sciences
Auckland University of Technology (AUT), New Zealand
http://www.geo-informatics.org/
{philip.sallis, subana.shanmuganathan, akbar}@aut.ac.nz

Abstract: - A review of wireless sensor network methods used for environmental monitoring of micro climates in vineyards is presented. The telemetry architecture used consists of a wireless grid of sensor arrays to log data in real-time and transmit it from nine locations in six countries to a database server located in New Zealand. Analysis of the data includes climate plotting against trends and macro environmental data over time, in addition to clustered characteristic based visualisations of grape variety, wine quality with vineyard location influences and other growing conditions. Algorithms for frost prediction and irrigation management are described with a proposal for integrating the technology using *in situ* remotely controlled robots and the consequent correlation of value-dependent variables as they relate to sets of quality grape growing characteristics and wine taste.

Key-Words: - viticulture, environmental influence modelling and frost prediction

1 Introduction

Recent developments in wireless sensor networks combined with modern mobile devices have enabled considerable progress to be made in building economically viable precision instrument sets for micro climate monitoring. This in turn has enabled a shift from the traditional centralised paradigm of monitoring mostly on macro scales to that of micro or meso bounded areas. With increased numbers of distributed sensors it is now possible to measure a variety of diverse environmental factors, such as climate and atmosphere, plant biological and ecological influences, simultaneously. Such networks of multifunctional nodes provide sensor data capture, logging and transmission at unprecedented temporal and spatial resolutions, extending the traditional GIS research challenges into the core realms of computing, such as data communications, database technologies and analytical algorithms. Major challenges include data fusion, geolocated queries, energy efficient data acquisition, transmission, analysis and interpretation. The networks as well allow for data acquisition to be undertaken on spatially far apart sampling locations. This paper presents an architecture for a real-time data capture, logging, transmission and comparative (or collective) analysis of grid data involving nine locations in six countries with some results relating to grape variety (wine taste), location and growing conditions. It also describes some future research directions for integrating the technology using *in situ* robots and the consequent correlation studies of value-dependent variables as they relate to sets of quality grape growing characteristics.

1.1 Wireless sensor networks in Viticulture

Recent technological advances in wireless sensor network components combined with modern mobile devices are now deployed for measuring a wide range of factors in a variety of application areas, including Precision Agriculture (PA) [1]. Wireless sensor nodes of contemporary design consist of sensing, data logging, transmission and processing, with communications components, all contained in very small and compact devices. These are available at steadily decreasing manufacturing and maintenance costs with longer battery life and energy optimisation features [2,3].

The literature reflects how Wireless sensor networks consisting of remote real-time sensor nodes with multiple functionalities could serve as a useful tool in precision viticulture (PV). This information base could enhance everyday on-farm management decision making, such as when to engage a helicopter to disperse cold air mass for avoiding frost or begin irrigation. Streamlining data collected through sensor networks via the Internet and visualising results in real-time is another advantage of this architecture. Examples of this contemporary approach to information management can be seen in [4, 5]. Further details on the recent Wireless sensor network are discussed in [6]

1.2 Challenges in Geocomputing

As a Consequence of the above described developments in Wireless sensor networks, the challenges confined to networking and node configuration have now been extended to the core realms of computing, giving rise to new fields, such as geocomputing and geoinformatics. As far as viticulture is concerned, the major challenge is in analysing grid location data captured via node sensors, combined with geo-corded data from other sources. Such analyses can contribute in the following areas within viticulture;

1) in vineyard management, such as irrigation, deployment of frost event prediction models for freeze burn prevention
2) for 1), for prediction of frost event points using meso-micro scale data
3) comparative (or collective) analysis of grapevine growth factors at meso scales with grid (micro) data with wine taste (human sensory perception data)
4) for 2) at macro scales with grid (micro) data and wine taste data.

The latter two are focused on the use of data captured via sensor network nodes and or from other sources for elucidating the effects of environmental factors on the growth of grapevine varieties, the produce, grapes and the final product of this, the wine and its quality, the latter discussed in terms of taste (human sensory perception). Some work conducted in frost event prediction and short term climate effects on wine taste is outlined in section 3.

2 GRC Wireless sensor network spread across six countries

A real-time data capture, logging and analysis grid involving nine locations in six countries is described with some results relating to grape variety, location and growing conditions, in this section.

2.1 Wireless sensor network architecture

The wireless sensor grid architecture consists of networks of nodes with sensors, transmitters and repeaters located in critical points within vineyards for monitoring weather, atmospheric and environmental conditions as well as sensing plant responses. So far, in this initial stage of the research, sensor networks have been installed in locations chosen for this research in Chile, Uruguay, USA, Japan and New Zealand. Each sensor node (in a network) refers to a location with one or more sensors attached to the node. Currently, nodes consist of sensor for monitoring weather and atmospheric conditions however, more for sensing plant responses, such as sap rise, leaf wetness, are being considered for inclusion. Data captured by each sensor could be transmitted within an interval as low as 10 seconds. The database of entities and their relationships relating to the raw data relating to the monitoring of major influences in weather, climate, atmospheric conditions, due to climate change or pollution and sensing plant physiological responses, such as sap rise is illustrated in Fig 2. The parameters that could be measured from various sensors are listed herein (underlined are the variables currently being monitored via the network system);

1) Temperature
2) Wind Speed
3) Wind Direction
4) Wind Chill
5) Humidity
6) Solar Radiation
7) Pollution factors (CO_2)
8) Rainfall
9) Barometric Pressure
10) Soil Moisture
11) Soil Temperature
12) Leaf Wetness
13) Sap Flow (volume and speed)
14) Dendrometer
15) Chromatographer

2.1 Wireless sensor data in modelling environmental influences grape vine varieties and on wine quality

The Wireless sensor network captures and relays real time data (displayed via the website www.geo-informatics.org) for analysis of the variability in climate, which can be compared with changes to plant physiology and grape crop well-being. The effects appear to vary according to grape variety and location. Because of this we model the relationships between climate change and atmospheric conditions using parametric variables for grapevine and wine quality in order to establish the cause-and-effect dependencies. These are modelled over time. Thus, a complex combinatorial model emerges, reflecting numerous nonlinear interactions, posing considerable modelling challenges [7]. The model used herein is expressed in (1).

$$Mn=\frac{\sum Si(l/v)}{T} \qquad (1)$$

Where, M = the model, Si = sensor data operated on by location (l) per variety (v), over time (t).
When human quality discernment (opinion regarding wine quality) data is added, instances of this model become exponentially more complex.

2 Wireless sensor data in vineyard management

The section elaborates upon the analysis of wireless sensor data currently being captured and transmitted to a central server in New Zealand.

ISBN: 978-1-61804-074-9

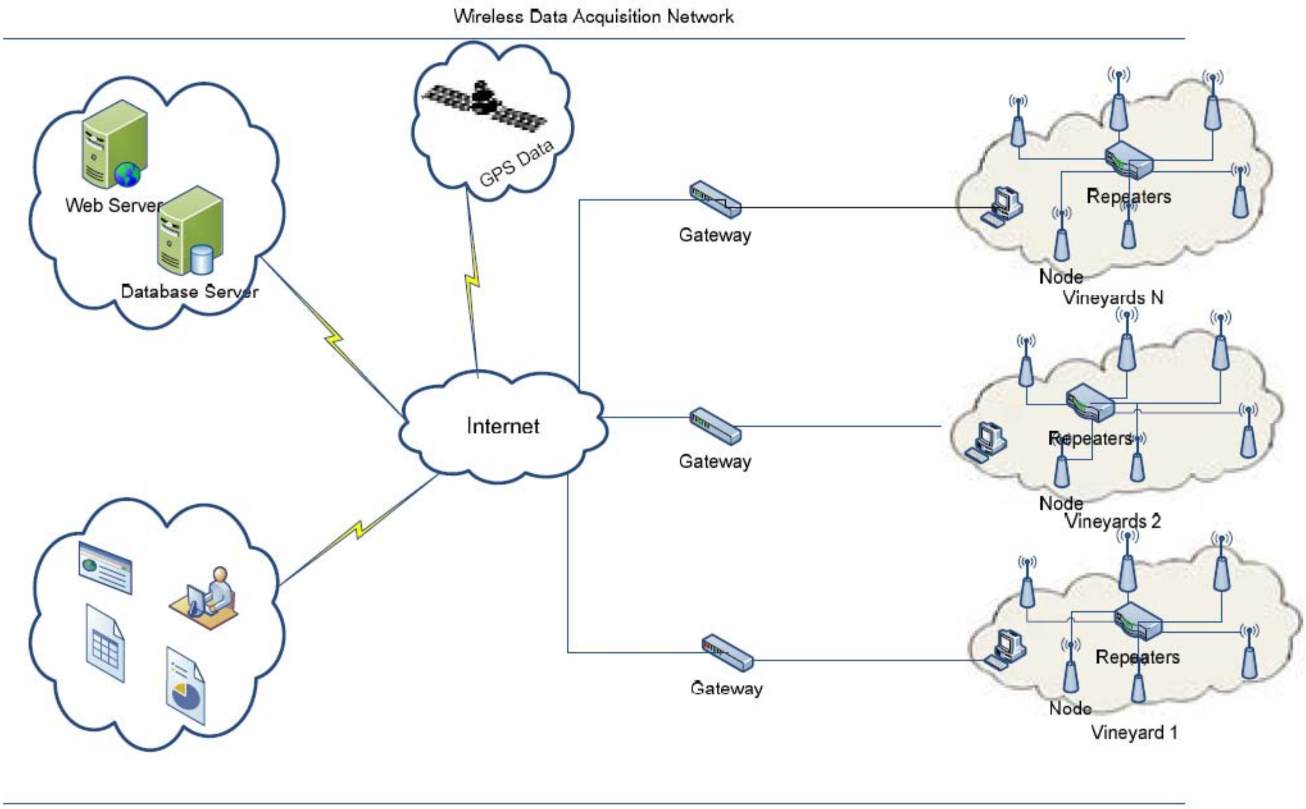


Fig. 1. Schematic diagram of a real-time Wireless sensor network layout for data acquisition for determining the influence of environmental effects (such as weather conditions) on grapevine growth and quality in different wine appellations.

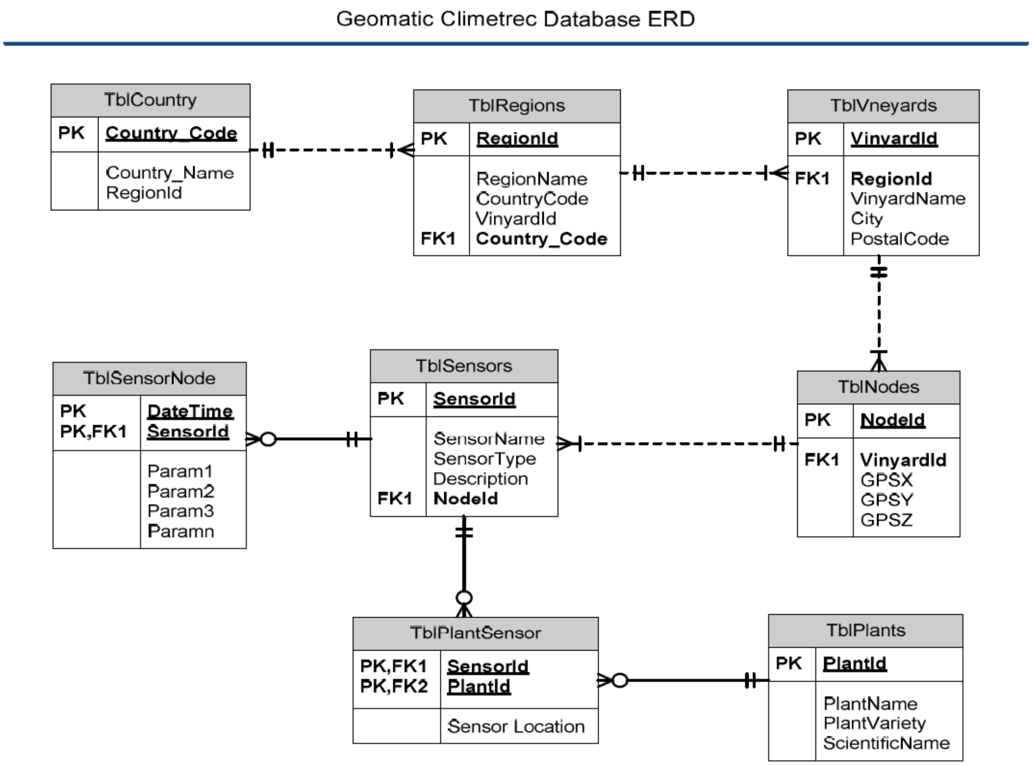


Fig. 2. Database showing the inter-relationships between the sensor data being collected from selected wine producing regions. Sensor data is being collected to model the environmental influence on grapevine growth and wine taste. TblNode contains information about a particular node including GPS coordinates. A node may associate with one or more sensors. TblSensors contain information about various sensors used (i.e., sensors for temperature, humidity, wind-speed, rainfall, etc). TblPlantZ contain all information about a plant being monitored. TblCountry contains name of all countries with their codes. TblRegions contain regions within each

3 Modelling environmental effects using Wireless sensor and other data

Two major subprojects are described below emanating from the overall research programme titled *Eno-Humanas*, so-called because of the mix of precise ecological and viticultural data and the less precise human quality discernment data on wine taste/ quality.

3.1 Climate change effects on grapevine growth and wine quality

Climate change effects on grapevine growth and wine quality can be basically classified into two major kinds;

1) Long term, such as global warming; the long term climate change influence in viticulture and enology is in many studies described to be an ongoing phenomenon as the relocation of vineyards from site/ region to site/ region seen to be happening for centuries now in search of that ideal geographical niche for ripening grapes with maximum sugar without comprising any colour, aroma and flavour proteins that would in turn enable the winemaker to produce finer wines in appellations produced in the world's major wine regions [8,9].
2) short term or vintage-to-vintage variability; the short term climate change could cause considerable deviations in grapevine phenology leading to some perceivable changes in wine appellation/style, specific and describable by sommeliers with a language consisting of wine descriptors that can be used to determine the wine characteristics not only in quality but in a quantitative manner as well (linked to numbers) [10].

Based on [11] in which climate variability is argued to be the main influencing factor on vintage-to-vintage (or inter-annual) variations in wine quality stating that the other three, i.e., grape variety, rootstock and soil type, as constants, in [12] authors investigated into the application of WEBSOM/web text mining approach to modelling the vintage-to-vintage climate variability in wine quality. In this latter study, sommelier comments (obtained from an online wine database called *wine enthusiast*) were initially converted into a matrix of 51 wine descriptors x 30 Kumeu wine (based on the descriptor frequencies in the particular wine and the whole comments set). Then using the WEBSOM approach, the matrix of wine descriptors were clustered into 12 wine descriptor groups (based on the descriptor co-occurrence frequencies). A visual representation of the correlation between the 12 wine taste descriptor groups and grapevine growing season temperature (September to March obtained from NIWA climate database) represented by standard deviation is shown in Fig. 5.

The 51 individual wine descriptors were also analysed using rigorous statistical methods for studying any correlations between the descriptors, wine ratings and

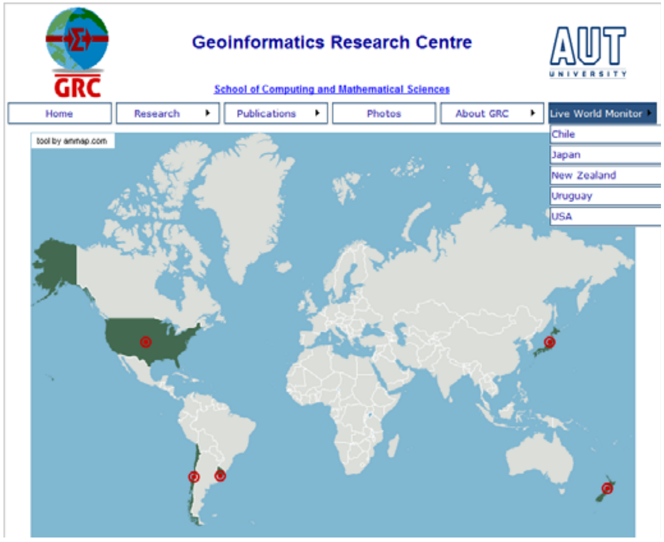


Fig. 3. Screen display showing the nine Wireless sensor network locations (vineyards) in six countries. (source, www.geo-informatics.org)

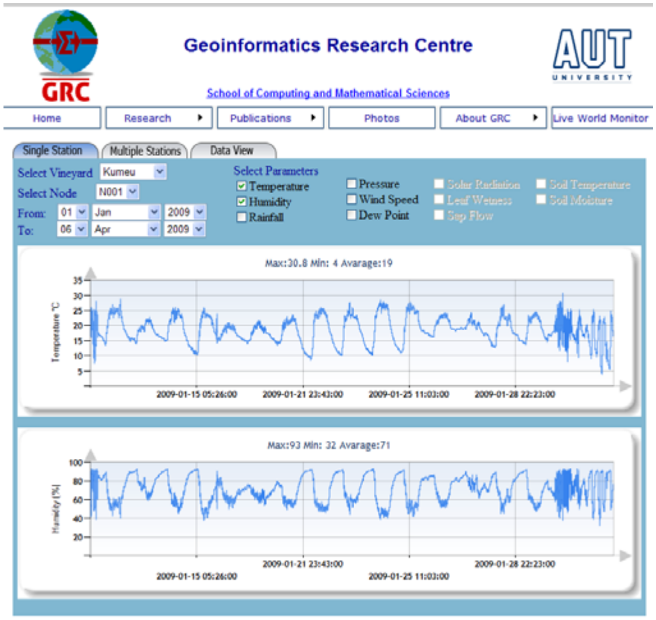


Fig. 4. Screen display of graphs showing the weather conditions (temperature and humidity) based on data captured in a vineyard in Kumeu, New Zealand (long=174.564081 lat=-36.778006)

vintage using cross cutting factors i.e., macro-meso-micro scale variables. The Kumeu wine study of discriminant analysis produced a model with 7 functions to predict the 9 vintage classes (1997-2006, both inclusive leaving out 2001) with 11 wine descriptors of the total 51 (of 30 Kumeu wines). The model correctly classified 76.7% of original grouped cases and 50.0% of cross-validated grouped cases (30 cases in total), the latter coincided with the 50% influence exerted by climate variables on vintage-to-vintage variability in wine quality as in an Italian study [13].

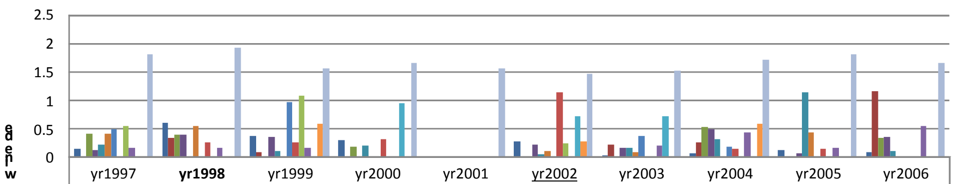
2.1 Wireless sensor data display and analysis

The use of multisensor network data to model the frost points by using vineyard terrain, soil and wind direction over spring is presented in [14].

In [15], *Eno-Humans* project team members looked at developing frost prediction models. Frost prediction models contribute significantly towards the successful growth and production of quality crop yield in horticulture, especially in PV where the benefits are significant because frost damage is well-known for its potentials leading to total harvest failure, with a follow-on regional or national economic impact outcome. This has increased interest among scientists and growers to advance their knowledge in relation to the inter-dependencies and possible correlations between meso-micro climate variables and associated plant and soil condition values. Included in this array of variables there are also site specific environmental factors such as pesticide saturation and carbon density.

3.1 Frost prediction models using Wireless sensor and regional (micro-meso)data

Recent interest in building computational models is focused on predicting frost events using both regional (metrological) and vineyard weather monitoring data gathered *via* remote low-cost sensors, in addition to vineyard-specific environmental attribute data. Based on an earlier research [16], the GRC team analysed the climate and atmospheric data, together with vineyard elevation and wind data in order to determine the inter-dependencies of variable values to inform enhanced frost protection measures.



	yr1997	**yr1998**	yr1999	yr2000	yr2001	<u>yr2002</u>	yr2003	yr2004	yr2005	yr2006
Sum of C 1: finish, black, *open*, vintag	0.147	0.612275	0.3865	0.306125		0.2835	0.034125	0.06825	0.1365	0.102375
Sum of C 2: fruit, miner nectarin, *complex fresh* intens, refresh	0.025942857	0.344914284	0.103771428	0		0	0.228785714	0.271771431	0.025942857	1.16502858
Sum of C 3: *zesti*, honei, soft *sweet*, white	0.4176	0.4	0	0.2		0	0	0.53522	0	0.3352
Sum of C 4: acid pear toast, bodi fine full, dry rich	0.13425	0.3913	0.363575	0		0.222275	0.1736375	0.5035375	0.0735	0.3657625
Sum of C 5: *citru* peach *pineappl*, bottl *structur*	0.22272	0	0.1148	0.21022		0.04772	0.16532	0.31536	1.1386	0.10512
Sum of C 6: melon, butter round *spice* subtl	0.4227	0.55004	0	0		0.1176	0.1	0	0.4403	0
Sum of C 7: smoke, herbac	0.48855	0	0.97715	0		0	0.3891	0.19455	0	0
Sum of C 8: cherri tart, mocha	0	0.2594	0.2594	0.3257		1.15233333	0	0.14583333	0.14583333	0
Sum of C 9: lemon, lime	0.544	0	1.08805	0		0.25	0	0	0	0
Sum of C 10: ripe, appl balanc crisp *tropic*	0.17782	0.17502	0.17502	0		0	0.2051	0.43064	0.16532	0.54824
Sum of C 11: *dri* herb smoki	0	0	0	0.95073333		0.72536667	0.72536667	0	0	0
Sum of C 12: oaki, live	0	0	0.58805	0		0.294	0	0.588	0	0
ssd/meanT	1.814285714	**1.928571429**	1.571428571	1.657142857	1.557142857	<u>1.471428571</u>	1.528571429	1.714285714	1.814285714	1.657142857

Fig 5. Histogram of Kumeu (New Zealand) wine descriptor frequencies in the 12 WEBSOM clusters summed up for each year (1997-2006). In the graph, each year appearing on *x* axis consists the total wine descriptor frequencies for that year (1 through 12) and lastly (in light blue colour), standard deviation/ mean temperature during growing season (ssd/meanT), as vertical bars and this enables the visualisation of wine descriptors and temperature variation over this period. An interesting observation that could be made on the graph is that year 1998, the year with the highest ssd/meanT within the period analysed consists of high descriptor frequencies for clusters C 2, C 3, C 6 and C 10 descriptors. Meanwhile, year 2002 with the lowest ssd/meanT consists of higher frequencies for C 5, C 8 and C 11 descriptors. Discriminant analysis run on the data set produced 11 words (in italics in the left) as contributing factors in determining the variable "vintage" (or year considered as a dependent variable on the 11 descriptors). The climate data comes from NIWA captured at Henderson weather monitoring station (Agent no.12327Network no.A64865 (15 November 1994 to 15 March 2009) Henderson long=174.63189 lat=-36.86261) [12:p10]

ISBN: 978-1-61804-074-9

Developing a model with supervised and unsupervised neural networks as a means for characterising the data used in the analysis, was the focus of the investigation.

While the results of this frost prediction study differed and was seen to have improved in precision with the use a radial base function (RBF) in a supervised mix with an unsupervised network, it was also established that the sample frequency as fundamental for the improvement of such a model and its prediction potential. Similarly, it was found that obtaining a large amount of time-dependent data for each of the variables in the set as critical for gaining greater accuracy in the prediction.

The research team concluded that the methodology employed in the research to be appropriate for the frost fall prediction problem domain with potential to produce robust models using these techniques that could assist greatly the crop management scenarios needed by growers to avoid damage caused by frost.

4 conclusion

The paper presented an overview of the *Eno-Humnas* project's wireless sensor architecture consisting of a wireless grid of sensor arrays to log data in real-time and transmit it from nine locations in six countries to a database server located in Auckland, New Zealand. The data captured at nine vineyards *via* node sensors on the vineyard networks system is transmitted and is used for comparative analysis of various dependent factors on grape variety, their location specific influences, such as soil, terrain, and other growing conditions, in sub projects, such as the effects of short term climate change on wine quality (taste), frost event prediction.

5 Future work

Algorithms for irrigation management are being developed with a proposal for integrating the technology using *in situ* remotely controlled robots and the consequent correlation of value-dependent variables as they relate to sets of quality grape growing characteristics and wine taste. The robot design team mainly considers employing robots to gather data from sensors, such as soil temperature, moisture and to calculate the criteria to initiate irrigation. This is to save sensor battery power wasted on transmitting data, considered to be draining more of the battery power.

Robots are also considered for moving around some sensors, such as plant sap rise, camera for capturing images, the latter to evaluate on fruit harvest conditions based on berry *veraison* and leaf colour.

At least, three more PhD research programmes are about to begin mid this year that would include the visualisation of data representing environmental influence factors of grapevine growth relating to varietal characteristics (cold tolerance), such as terrain, micro climatic data, describing specific details of vineyard location as well as variations within vineyards.

Research into developing an e-nose for discriminative characterisation of wine aroma using gas chromatography (based on phenol derivatives in wine and grape berries) and other chemical components and properties as well is being considered.

Acknowledgments

Robbie Young and Sara Zandi, Summer Student Interns, are acknowledged for the initial prototyping, final design and implementation of the database as well as web based display of the wireless sensor data gathered from six countries. Professors Ajit Narayanan, Olaf Diegel and Krishanmacher Prasad from Auckland University of Technology in New Zealand are thanked for their valuable advice and contribution. The authors wish to record the contribution by GRC's academic research partner institutions and individuals, namely, Professors Mary Carmen Jarur Munoz and Marcelo Trujillo of Universidad Católica del Maule, Chile, Professors Monte Cassim, Bill Claster and Ms Chisato Kudo from Ritsumeikan Asia Pacific University in Beppu, Japan as well as our Private sector partners who are listed on our website at www.geo-informatics.org

References:

1. Xianghui Cao, Jiming Chen, Yan Zhang, and Youxian Sun Development of an integrated wireless sensor network micro-environmental monitoring system. *ISA Transactions,* Volume 47, Issue 3, July 2008, pp 247-255.
2. Jennifer Yick, Biswanath Mukherjee, and Dipak Ghosal Wireless sensor network survey. *Computer Networks,* In Press, Uncorrected Proof, Available online 14 April 2008.
3. Won-Suk Jang, William M. Healy, and Mirosław J. Skibniewski. Wireless sensor networks as part of a web-based building environmental monitoring

system, *Automation in Construction,* Volume 17, Issue 6, August 2008, pp 729-736.

4. Pierce F.J., and T.V. Elliott., Regional and on-farm wireless sensor networks for agricultural systems in Eastern Washington, *Computers and Electronics in Agriculture*, Volume 61, Issue 1, April 2008, pp 32-43
5. Harvest Electronics, http://harvest.com/ last accessed 10 June 2008
6. Shanmuganathan, S., Ghobakhlou A., and Sallis P. Sensor data acquisition for climate change modelling. *WSEAS Circuits & Systems, Issue 11, Volume 7, Nov. 2008. ISSN: 1109-2734* pp 942-952
7. Ankur Suri, S.S. Iyengar, and Eungchun Cho Ecoinformatics using wireless sensor networks: An overview. *Ecological Informatics, Volume 1, Issue 3, November 2006*, pp 287-293.
8. Jones, G. V., "How Hot Is Too Hot?" *Wine Business Monthly, February 2005*:1-4.
9. Jones, G. V., Making Wine in a Changing Climate. *Geotimes, August 2004, Vol. 50, No. 7:* 22-27.
10. Brochet, F. and Dubourdieu, D. (2001), Wine Descriptive Language Supports Cognitive Specificity of Chemical Senses, *Brain and Language Vol. 77, Issue 2, May 2001*:187-196.
11. van Leeuwen, Cornelis, Friant, Philippe, Chone, Xavier, Tregoat, Olivier, Koundouras, Stephanos, Dubourdieu, Denis. (2004). Influence of Climate, Soil, and Cultivar on Terroir. *Am. J. Enol. Vitic. 2004 55:*207-217.
12. Shanmuganathan, S., P. Sallis and A. Narayanan, Unsupervised Artificial Neural Nets for Modelling the Effects of Climate Change on New Zealand Grape Wines being reviewed for inclusion in the *18th World IMACS / MODSIM Congress, Cairns, Australia 13-17 July 2009* http://mssanz.org.au/modsim09
13. van Leeuwen, Cornelis, Friant, Philippe, Chone, Xavier, Tregoat, Olivier, Koundouras, Stephanos, Dubourdieu, Denis. (2004). Influence of Climate, Soil, and Cultivar on Terroir. *Am. J. Enol. Vitic. 2004 55:*207-217.
14. Beckwith, R., Teibel, D. and Bowen, P., Report from the Field: Results from an Agricultural Wireless Sensor Network, *Proceedings of 29th Annual IEEE International Conference on Local Computer Networks (LCN'04), 2004* pp.471-478
15. Sallis, P., Jarur, M., and Trujillo, M., Frost Prediction using a Combinational Model of Supervised and Unsupervised Neural Networks for Crop Management in vineyards being reviewed for inclusion in the *18th World IMACS / MODSIM Congress, Cairns, Australia 13-17 July 2009* http://mssanz.org.au/modsim09
16. Sallis, P., Jarur, M., and Trujillo, M., Frost Prediction Characteristics and Classification using Computational Neural Networks in *Australian Journal of Intelligent Information Processing Systems (AJIIPS) volume 10.1, 2008 (ISSN 1321-2133)* pp50-58.