Keynotes
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Terrestrial Monitoring and Modelling in Agrometeorology

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Agronomy can be considered as combining agriculture, viticulture and horticulture. For each of these crop production contexts, timely and accurate environment impact information is critical for decision-making precision. Climate in particular, plays a significant role in determining crop yield and quality. The term agrometeorology has emerged to represent the area of research specifically related to climate studies in the agronomic domain. This presentation will describe how work in the area of agrometeorology relates to geocomputation, which is another so-called 'new 'multi-disciplinary (some use the term trans-disciplinary) field that combines mathematics, computer science, information systems, electrical engineering, geodetic science , geography, econometrics and various associated disciplines such as plant biology and physiology, soil science and a range of environmental sciences.

In this presentation, as an example of agrometeorolgy, an international collaborative research project will be described with particular reference to vineyard management. A wireless sensor network (WS) terrestrial telemetry architecture is outlined together with a description of its implementation from concept, through design and development, to deployment in the field. Details of the sensors, their calibration and testing will also be provided. The sensor arrays are housed in a framework with their own (solar) power supplies, GPS, Wi-Fi transmitter and micro-computer for in situ signal processing and data communications protocol processing. Data is passed from individual sensor arrays at parameterised intervals through a coordinating node (a gateway) to an Internet enabled upload process to a central server. This server acquires data from all the international locations. Monitoring software on the server provides immediate real-time reporting to each location while also populating a 'public' website, which illustrates analysed data in terms of actual and trend information. This information system and its use is outlined.

Processing the monitored data for a variety of purposes requires geostatistical analyses and mathematical modelling. Some data is interpolated (using inverse distance weighting, kriging, etc) for use with GIS applications (some examples will be given) and in the case of estimation or prediction of single data values or events, models with more sophistication such as the ensemble Kalman filter (EnKF) are used.

The real-time monitoring system and web-based information system are designed for use by decision-makers. Some examples of this information being used by crop managers will be described, as will some research projects underway by members of the international scientific team.

Author's Biography

Dr. Philip J. Sallis completed a PhD in the area of meta- information process modelling at City University London in 1979. Since then he has held academic position in England, Australia and New Zealand, with past and current research professorships in the USA, Hong Kong and Chile. He was appointed to the Foundation Chair in Information Science at The University of Otago, New Zealand in 1987, a position he held for 13 years. In 1999 he became Deputy Vice Chancellor at the Auckland University of Technology (AUT) where he led the academic, research innovation and enterprise activities of the university. Choosing to leave that role after a decade, he returned to full-time research and is now Director of the Geoinformatics Research Centre at AUT, while also retaining the position of Pro Vice Chancellor, assisting the Vice Chancellor with a range of strategic planning and ambassadorial tasks.

Philip's return to full-time research was for the most part because he wanted to pursue some ideas he had for environment monitoring and modelling related to agronomy. His keynote lecture describes how this idea took hold and how it has provided him with an opportunity for leadership of an innovative international collaboration of academics, scientists and practitioners, especially in the wine industry. He will outline the overall concept for the research programme, the wireless sensor Network (WSN) he and his colleagues have designed, built and deployed across eight countries together with the real-time environment monitoring software and web-base information system designed for use by managers and decision-makers in the field. He will also describe the data modelling approaches being used for estimation/prediction of event information and the range of projects being worked on by members of his international research group.

Since completing his doctoral studies Philip has been at the forefront of tertiary computing education for 35 years and held senior academic and research development positions. He has been a regular conference speaker, publisher of journal articles and books, designer of curriculum and member of numerous review committees including ACM, IEEE, SEARCC, the BCS and other international computing groups. He was for 3 years President of the NZCS during which time he was a chair of three NZ government commissions relating to computing in schools, science curriculum and information technology with industry. His awards include an IBM doctoral research scholarship, a Davidson Trust Research Fellowship, a United States Library of Congress (National Digital Mapping Archive) research award, two Australian and two New Zealand research awards, two professional fellowships and several research funding grants in the UK, USA, Australia, New Zealand and Chile.

With his wife Dr Kathy garden, he spends several months each year in Chile where from his position as Adjunct Research Professor at the Catholic University in Maule (Geospatial information Processing Laboratory) he coordinates the work of the GRC throughout South America. He also works closely with the Environmental Research Laboratory at Ritsumeiken Asia-Pacific University to which he makes frequent visits.

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Evaluating the Quality of Mathematical Models

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There is no single way to construct a mathematical model of a complex system. Given a choice of different mathematical alternatives, how could you choose the "best" one? The application for which the model is to be constructed will obviously have some bearing on the choice of mathematical formulation. For example, if the model is to be used as a training simulation over a known limited range of conditions, then any mathematical formulation that mimics the system's behavior over that range of conditions is satisfactory. However, if the purpose of the model is the interpretation of experimental data, the testing of hypotheses about the internal structure of a system, or learning about the system by performing "experiments" on it, then the details of the mathematical formulation are important.

In this tutorial, nine criteria for evaluating the quality of a mathematical model will be described. Some of the criteria are quantitative, i.e. evaluation requires implementing model equations and finding solutions, while other criteria are qualitative meaning that evaluation can be estimated by looking at the model equations without the necessity of finding solutions. Since it is rare that model equations for realistic systems can be solved analytically, the criteria will be described in terms of computer solutions to model equations and numerical approximations to derivatives. However, the criteria also apply to system models with analytic solutions.

1. Reproduce system behavior. To be useful in any context, a mathematical or computer model must at least approximately reproduce the behavior of the system under study. Ideally, a model should match the data to an accuracy comparable with the experimental error in observing the system.

2. Free from internal errors. Given the mathematical equations making up a model, it is essential that they be programmed and solved correctly. Syntax errors are usually revealed by the simulation software; other programming and numerical errors are often not so obvious. Errors are possible in the preparation of the model equations, for example, in rearranging equations or changing units. One good test of equations is that state variables always have physically reasonable values (e.g. no negative concentrations). Where feasible, a hand calculation should be compared with the results of a simulation program to detect errors in rearranging or programming the model equations. Any numerical solver algorithms used in the simulation program must also be applied correctly.

3. Consistent with other theories. A mathematical or computer model should be consistent with accepted theories and other models widely accepted as valid. This is not to say that the validity of classical models should not be challenged, but it should be done knowingly and with good reason! Particularly important is the requirement that no fundamental physical and chemical laws should be broken.

4. Describes internal mechanism. The purpose of computer models in research and teaching is to increase understanding. At a superficial level, understanding means familiarity with the system's behavior. A more basic meaning of understanding is explanation in terms of internal processes, especially processes that have been studied independently or have been found to underlie other complex systems. A mechanistic model is thus of higher quality and contributes to understanding more than a model constructed of arbitrary functions.

5. Appropriate level of abstraction. No model can be expected to incorporate all known facts about a system. Choices have to be made as to which factors to include and which to exclude, and those choices depend on the purposes for constructing the model. Enough influences have to be included to make the model interesting and realistic; including too many influences may make solution impossible and may

introduce factors that do not play a significant role in the desired results. One useful rule of thumb is that the number of adjustable parameters in the model should be a small fraction of the number of experimental data points for fitting.

6. Reasonable parameter values. A valid model must have physically reasonable values for any parameters that can be given physical meaning.

7. Testable predictions. Occasionally, a model may be needed simply to mimic the behavior of a complex system, for example, for training purposes. More generally, however, a model must be able to make testable predictions if it is to be useful. A good model will suggest new experiments and point out inconsistencies in existing data.

8. Parameters are identifiable. It is not always possible to measure all of the state variables in a complex system. It may be that some of the model parameters may not influence the subset of measured state variables. Such parameters are unidentifiable and cannot be evaluated by fitting the model to the data. A further complication is that parameters may be identifiable over a range of the model behavior and unidentifiable outside that range. A desirable quality of a model is that all or most of its parameters be identifiable in the range where experimental data are available. A numerical procedure is available for evaluating the identifiability of parameters in a model over the domain of the independent variable where the experimental data are located. The identifiability calculation does not require experimental data and thus can be computed in advance of experimentation to assist in planning experiments.

9. Parameter sensitivity and robustness. If a parameter is to be evaluated by comparing data with model calculations, the model results must change when the parameter's value is changed. Sensitivity and robustness have to do with how much the state variables change with changes in parameters. The first requirement is that the model has enough sensitivity to changes in each parameter. For example, a 10% change in a parameter's value should cause a significant change in at least one of the model's state variables. If there is little or no change in any state variable, there will be little chance of arriving at a correct value for the parameter and its role in the model should be questioned. On the other hand, a small change in a parameter's value should not cause very large changes in the behavior of a model. For example, if a 1% change in a parameter's value causes a 20-50% change in a state variable, the model is not robust and its predictions may not be reliable. Like the identifiability, parameter sensitivity is a model characteristic and can be calculated in advance of experimental measurements. Sensitivity calculations can, in fact, help in the planning of experiments by showing ranges of variables where the sensitivity is good or poor. Using this knowledge, data collection can be made more efficient by concentrating on regions where the parameter sensitivity is good and recording fewer data points where the sensitivity is poor.

Author's Biography

Dr. J. Mailen Kootsey has had a 40 year career in university education, with experience as a professor and researcher, department chair, academic dean, academic vice president, and chief information officer. His interests have consistently been multidisciplinary, associated at various times with departments of physics, physiology and pharmacology, computer science, and biomedical engineering.

Dr. Kootsey received a BA degree in physics from Pacific Union College in 1960 and a Ph.D. in (nuclear) physics from Brown University in 1966. Dr. Kootsey chose to apply his experimental and quantitative skills to the study of the origin and propagation of electrical activity in the heart, spending 20 years as part of a research team in the School of Medicine at Duke University. While there, he initiated and directed a national research resource in biomedical computer simulation, providing services and training to more than 80 research projects and teams across the United States and in several other countries. Dr. Kootsey has authored more than 60 papers in professional journals and several book chapters. He is co-author of two patents: one in clinical instrumentation and one in software. Dr. Kootsey has taught a variety of courses in physiology, pharmacology, computer science and management information systems, and biomedical engineering to undergraduate and graduate students.

Dr. Kootsey is the principal author of two software systems for interactive computer simulations for research and teaching: NumberLinX for building interactive simulations in Web pages and SCoP for advanced interactive simulations. Formally retired from Loma Linda University in 2005, he now spends his time developing simulation software and working on startup projects in education, computation, and health care.

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