Contributions Towards Decision Support for Site-Specific Crop Management

A study of aspects influencing the development of knowledge-intensive differential management decisions

Ronaldo Pereira de Oliveira
MSc. Geoinformation Systems for Rural Applications

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degree of Doctor of Philosophy

Australian Centre for Precision Agriculture
Faculty of Agriculture, Food and Natural Resources
The University of Sydney
New South Wales
Australia

Australian Centre for Precision Agriculture

MMIX

Certificate of Originality

I hereby certify that the text of this thesis contains no material that has been accepted as part of the requirements for any other degree or diploma in any University, nor any material previously published or written unless the reference to this material is made.

Ronaldo P. de Oliveira
July, 2009

Dedication

To the Land, the People, and the Dreaming
in my Walkabout

Acknowledgements

The submission of this thesis consolidates an overseas endurance that was relative to a half world of dissimilarities and a huge ocean of changes to my family and I. For that, I shall let myself draw a parallel to the heroic era of the British Imperial Trans-Antarctic expeditions, to the event of “Endurance Expedition” led by Sir Ernest Shackleton (1914–16). Although Shackleton failed to cross the Antarctic continent, he is now known for his effective leadership skills through events of uncertainty, ambiguity, and sudden change. Today his approach is recognized by the technological industry for knowledge intensive management. Sir Shackleton was able to: i) maintain an optimistic outlook while grounded in reality; ii) display infectious tenancy looking for the next step forward amongst multiple solutions; iii) assemble a strong team that would increase the likelihood of success; and iv) keep focus on his ultimate aim.

My yield as a sailor in this overseas endeavor has been the change from clean air of computer labs with standard black-box solutions; to the dusty reality involving the vagaries in farm managements, where simple solutions are to be inspired by an ocean of knowledge in which I’ve been immersed while working at ACPA.

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To Australia for the standard friendship and fair attitude of its people allowing for a perfect journey, which will therefore procreate a feeling belonging that will last for the generations to come. In my Walkabout, the dreaming is inspired in unique, vibrant, and exotic nature that has changed my life forever, contrasting the long lurking of bare soil to the heavenly green walls crashing with astounding force over hundred miles of sculptural reef breaks.

Abstract

The thesis **Preface** first introduces the overall research context of Precision Agriculture (PA) and the specific aims of this work. Aims are particularly related to aspects of the opportunity for the adoption of Site-Specific Crop Management (SSCM) technology, which underline assumptions of efficient production management and environmental-economic principles. The body of the investigation is structured in three parts concerning the background information on Decision Support Systems (DSS) for SSCM, the proposal of methods supporting SSCM decisions, and the general impact of this work with appendices.

A historical data set (1996-2006) of yield monitoring, crop reflectance imagery and soil electrical conductivity (EC_a) was gathered from 80 broad-acre grain crop fields across three agronomic regions in Australia. These are 5 farms in South Australia, 3 in the Riverine and 8 in Northern New South Wales, which form part of a non-profit growers network built on the cooperative sharing of information and experience on the promotion, development and adoption of PA as a means for profitable and sustainable farming. In total, 218 field-year samples over a decade of intensive monitoring include several grain crops.

Part I includes a literature review identifying aspects and requirements concerning the structure of agricultural decision support, trying to understand "how it should be" and "what it is composed of". Further attention is given to current system solutions potentially leading to limited technological adoption. The first chapter presents a literature review identifying aspects, concepts and typical components to be considered in the development of DSS for PA, according to the research context and aims as further introduced. A broad analysis of past experience is addressed, analysing how they may have influenced present DSS standards for SSCM. A complementary chapter extends the review, with system development aspects for decision tools for PA. It reports on a wide range of Web-based decision support applications closely related with SSCM decision-making, also including a technical survey on the implementation and the design aspects specific to current PA DSS developments.

Part II initially addresses the lack of analytical and integrative capabilities in available decision support tools by introducing a new method of application for a DSS conceptual framework for SSCM. This system design uses object-oriented diagrams to describe processes for the quantitative assessment of within-field crop variation and the associated opportunity for the segmentation of management zones. It considers a knowledge intensive support to management processes, which would theoretically facilitate an integrated access to agronomic

models directly available to farmers. Further research is to populate this framework with quantitative assessments of spatio-temporal within-field production variability. For this, a numeric opportunity index for the merits of investment in PA is suggested considering components of crop production variation magnitude and spatial structure, as observed with different intensive monitoring devices (i.e. crop yield, soil electrical conductivity, and remotely sensed imagery). The use of alternative indices appears to support more dynamic crop production variability analysis, which could account for pre-season, in-season, and post-season observations and decisions. The introduction of a parametric method rendering the degree of management-responsive crop variability proved robust and could provide a simple ranking mechanism to identify fields of greater potential for further investment in differential crop management. It is hypothesized that the availability of several indices could support a more efficient step wise SSCM adoption via parameters that are less dependent on management practices. Summing up the use of opportunity indices ($\mathbf{Y}_i$, $\mathbf{I}_i$, & $\mathbf{S}_i$), a decision model is proposed systematizing the use of index benchmarks for decision pathways using the most appropriate monitoring technology according to the individual stage of SSCM adoption. Finally an economic evaluation is proposed to estimate the financial advantage from zone management using variable-rate application of inputs. The model uses a net worth analysis for a single intervention for within-field differential Nitrogen management, which is conducted as a simple way of comparing segmentation methods applied to zone management. The evaluation of segmentation methods has considered object-oriented image processing algorithms based on spectral and morphological relationships, which proved effective through the hybrid segmentation approach proposed. The combined use of multiresolution segmentation with a hierarchical watershed transformation and region grow algorithms appears to provide a favourable partitioning of within-field management zones.

Part III presents a concluding chapter that includes closing remarks regarding the specific research aims, general conclusions and major issues concerning future research, as well as appendices with extended methodological references and detailed experimental outcomes. The final chapter complements the detailed discussion provided in each chapter by highlighting general aspects of the context of exploring simple means to characterize the opportunity for the adoption of site-specific differential crop management. A concluding evaluation of the applicability of the proposed methods is provided. This evaluation adds general points about the implications of this thesis work in the development of automated methods for spatio-temporal analysis of site-specific data.

Thesis Organization

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Research Context & Aims

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Chapter 2 – Methods for development of SSCM decision tools

PART II – *Methods Supporting Decisions on the Adoption of SSCM*

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Chapter 6 – A decision tree for the opportunity in adopting SSCM technology

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Glossary of Terms and Abbreviations

Acronyms	*Description*
ABARE	Australian Bureau of Agricultural and Resource Economics
ABM	Agent Based Model
ABS	Agent Based Systems
ABS	Australian Bureau of Statistics
aDSS	Agricultural Decision Support Systems
AGROVOC	Agronomic Thesaurus Web-Service
AgroXML	Agricultural eXtensible Markup Language
AgXML	Agricultural Markup Language Standard
AI	Artificial Intelligence
AIC	Akaike Information Criteria
AOS	Agricultural Ontology Service
API	Application Programmer Interface.
APSIM	Agricultural Production System Simulator
ASC	Agris/Caris Classification Scheme
CAT	Chinese Agricultural Thesaurus
DCITA	Australian Department of Communications, Information Technology and the Arts
DSS	Decision Support Systems
DST	Decision Support Tools
EC_a	Soil Electrical Conductivity
EDA	Exploratory Data Analysis
EDSS	Environmental Decision Support System
EFITA	European Federation for Information Technology in Agriculture
EMI	Electro-Magnetic Induction
EVAO	Estimated Value of Agricultural Operations
FAO	Food and Agriculture Organization
FTP	File Transfer Protocol
GGF	Global Grid Forum
GIG	Global Information Grids
GIS	Geographic Information Systems
GML	Geography Markup Language
GUI	Graphic User Interface
HTML	Hyper Text Markup Language
HTTP	Hypertext Transfer Protocol
ICT	Information & Communication Technology
IDE	Interactive Design Environment
IDE	Interactive Development Environment
Internet	A network consisting of millions of hosts around the world.
IP	Internet Protocol.
IT	Information Technology
JPEG	An image file compression standard format (Joint Photographic Experts Group)
JRE	Java Runtime Environment
JVM	Java Virtual Machine
KBS	Knowledge Based System
KIF	Knowledge-Intensive Firms
MDA	Model Development Approach
Mosaico	A program proving a simple GUI to access data stored on the internet.
MZ	Management Zones

Acronyms	***Description***
NASS	National Agricultural Statistics Service of America
NDVI	Normalised Vegetation Index
OASIS	Organization for the Advancement of Structured Information Standards
OGC	Open Geospatial Consortium
OMG	Object Management Group
OO	Object-Oriented
OOD	Object-Oriented Design
OOP	Object-Oriented Programming
OWL	Web Ontology Language
P2P	Peer to Peer, person to person data and information exchange environment.
PA	Precision Agriculture
PADS	Principles of Advanced Distributed Simulation
PALM	Precision Agriculture Markup Language
PCA	Principal Component Analysis (e.g. PCn – n^{th} Principal Component)
POC	Plant Ontology Consortium
POESIA	A semantic Web Ontology for the Brazilian Agriculture
R&D	Research and Development
RDF	Resource Description Framework
RDFS	Resource Description Schema
RMSE	Root Mean Square Error
RPC	Remote Procedure Call.
SDE	System Development Environment
SDK	Standard Development Kit
SDM	System Development Methodologies
SDML	Simulation Description Markup Language
SGML	Standardized, Generalized Markup Language.
SOA	Service Oriented Architecture
SOAP	Simple Object Access Protocol
SPAA	Southern Precision Agriculture Association
SSCM	Site-Specific Crop Management
TCP/IP	Transmission Control Protocol based on the IP.
TKCS	FAO Technical Knowledge Classification Scheme
UDDI	Universal Description, Discovery and Integration
UML	Unified Modelling Language
UN	United Nations
URI	Universal Resource Identifier
URL	Uniform Resource Locator.
USDA	United States Department of Agriculture
VRA	Variable Rate Application
VRT	Variable Rate Treatment
W3C	World Wide Web Consortium
WCS	Web Coverage Service
WFS	Web Feature Service
WMS	Web Map Service
WPS	Web Processing Service
WSDL	Web Services Description Language
WWW	World Wide Web. The web of systems and the data that is in the Internet.
XML	eXtensible Markup Language

Preface

This thesis aims to investigate foundations for a semantic bridge between realms of agronomy and computer sciences within operational and tactical decision processes in SSCM. For this purpose, recently established standards from Information Technology (IT) are suggested as a means to facilitate the representation and the implementation of effective and accessible decision tools. This approach is based on the fact that IT methods appear to be little considered beyond site-specific monitoring instrumentation, which may influence a recognized PA technological gap in the development of DSS. However, the core investigation concerns quantitative models for agronomic and economic spatial relationships, which are formalized, prototyped and documented within a system developments point of view.

Although this approach may impose a system-development jargon, the contents are aimed at agronomic related audiences and focus on the spatial and temporal aspects in crop production variation. Biophysical and production management comments are limited to the specific observations in this research and based on ad-hoc production system expertise reports. Still, the system perspective is introduced in order to call the attention of agronomic users and model developers to the importance of using basic system concepts that may promote more effective implementation of tools directly available to farmers. For this reason, extended concepts for system development processes are given in appendices 2 and 3.

From an electronic engineering and computer science mixed background, it is evident a great technological mismatch between current PA standards for data gathering and data usage. A lack of automated spatial analysis and integration of production data to generate meaningful information is seen to contrast with advanced robotics used for within-field monitoring and operational control. However, after a more in depth examination of site-specific agriculture it became less clear as to whether the comprehensive use of software development technologies will suffice for bridging the present gaps in agronomic knowledge and spatial reasoning.

Looking 20 years into the future, I can foresee field-scale operational practices that would regularly apply nanotechnology-based mechatronic worms capable of remotely reporting soil biophysical and structural conditions, along with root development stages, hopefully using sustainable energy sources. However, an intelligent farm management and control system that matches the current standards of accessibility and security provided by retail automated banking systems, is difficult to predict.

Research Context

The fine tuning of farm management decisions has always faced challenges of balancing production requirements, knowledge and applied technology. In the past, decisions towards short-term benefits from broad-acre and uniform management practices may have delivered environmental costs as they were often taken up without a full understanding of long-term risks. The recent information revolution has been helpful in shaping more efficient farm management through the adoption of technology. This process has become more evident as farming uncertainty increases and new market and environmental standards have been imposed on managers. However, the uptake of technology has been restrained due to a lack of clear scientific evidence and proven benefits for new tools.

Advantages in the adoption of information-intensive agriculture practices, referred to as PA, can be positively interleaved in the tripod of sustainability aspects (**Figure 1**). PA has already been pitched as a solution to counteract deleterious consequences such as input waste, long term yield reduction, and soil, water and atmospheric degradation, even though a localized short term history of outcomes is still limiting more conclusive investigations. Therefore, questions can be raised about the relatively limited spread of this technology given the potential of IT to support farm management.

This investigation context is limited to questioning the current situation in terms of available technology supporting the form of PA denoted as SSCM. The present situation shows fast advances in firmware and wireless communication bringing into common practice a comprehensive set of tools for intensive field monitoring and operational management. In decision making, often the outcome of this adoption of fine resolution data gathering technology has been an overwhelming amount of information to feed into traditional management approaches. Moreover, the recursiveness and density of data sets have not easily answered management questions by themselves. This contrast supports the notion that gathering technologies are not matched by appropriated developments of complimentary analysis tools which can promote analysis and informed reasoning for effective decision support.

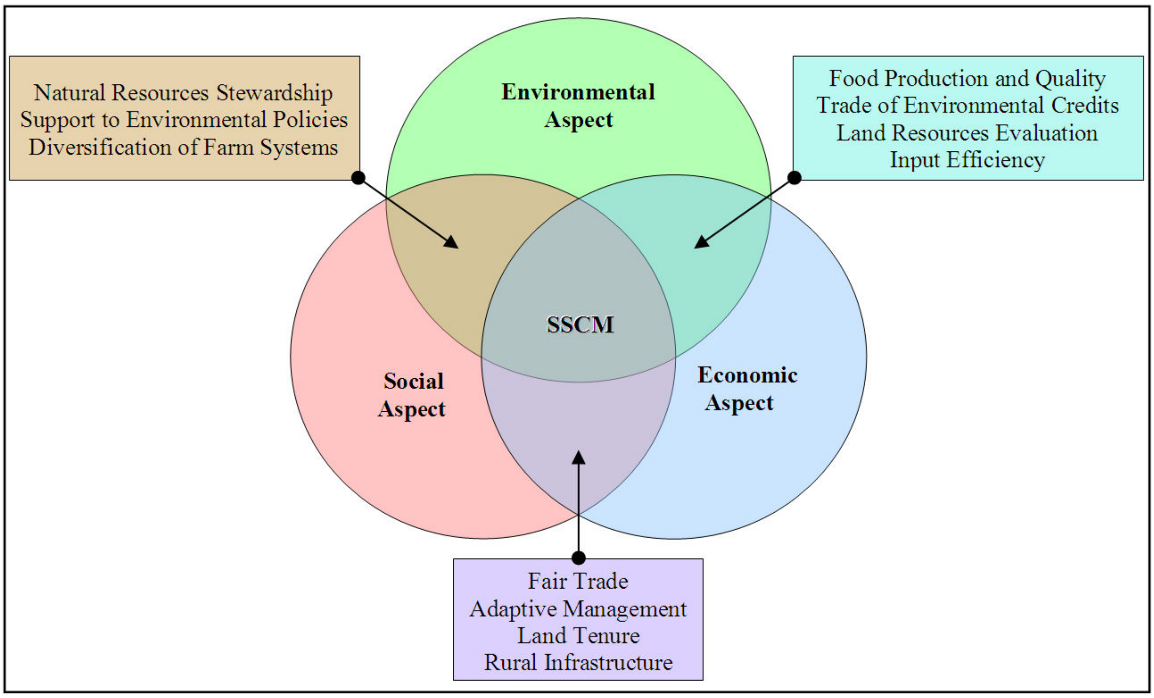


Figure 1: General aspects of SSCM towards sustainable agriculture.

Ideally, analysis and understanding of this data should match the speed at which it has been generated. But, even if yield maps can immediately display variability patterns of a specific crop season, the analysis and understanding of this variation is still dependent on both quantitative methods and spatio-temporal association rules. The proper development and management of this analytical knowledge is important for the adoption of SSCM, supporting managers to justify investments in technology and determine when, where and how to optimize differential management practices. Research is still far behind in the development of these tools, but their construction is crucial if farm managers are to be convinced that PA techniques have a potential payoff. This process is fundamental to proving PA to be the new agricultural standard.

It is understood that the development of DSS to answer questions in PA is still a critical research gap, which potentially dims the adoption of SSCM technology. The use of the DSS acronym is mostly associated with standalone tools of dissimilar typology and proprietary data structures, lacking spatial reasoning functionality and software development standards. It appears that there is still no proper knowledge on the basic decision questions and system development requirements necessary to supply pragmatic within-field management tools.

This work argues that the use of appropriate development methods and standards for system analysis and design can potentially facilitate the generation and re-use of tools that use quantitative and spatial crop management models. Development methods can be further used to embed agronomic models and practical knowledge in knowledge management frameworks that could increase the efficiency of traditional crop management practices. Methods supporting more flexible and open software developments are already maturing and could be applied to address the overall context of SSCM decision-making processes.

Clearly, adaptive farm management can be facilitated through a framework enabling decision support via interactions of several interoperable modelling tools with outcomes being swayed by knowledge of individual farm management systems. Tailored solutions could be individually composed, providing outcomes that are simply to understand and interpret by managers. New trends in PA development are already reflecting a more mature understanding of how to model the diversity in SSCM decision making, including: i) participatory approaches to model practical decision-criteria factors; ii) simpler mathematical representation and autonomic data handling and analysis addressing simplicity in human interactions; and iii) tools in conformity with Service-Oriented Architectures (SOA).

The focus of research in this work is to investigate and summarize the contextual and practical issues about within-farm crop management decision-making processes using SSCM technology and data. Aspects influencing the adoption of PA technology are explored with conceptual system development methodologies. In addition, methods addressing spatial agronomic knowledge gaps are focused on quantifying complex yield variability while providing easy to understand assessments. The general hypothesis is that the use of knowledge management tools could provide a pragmatic way to complement knowledge assets (scientific and tacit), thereby increasing the usefulness of management support tools and leading to increased production efficiency with the appropriate adoption of SSCM technology.

Aims

The aims in this investigation are itemized below according to an overall objective of exploring simple quantitative and automated methods for characterizing within-field variability. Experiments are conducted within a “building a bridge” perspective, between system development methods and agronomic modelling, when addressing practical decision questions in the adoption of site-specific crop management.

- To examine the literature from different domains related to the philosophy, logic and development of decision support systems to identify and understand minimum requirements towards a conceptual framework and implementation in SSCM.
- To provide a thorough literature review of SSCM software to identify methods, functionalities, and missing requirements.
- To propose an object-oriented conceptual design of a DSS framework supporting questions on the adoption of SSCM technologies.
- To model the magnitude and the spatial structure in yield data variability to propose a normalized variability index that can be applied for general grain crop production in decisions involving investments in technology.
- To apply the proposed normalized yield-based variability index in remote and proximal sensing data sets to evaluate less invasive monitoring methods.
- To define a decision tree using variability indices from different monitoring technologies to support SSCM decision processes.
- To optimize the number of potential management zones, while modelling the spatial segmentation of within-field agronomic attributes, to determine where and how to apply differential management.

PART I

A Literature Review in Decision Support

for

Precision Agriculture

Chapter 1

Decision support for site-specific crop management (SSCM)

Summary

This chapter presents a literature review identifying aspects, concepts and typical components to be considered in the development of Decision Support Systems (DSS) for Precision Agriculture (PA), according to the context and aims in the introductory chapter. A broad analysis of past experience is addressed, analysing how they may have influenced present DSS standards for Site-Specific Crop Management (SSCM).

Issues regarding the limited adoption of SSCM technology are subject to more specific analysis, as they have been strongly associated with ineffective developments of decision-support tools. Previously proposed system approaches, agronomic models, and software requirements are discussed and summarized through a critical analysis of functionalities offered by commercially available tools, also considering human-related aspects favouring farmer's adaptive learning. As a result, this review aims to build up a reference on general aspects of farm decision-making that influences the adoption of SSCM technology.

In PA, the DSS acronym has been mostly associated with standalone tools of dissimilar typology and proprietary data structure, which usually requires advanced computer literacy from agronomists, consultants, and farmers. There is also a lack of knowledge on how to integrate scientific and practical crop management knowledge in order to supply effective decision support.

1.1 - Introduction

Profitable agricultural production systems are most likely to consider aspects beyond on-farm operational activities, usually involving strategic decisions about a compliant adoption of new technologies. Basic adoption questions traditionally regard the appraisal of a short term increase in production against machinery or input investments. The adoption of new farm technologies has been historically slow, due to decisions that often involve perspectives other than agronomic reasoning, such as stock market variation, environmental polices, and computer literacy. The present dynamics in the agribusiness sector has contributed to an increase of influencing factors, suggesting that decision processes need to be systematically revisited in order to provide guidance as new questions are imposed to farm managers. Questions such as: How can I know if the spatial variation of my crop yield shows opportunity for investments in PA? How to evaluate if I have environmental credits for a carbon trade market? How to measure the sustainability of my production system?

PA is a knowledge domain demanding significant support from Information Technology (IT). In particular, information systems that could help manipulate dense datasets with multiple variables to put decision-making on a more rational basis regarding agricultural and environmental management. Requirements for a greater integration of technological, environmental, market and political factors demand computational management tools conceived to target specific questions and to be also understood as interoperable components of multilevel and cooperative Knowledge Based Systems (KBS). There is a need for integrating diverse data sources, software modules and whole systems, because the lack of effective decision support tools has been a critical limitation for a wider adoption of PA.

Twenty years of PA have brought great improvements in auto-steering, continuous monitoring and timely delivered datasets, contrasting with available software solutions which are still inappropriate for routine decision reasoning. The ability of intensive field monitoring has generated extra information layers from which no clear evidence of improved management has often been given. Tailored experiments facing methodological uncertainties and high investments have shown a great variance in economic returns (Lambert & Lowenberg-DeBoerg, 2000; SPAA, 2008).

Evaluation methods supporting agronomic and economic crop management generally impose a great deal of learning from agronomy consultants and/or farmers to induce decision knowledge. DSS also require time from farmers to deal with data management, system maintenance and human-computer interface issues. This contrasts a lot with the traditional farm management knowledge mostly based on relatively simple rule-based tools and intuitive decision making. Still, investments in technology have not yet given evidence of effective analysis capabilities. In a domain relying on georeferenced monitoring, PA tools rarely offer some kind of spatial pattern analysis capabilities. Analytical functionalities are still missing to facilitate multi-scale, spatial, and temporal relationships.

Intensive monitoring may not have changed the agronomic knowledge behind field activities, but the lack of effective interpretation of the observed crop variation may have imposed new challenges for the abstraction of useful information. It is also not clear whether limitations of available DSS tools have been increased by relatively limited attention to system development methods. Reason why further discussions in this work (**Chapters 2 & 3**) concern on IT methods currently used in PA software development and recent system modelling standards not yet considered. Still, the main focus of research should be the incorporation of agronomic knowledge and practical farm management into spatial systems that could facilitate decisions through scientifically based simulations as a test mach tool of farmers' experience. This new generation of decision tools should make use of new IT approaches that could facilitate the design of a single decision tool that could answer questions such as: Should I invest in SSCM?; Which monitoring tool is most appropriate to my field?; When should I use it?; and How do I interpret the yield spatio-temporal variation?. Overall aims should address the use of simple quantitative methods and system design architectures that could offer a means to transform intensive monitoring datasets into more informed decisions.

In the long run, integrated and accessible software could promote the adaptive learning of individual farm management, assembling field information into management knowledge. A generic knowledge management infrastructure supporting local farm management decisions should be designed for interoperability and composability of system components to facilitate the sharing and integration of knowledge assets. As single perspectives can not support modern farm management, the broad integration of analytical methods through composable tools is expected to address knowledge gaps to blend operational, biophysical and socio-economic actors.

This literature review further analyses the role of recent IT trends supporting new perspectives of knowledge support for decision-making, considering the use of unified modelling methods and Web of knowledge architectures. These approaches have already been adopted by the software industries of several knowledge domains (e.g. e-Commerce, urban planing, forestry, and bioengineering) but so far mostly disregarded in agricultural tool developments. They may provide foundations for the proper development of decision support tools that could meet unfulfilled requirements from farmers and researchers, supporting data integration, system interoperability, and knowledge management for an improved PA decision-making.

1.2 - Agricultural decision support systems (aDSS)

1.2.1 – To what extent are DSS still relevant to agriculture?

A twenty-five year collection of reports claiming the ineffectiveness or failure of agricultural decision support systems (Brook & Hearn, 1983; Gelb & Parker, 2006; Matthews *et al.*, 2008) may lead to questions of how relevant these computational tools still are to agricultural research and farm management. Matthews *et al.* (2008) term agricultural decision tools as "aDSS" and argue, following McCown (2002), that they are subject to cyclic phases from unrealistic expectations to disbelief or evident abandonment. Several articles have stressed alternative system approaches (McCown & Parton, 2006); soft system (McCown *et al.*, 2006; Fountas *et al.*, 2006), human learning (Loevinsohn, 2002; Seppänen, 2002), and user participation aspects (Lynch & Gregor, 2004) over computational perspectives (Lynch *et al.*, 2000; Nguyen *et al.*, 2008; Matthews *et al.*, 2008), perhaps characterizing period of disappointments. Although addressing important aspects, they may reflect some degree of unrealistic expectations from system developments. The European Federation for Information Technology in Agriculture (EFITA) has addressed similar questions in trying to respond to: Is Information and Communication Technology (ICT) Adoption in Agriculture and Rural Development still an issue (Gelb & Parker, 2006)?

Contemporary reviews on aDSS still sustain positive expectancies for the future of new applied technology (Massey *et al.*, 2008; Lamb *et al.*, 2008), even given a history of unfulfilled projections and disappointments with limited impact in rural computer use (McCown, 2002; Lamb & Bramley, 2002). Most reviews try to re-appraise the role of decision support in a whole-farm management research context (McCown, 2002a; Lynch, 2003; Fountas *et al.*, 2005; Lamb *et al.*, 2008), the appropriate approach to reinforce farmers participation and farm management knowledge (Lynch & Gregor, 2004; Robinson, 2004; Fountas *et al.*, 2005; Nguyen *et al.*, 2008), or feasible frameworks for software development (Gorddard *et al.*, 2001; Öhlmér, 2006; Murakami *et al.*, 2007; Nash *et al.*, 2006).

Initial expectancies were, in part, promoted by projections of increasing computer use in rural areas and decades of abundant research in process-oriented agronomic modelling (Zadoks, 1986; Boote *et al.*, 1989; Jones *et al.*, 1991; Hoogenboom *et al.*, 1994; McCown *et al.*, 1996). Investments in simulation models and expert systems have promoted major process-oriented software (Hoogenboom *et al.*, 1989; Uehara & Tsuji, 1993; Ten Berge, 1993; Jones, 1993; Bouma *et al.*, 1996) and collaborative networks for systems approach (Ritchie & Bouma, 1995), contributing to a wider understanding of agricultural production systems (Jones *et al.*, 2000; Bouma & Jones, 2001). However, a contrasting situation exists between a rich experience in quantitative process modelling and a limited availability of effective tools and limited technological adoption by farmers. Therefore, this is the knowledge gap that DSS are required to bridge, where precise simulation models are often divorced from real-farm situations. Walker (2002) suggests that the contrasting situations involve limited knowledge representation and irrelevant decision processes, also reflecting great diversity in objectives of system development paradigms.

A software perspective is given in the paper by Gelb *et al.* (2006), which analyses a decade of major changes in farm management technology adoption and summarizes factors limiting the use of IT by farmers and extension services. Gelb *et al.* (2006) include results of an EFITA survey (Gelb *et al.*, 1999) and findings from commercial software reviews, which were considered as indicators of the content and level of adoption. There is now a consensus indicating that despite the abundant agricultural modelling experience, practical tools are still a major issue and potentially a critical concern (Griffin *et al.*, 2004; McBratney *et al.*, 2005; Fountas *et al.*, 2006; Matthews, 2007).

It can be argued that explanations for the lack of success of aDSS may have been premature, if limitations have been mostly imposed by poor agronomic knowledge or inappropriate system developments. These reviews would stand on premises where either software development technologies were not actually available, or agronomic models were not comprehensive for the proper abstraction of the agronomic and managerial processes. It is not clear whether the timely and tangible technology was actually available in order to support knowledge gaps accounting for farm management and/or knowledge representation methods not yet exploited.

It is also possible to argue that limitations in aDSS could be related to common issues of human-computer interactions (Smith & Green, 1980). Ineffective DSS tools are likely to have structural issues (Rus *et al.*, 1993), characterizing contrasts between hardware and software developments. A similar analysis may be drawn for the cyclic process of SSCM between the gathering/application and the interpretation steps, where great advances in monitoring sensors

(King & Wall, 2001; Lamb & Brown, 2001; Selige & Schmidhalter, 2001; Eigenberg *et al.*, 2002; Bramley & Lamb, 2003; Sudduth *et al.*, 2004; Vrindts *et al.*, 2003; Adamchuck *et al.*, 2004) can be perceived during disappointment phases of aDSS (Robert, 1999; McCown, 2002; Dobermann *et al.*, 2004).

1.2.2 - When technology plays its role

Often, the lack of conclusive economic-environmental evaluations and effective DSS tools has frustrated the expectations of early users, potentially restraining broader adoption. The proper design, functionality and user participation in farm decision tools have been extensively discussed, perhaps pointing to renewed expectations on alternative development paradigms (Fountas *et al.*, 2006; Matthews, 2007; Nguyen *et al.*, 2008). Reviews on the user's perception for the adoption of computational decision tools across time have not questioned whether the strategic importance and usefulness of knowledge-based DSS for farmers and advisors still remains (Hochman *et al.*, 1994; Stone & Hochman, 2004; Gelb & Parker, 2006). These general aspects may also be inherited by new technology in PA.

Ten years after initial SSCM evaluations pointing to limited adoption and inconclusive benefits (Lowenberg-DeBoer & Boehlje, 1996; Lowenberg-DeBoer & Swinton, 1997; Lambert & Lowenberg-DeBoerg, 2000; Stafford, 2000), recent experiments on trade-offs from intensive technology farming (Thorp *et al.*, 2008; Brennan *et al.*, 2007) may be still reinforcing the fact that an inability to properly quantify the fiscal value of technology is a restriction to wider PA adoption (McBratney *et al.*, 2005). Although quantitative estimations are difficult to make, the technology has mostly reported positive benefits (SPAA, 2008).

In contrast to the questionable adoption results at field level, the world-wide efficiency of agribusiness has as a common trend regarding new technology when facing market and environmental constraints. As an example of economic pressures, the Australian grains industry is suffering from increasing fluctuation in market prices and production outcomes due to stronger and more dynamic variations in trade and climate. Wylie (2001) reports in this industry of a decline in the terms of trade factor of 3% per annum and 60% of large grain farms not making a profit (ABARE, 2001). Still, indications are that IT will remain the main driver of productivity growth in Australia for the next 20 years (DCITA, 2006).

It is also a common aspect, that losses due to climate conditions could be bigger without the use of today's farming technology. Strong growth in technology-based productivity has been averaging between 3% and 4% per year over the last 10 to 15 years in the US, Brazil, and

European Union (Umbers, 2006), suggesting it as a major reason for grain producers remaining in business.

However the overall situation is not stable or showing great benefits over different periods and production systems. In the late 90's, Australian improvements in performance have shown profits of 3.2% for two years in grain farms over two decades to 1998-99 (ABARE – Productivity Growth in the Australian Grains Industry, 2000), slightly overtaking the decline in terms of trade for the same industry. In another moment, the average production expenses per farm in the USA have increased by 14.1% in the period from 2002 to 2007 (USDA, 2007) where average production cost increased 3% per annum in the same period (total of 15%).

While new varieties have increased their share of research investments, it is understood that better farming practices have done the most to improve productivity while preserving natural resources. Even if not yet characterized by great profits, long term projections have shown highly variable, but significant, PA returns. From 14 broad-acre fields across Australia, the median annual benefits from PA is estimated in AU$ 20 per ha (SPAA, 2008), ranging from $10 to $37 per ha for several types of grain crops. Other studies in sugar beet have shown estimated returns from PA varying from US$ 0.01 to $48.25 per acre (Lambert & Lowenberg-DeBoerg, 2000) for different management systems (e.g. N, lime, weed) and median wastage from uniform fertilizer application of AU$ 33.00 per ha on 17 field experiments (Whelan, 2007). New PA technologies have contributed to overall figures of yield improvements, with an average increase from 5 to 8 tonnes/ha over 30 years (Wylie, 2001), and reduction of fertilizer losses in the grains industry, which accounts for total estimated N losses ranging from AU$ 55 to $ 138 million (Grace, 2006).

1.2.3 - The context of PA and SSCM

A vast amount of literature is available defining PA through several different aspects (Verhagen *et al.*, 1995; Stafford, 2000; Zhang *et al.*, 2002; Bramley & Janik, 2005; McBratney *et al.*, 2005; Brennan *et al.*, 2007). These aspects are compliant with principles of sustainable production systems, as shown in **Figure 1** (**Research Context**), and directly related to major components (i.e. spatial referencing, resource monitoring, attribute mapping, decision support, and differential action) of the SSCM adoption process (Stafford, 1996; Whelan, 1998). In this research, PA will be broadly understood as extending the categorical levels of traditional farm management (e.g. strategic and tactical (Kay *et al.*, 2004)), which independently consider the three common farming functions (e.g. planning, implementation, and control) to generate new managerial information at different levels (Kay *et al.*, 2004; Doye, 2008). From farm to field level an operational management requires fine scale decision-making capabilities when based on several field intensive monitoring technologies. It is relevant to consider that this new management level not only supports a fine tuning of operational crop management within a field, but it may also brings new means to integrate different levels of information abstraction into a broader and new perspective in farm management (Bouma et al., 1999).

At the field level, the overall goal of SSCM can be considered to be the precise application of variable-rates of precise amounts of inputs to within-field production zones to achieve efficient management through maximizing net returns and minimizing environmental impacts (Batchelor *et al.*, 2002). This type of precision farming demands intensive field data acquisition and interpretation as a key to understand production variation, where sensors and information networks are expected to provide real-time field management capabilities.

15 years of applied PA has brought great improvements on mechanization, automation, data gathering, and simulation (Zhang *et al.*, 2002). However, expected outcomes from the interpretation phase following intensive monitoring investments have not developed as fast as new agribusiness standards have been imposed to farmers (McBratney *et al.*, 2005; Dobermann *et al.*, 2004), perhaps reflecting a significant lack of analytical support to characterize spatio-temporal yield variation (van Es *et al.*, 1999; Pringle *et al.*, 2003) and the delineation of management zones (Fridgen *et al.*, 2000; Whelan & McBratney, 2003).

This contrasting situation may also be related to design and development of practical farm management processes in which individual manager considerations can be underpinned by common scientific knowledge via intelligent software (Zhang *et al.*, 2007) in order to facilitate human aspects as self-learning and adaptive learning. It is understood that a common knowledge management framework facilitating the integration of knowledge assets could address basic questions like: How can I evaluate if my production system is sustainable?; How to measure the opportunity for the adoption of SSCM technology?; How to optimize the management of within field production zones?; and How to incorporate the current knowledge into pragmatic decision trees guiding the effective adoption of technology?

1.3 - Decision support in differential crop management

Historically, the system approach perspective in the development of agricultural decision support systems is based on process-driven simulation models; for crop (Jacobson & Jones, 1996; McCown *et al.*, 1996; Hoskinson & Hess, 1998), climate (Audsley *et al.*, 2001), and canopy stress (Jones *et al.*, 2000; Jones *et al.*, 2003); mostly taking into account point estimations as average values of geo-objects (e.g. polygons) or sampling approaches (grid points or cells). Although they have been successfully used for PA evaluations and agronomic reasoning (Shaffer *et al.*, 2000; Hargreaves & Hochman, 2004; Matthews *et al.*, 2008), tailored field trials (Carberry *et al.*, 2002; Hunt *et al.*, 2006) and spatial analysis (Hartkamp *et al.*, 1999; Wu *et al.*, 2005) they are not easily reproduced on the broad scale. They require cumbersome methods and data management to be adapted for analysis of spatio-temporal production variation (Batchelor *et al.*, 2002; Ahuja *et al.*, 2002; Brennan *et al.*, 2007), differential management systems (Braga & Basso, 2003; Jones *et al.*, 2004), and ecologic-economic assessments (Thorp *et al.*, 2008).

Major claims for proper capabilities for PA tools were compiled in Robert (2000) from thirteen Decision Support Tools (DST) workgroups in the 5th International Conference for Precision Agriculture, where several requirements where reported and are further discussed here (**Subsection 1.3.3**). The amplitude of issues reported may indicate that a wider perspective of what system approaches actually mean is missing, and that alternative solutions other than process-based models may have had limited follow up (Hodges *et al.*, 1992; Gauthier, 1992; Gauthier & Néel, 1996; Sonka *et al.*, 1997; Saraiva *et al.*, 1997; Whelan & McBratney, 2001; Pringle *et al.*, 2003; Griffin *et al.*, 2004; Nakamori *et al.*, 2007). Therefore, an evolutionary system development perspective needs to be extended in order to facilitate the proper use of software methods that may promote a composable and user driven knowledge management systems.

1.3.1 - Available DSS solutions

The DSS acronym in agriculture has been overwhelmingly used for dissimilar frameworks and modelling methods which have not yet routinely supported SSCM analysis of the vast number of new, intensive observations of major factors in production systems. On the other hand, the spread of solutions does resemble the broad scope of processes to be considered in the overall adoption of SSCM technology. This overall context of farm decision-making processes actually requires the consideration of different aspects (McBratney *et al.*, 2005) (e.g. agronomic, economic, environmental) from several sampling frequencies in space and time (Sadler *et al.*, 2007) (e.g. within field, whole farm; daily, and annual) at distinct managerial levels (Fountas *et al.*, 2006) (e.g. strategic, operational).

General categorizations of the decision-making process have been suggested at either two levels (McCown, 2002a, Blackmore, 2007), management control and strategic planning, or three levels (Bouma, 2000; Hayman, 2004; Fountas *et al.*, 2006), namely operational, tactical and strategic. The strategic level generally considers overall farm development plans, reduction of inputs, social and public regulations, human health and development, and market driven production. Tactical decision-making involves ecological control (e.g. pesticide/fertilizer optimization, water use efficiency/contamination), soil management (e.g. fertility, storage capacity, erosion, compaction, and contamination), weed and tillage management, and crop yield and quality. Operational decisions target improved tracking and steering; machinery maintenance, monitoring/sampling, irregularities in production areas (e.g. boundaries, gates, accessibility, protected areas), payroll, and improved performance. The abstraction of these management levels follows a generalization hierarchy that aims to facilitate the search for simpler indicators of production systems (Hayman, 2004).

According to Meinke *et al.* (2001), a DSS can describe any normative information-based system, including software products and dissemination of such information via printed or web-based media. Lynch (2003) called these systems 'intelligent support systems'. Hayman (2004) noted that the use of DSS in Australian broad-acre farming has been reviewed from several human related perspectives. In this context, studies have included a soft systems approach (Macadam *et al.*, 1990; Power *et al.*, 2008), designs that are less dependent on computational solutions (Cox, 1996; Cox *et al.*, 2008), and the degree of end-users' involvement (Lynch *et al.*, 2000; Mackrell, 2006). Robinson (2005) reviewed various guidelines for designing a DSS. These guidelines were compiled from several authors, increasing the number of key factors for the development of a successful DSS.

An overall IT development contrast (hardware vs. software) may, in part, explain the inability of PA tools to deliver resilient and meaningful information supporting crop management. It is suggested that the underdevelopment of farm management DSS has hindered the fine tuning of dense datasets into efficient actions (Dobermann *et al*., 2004; McBratney *et al*., 2005).

Conceptual and methodological considerations of DSS tools available for Australian farming systems research are suggested in Robinson (2005) and Nguyen *et al.* (2008). The research presented by Robinson (2005) uses twenty-four criteria compiled from prior studies (Dillon, 1979; Malcolm, 1990; Hamilton, 1995; Cox, 1996; McCown, 2001; Lynch *et al.,* 2000; and Lynch, 2002), in order to evaluate the usefulness of agricultural DSS applied to 6 case studies of farming system research. Robinson (2005) focused on the weighing of decision alternatives for a better understanding of farmer's models of decision making. Although pointing to relevant aspects from cognitive decision-making, Robinson (2005) only outlines conceptual guidelines for an effective re-engineering of DSS tools (e.g. a decision-oriented development, motivated and committed audience, thorough understanding of the decision context, contrasts between research and farm cultures). As a matter in fact, some of these aspects given by Robinson (2005) simply characterize typical system requirements already known from knowledge-based engineering methods. They should never have been separated during development. Still, Robinson (2005) correctly concludes that improvements in farm decision tools will be evolutionary rather than revolutionary, additive rather than competitive. Nguyen *et al.* (2008) conducted a survey among agricultural scientists and leading practitioners aiming to understand DSS adoption patterns, from which only subjective guidelines are summarized in relation to soft system approaches, which stress the user's participation. Analysis of these surveys can be considered biased in terms of system design and development methods as both authors have restricted the understandings of DSS to crop growth analysis and simulation tools (McCown, 2002a).

1.3.2 - Enabling technology

The enabling technology for SSCM can be broadly divided into two main processes of data gathering and data use, which have been to date mostly applied for agronomic experimentation and operational management efficiency. In the overall process, IT has been a key factor for the growth of SSCM methods, which have been mainly focused on real-time data gathering and storage. Intensive field monitoring and auto-steering capabilities have had the support of fast advances in mechatronics, leading to the development of proximal sensors and record keeping tools. Data use and interpretation processes, in contrast, have yet to respond to challenges such as the non-stationary aspect of crop variations and the multi-scale integration of agronomic and spatial reasoning. Emphasis on data gathering has generated an overload of information layers that usually are not ready for direct analysis or data integration. Tactical and strategic evaluations have been mostly based on averages, avoiding a great deal of analysis of these high resolution datasets which could supply proper information to turn data into effective decisions (McBratney & Whelan, 2001).

Still, a great potential is available for SSCM technology to favour the integration of bottom-up and top-down system development approaches. Bottom-up approaches provide the opportunity to explore massive and diversified monitoring datasets using neural networks, machine learning and agent based models. Top-down approaches provide the opportunity to apply the existing agronomic knowledge to spatial databases and crop growth simulation to evaluate causes in yield variations. The integration of the different approaches into a common information system for decision support has been suggested through several architectures (Hartkamp *et al.*, 1999; Bechini & Stöckle, 2007).

This section does not intend to cover a comprehensive list of equipment, methods, services, or costs of the SSCM enabling technology, but to briefly discuss major aspects and issues that could provide an overall picture of technological gaps affecting a wider PA adoption. Generally speaking, agronomic and environmental decision support tools should involve three basic components: a Geographic Information Systems (GIS), quantitative methods (statistics and spatial structures), and process simulation models (empirical and mechanistic). Specific components of the SSCM technology are next introduced, according to major research developments for farm management tools, as no single solution is available simultaneously addressing all the required functionality (Symanzik et al, 2002).

GIS

Some publications consider the integration of GIS, statistical tools and crop simulation models as the ultimate solution to solve the agricultural DSS gap (Symanzik et al, 2002; Wu *et al.*, 2005). However, customized farm GIS tools for the PA market are predominantly supported by stand-alone, proprietary, and incomplete packages (Paz, 2009), which require farmers and advisors to invest time to learn and maintain various pieces of software (Hartkamp *et al.*, 1999; Paz, 2009). In fact, analysis related to spatial dependency of production factors is still unavailable in commercial software. Farm GIS products are of limited functionality addressing the spatio-temporal production variability and the integration of results with practical decision making processes (Bouma & Jones, 2001, Matthews *et al.*, 2008).

Specific to DSS use for precision viticulture in Australia, Taylor (2004) has pointed to the strong product tracking, winery quality assurance and sales management slant of current tools, while lagging far behind basic GIS functionalities. In this sense, the application of GIS in SSCM has been to add visual interpretations and manual management of boundaries, through cumbersome handcrafted user interactions. Often, their use may be understood as a sophisticated geographic record keeping tool, mostly serving for the overlay of several data layers generated by commercial monitoring systems (e.g. yield monitors, Farmstar, remote imagery, Yarra N-Sensor, Veris, EMI-31, EMI-38, Greenseeker, Crop Circle, AccuHarvest) and advisory services (e.g. Terrabyte, Silverfox, AgreView, FarmGIS, CropView, Aster).

A greater attention to the coupling of GIS and robust quantitative methods to increase spatial reasoning is missing (Berry, 1995). This mixed methods approach has been now referred to as Quantitative GIS (Cope & Elwood, 2009) and could favour a better spatial cognition explaining factors and suggesting solutions for changing patterns in yield maps. Equipping spatial analysis tools with mathematical description languages and quantitative models may facilitate the implementation of stochastic and deterministic crop models in the same spatial resolution as the monitored data.

Simulation models

Process-oriented simulation models have been a great instrument in several areas of research, promoting insight, prediction and advisory capacity, and also contributing to a wider understanding of agricultural production systems (Jones & Ritchie, 1991; Bouma & Jones, 2001). Empirical or mechanistic simulation tools have been in use for a long time, for a wide variety of purposes, including crop management (Fetcher *et al.*, 1991), climate change impact studies (Alexandrov & Hoogenboom, 2001), sustainability research (Quemada & Cabrera, 1995), and PA (Paz *et al.*, 2001; Paz *et al.*, 2003). However, the support given to PA applications has been only based on field average values due to the punctual approach of process simulations, lacking behind the spatial aspect of within-field variations. Therefore, the non-spatial perspective of simulation tools can not fully support SSCM decisions, even if new trends in Web developments considering Principles of Advanced Distributed Simulation (PADS; Tolk, 2006) have been, to some extent, considered by online crop simulators (Pan *et al.*, 2000; Paz *et al.*, 2004; Hunt *et al.*, 2006a) and agronomic services (e.g. Apollo, FarmScape, Yield Prophet, and Whopper Cropper) that also support soft systems approaches (Cox *et al.*, 2008).

Crop-growth simulation models provide a dynamic way to estimate the potential return to producers for different variable-rate management strategies, where outcomes from specific experiments are often calibrated for a number of other regions and/or crops (Hunt *et al.*, 2006a). The majority of simulations of climate, crop growth and soil process are abstracted at the single process level that only matches point representations in spatial analysis. These models generally describe step-wise procedures emphasizing data flows through algebraic functions, which often account for questionable parametric parsimony (Cox *et al.*, 2006) and massive data input requirements for a single run. However, the required data is not always available (Batchelor *et al.*, 2002), and the software has a tendency to become isolated or discontinued, much to the frustration of successful thematic modelling initiatives (Walker, 2002; McCown, 2002).

Thorp *et al.* (2008) describe a legacy agricultural DSS, the DSSAT (Decision Support Systems for Agrotechnology Transfer), which serves to illustrate typical structures of simulation tools for supporting integrated farm management (Aggarwal *et al.*, 2006). The DSSAT includes modules which simulate the growth of 16 different crops and use common basic modules for soil–plant–atmosphere interactions. Typical data requirements include weather inputs (daily temperatures, rainfall and solar radiation), soil classification, and crop management practices (variety, row spacing, plant population, and fertilizer and irrigation amounts, intervention dates).

Agricultural simulation model developments have been mostly target to several areas such as: a decision calculus tool for researchers, a learning tool for farmers, and a knowledge transfer tool for agronomic advisors. For site-specific analysis however, they must be refined for accuracy and non-stationarity in data at smaller scales, interoperability with spatial models, and stability across a diverse range of agronomic and managerial contexts (Batchelor *et al.*, 2002).

Within-field variability

An efficient protocol to interpreting variations in crop yield and crop quality is still considered a key PA knowledge gap. Yield monitors have shown to producers and researchers alike that large yield differences commonly exist within a field, often also documenting unexpected changes in yield variability patterns from year to year (Lamb *et al.*, 1997; Dobermann *et al.*, 2003; Schepers *et al.*, 2005; Massey *et al.*, 2008). Still, the direct measurement of spatial crop productivity by yield monitoring is considered a fundamental way to determine field related variability (Stafford *et al.*, 1996). However, yield maps may be a reflection of many potential causes of production variability, which are also subject to great variation over time (Pierce *et al.*, 1997). Averaging multiple years of yield maps has been suggested as one way of establishing stable yield productivity patterns related to soil water (Stafford *et al.*, 1996; Kitchen *et al.*, 1995). It is highly possible that high producing areas during "dry" years may become low producing areas during "wet" years (Colvin *et al.*, 1997; Sudduth *et al.*, 1997). Other aspects of production variation are recorded by monitoring devices for protein, soil parameters, and temporal crop imagery. Examples of alternative methods to characterize variation in crop production have been the use of a crop simulation model for variable rate N-management (Thorp *et al.*, 2004) and an integrated environment composed by simulation models and linear programming approaches for whole-farm planning (Recio *et al.*, 2003; Florin *et al.*, 2008).

Research methods supporting the interpretation of within-field variability are lacking definitive analysis of spatial patterns in crop production. Unsolved questions include: the quantification of the spatial structure of production variations and their temporal stability (van Es *et al.*, 1999; Pringle *et al.*, 2003), the evaluation of the production profitability (Liu *et al.*, 2005), and tradeoffs for environmental sustainability (Robertson *et al.*, 2008)

Delineation of management zones

While real-time SSCM is still a utopian goal, distinct processes for monitoring, analysis and action can be conducted in sequential steps for crop management decision-making. The ability to apply differential treatments as required across several Management Zones (MZ's) is directly related to the successful implementation of PA to simultaneously achieve maximum profits and minimum impacts. To provide this efficiency, it has been proposed to determine the optimal subdivision of a field into more homogeneous production zones (Taylor *et al.*, 2007). It has been suggested that the degree of spatial yield variation is a key indicator for the potential use of production zones (Whelan & McBratney, 2000, Pringle *et al.*, 2003).

The use of continuous soil measurements of apparent electrical conductivity (EC_a) has also been reported as a potential input for predicting crop production variation caused by soil water differences (Jaynes *et al.*, 1993; Sudduth *et al.*, 1995), and therefore potentially useful for the delineation of management zones. Remote sensing imagery is another potential technology for identifying plant response zones in a field (Haboudane *et al.*, 2007), with the advantage of reduced monitoring efforts (Batchelor *et al.*, 2004). For that, Taylor (2004) has presented specifications of spectral, spatial, radiometric and temporal characteristics of sensors for satellite- and aerial-borne imagery commonly used in Australian agriculture.

As a tool for decision support, the application of MZ's has mostly explored yield averages using clustering analysis (Lark & Stafford, 1997). Hoskinson & Hess (1998) introduce a decision support tool, the Dss4Ag, which considers Artificial Intelligence (AI) methods for cluster analysis and has been applied for Potato (Hoskinson *et al.*, 2000) and Corn (Shearer *et al.*, 2000) production systems. Van Alpen & Stoorvogel (2000) address a functional characterization in support of PA using a fuzzy *c*-means classifier, which has shown that more than 65% of the spatial variation could be accounted by functional properties such as: water stress, N-stress, N-leaching, and residual N-content at harvest. Fridgen *et al.* (2000) used a fuzzy *k*-means unsupervised continuous clustering algorithm with inputs of soil samples and grain yield maps, which explained up to 35% of the variation in grain yields. Shatar & McBratney (2001) have subdivided within-field zones based on yield and environmental inputs, but constraining the hard *k*-means cluster analysis to ensure spatial contiguity. Whelan & McBratney (2003) provides a process of *k*-means clustering for delineating potential management zones that is based on zonal yield differences from kriging prediction variances in yield, soil electrical conductivity and elevation information. Schepers *et al.* (2005) evaluated the use of Principal Component Analysis (PCA) of landscape attributes with unsupervised classification of PCA scores, showing the significance of the temporal variation altering yield spatial variations even under irrigated crop regimes. Vrindts et al. (2005) also uses clustering techniques aiming to characterize correlations between soil compaction and yield data. Jaynes *et al.* (2005) used a cluster analysis of multi-year soybean yield maps to partition a field into similar temporal yield patterns. Yan *et al.* (2007) have mixed a PCA and a fuzzy *c*-means clustering algorithm to optimize the application of inputs.

Amendments for the standard *k*-means analysis have been suggested. Shatar & McBratney (2001) argue that clustering methods often produce non-contiguous subdivisions, increasing the number of small, random management zones in contrast with the highest potential of the technology applied to a few, larger areas. Other approaches are also reported: Kitchen *et al.* (1998) use average area-weighted correlations between grain yields and soil attributes, classifying sub-fields according to topsoil depth and elevation. Fleisher *et al.* (1999) have mapped the probability of exceeding a threshold with indicator kriging for optimization of pesticide applications. The algorithm introduced in Fridgen *et al.* (2000) provides concurrent output for a range of clusters from which the user can select the number of zones to be used.

Recently, more contiguous delineation approaches using segmentation algorithms have been suggested (Roudier *et al.*, 2008). Several image processing applications have shown growing attention given to object-oriented image processing and interpretation (Wang, 2008). The use of the object concept offers the opportunity of information extraction that can combine spectral and shape feature constraints. Due to the fact that associative and behavioural functions of spatial objects can be also described through expert knowledge, object-based segmentations are expected to have more robust noise reduction capability (Zheng & Sun, 2008; Wang, 2008). In particular when considered with watershed and region-based segmentation algorithms, the object approach has been applied in several areas of research for image feature extraction considering spatial relationships. Relative to PA, Roudier *et al.* (2008) introduce a modified watershed algorithm for management zone delineation tested on high-resolution bio-physical imagery in France. An object-oriented watershed algorithm is further considered and discussed in **Chapter 7**.

1.3.3 - Typical requirements

A representative analysis regarding the development of DST has been compiled in Robert (2000). It summarized goals, issues and requirements from the initial period of PA implementation. The resulting outline was formatted to describe DSTs through: main goals, DST types, functional requirements, essential data layers, and issues limiting the development. The content can be considered comprehensive in terms of expressing several aspects of SSCM technology as interpreted by the producer, agribusiness, agronomic research, and government views. Under a system perspective however, it is easy to identify the lack of proper methodology that could effectively contribute towards standard guide lines in system development. Some redundancy in the terminology of requirements can be observed and is reinforced by communication issues in multidisciplinary teams, but often it is indicative of a weak understanding of the software industry jargon and technological trends.

As an example, a requirement for "Internet based plug & play systems where different components can be added or removed to suit different cropping systems, states, countries, etc." is concerned with issues of "usability, complexity (holistic system), compatibility, and adaptability", and they can be now translated to system requirements, such as the need to consider both "model composability" (Petty & Weisel, 2003) and "Grid computing simulation" (Foster *et al.*, 2001; Pullen *et al.*, 2005). This analysis may indicate two points. First, system requirements as given by PA practitioners are, at many times irrelevant, or even misleading to system engineers just as much as available DST may have been to farmers. Second, system development technologies that can supply long missing functionalities have only recently become available and been considered in PA system research (Sørensen, 2008). Considering these arguments, it is possible to argue that all DST contributions to date have been significantly successful in relation to factual means available for software development. Despite the actual lack of DST, failure claims may sound either like: "The death of the aborted knowledge-system design" to designers; or "The failure of the never implemented decision support code" to system programmers.

Other important contributions in PA DSS requirements have been made in Saraiva *et al.* (1997), Lütticken (2000), Lynch *et al.* (2000), Fountas *et al.* (2002), Sørensen *et al.* (2002), Backes *et al.* (2003), Korduan (2003), Pedersen *et al.* (2003), Adrian *et al.* (2005), Robinson

(2005), Mackrell (2006), and Florin (2008). Again, they have been mostly characterized by specific farming systems or agronomic related analysis. In particular to the PA context, the requirements are compiled below, and suggest 3 groups of requirements according to major aspects which are discussed in **Section 1.4**. Groups are derived from principles of sustainability in SSCM, as shown in **Figure 1** (**Research Context**), and the underlying technology.

Requirements reported by the above authors suggest that DST for SSCM should be:

- According to social & human aspects: Designed to meet the specific needs of the farmers (e.g. inexperienced with software; simple user-interface and analysis methods; training; data security; perceived usefulness; women participation; whole-farm PA analysis; operational accountability; SSCM cost-benefit analysis; selection of crops; practices and technologies; complete process and simulation control; improved technical support; customizable to different management profiles; easy local or remote access to data; storage and mining of user-defined rules; links with market and services information).
- According to environmental and economic aspects: Designed to meet applied research and development needs supporting an improved knowledge and evaluating site-specific, field-specific and whole-farm management (e.g. to accommodate legacy systems; seamless integration of simulation packages; distributed and heterogeneous open database access; use of unified modelling methodologies; collaborative on-line libraries of experimental algorithms and source codes; multidisciplinary developments; expert and managerial knowledge representation; opportunity to fine-tune models to local conditions; platform independent models; composable environments with GIS, geostatistics, quantitative methods and visual modelling extensions).
- According to system development aspects: Designed to meet data interoperability, system integration and composability, and optimized development (e.g. low cost; automated data processing; fast performance; open architectures, integrated systems; inclusion and programming of new methods; scalable and distributed systems; open standards; software-interfaces and protocols; intelligent DSS; Web DSS; and reduced need for technical support).

It is unlikely that a single proprietary system will ever meet all of these requirements because of their complexity and comprehensiveness. That is why an open platform applying system behaviour modelling seems more appropriate to address the problem (Saraiva *et al.*, 1997; Lütticken, 2000; Murakami *et al.*, 2002; Nash *et al.*, 2006; Sørensen, 2008). An important point in open-structure component-based solutions is that the practice of precision agriculture still has many uncertainties that are the subject of ongoing research. New design and development methods need to be incorporated into PA information systems research by means of sound software engineering techniques and concepts. Available tools should conform to simple quantitative and spatial reasoning models. Consequently, two broad subjects of study may require further attention during empirical investigations of this thesis; (a) new methods of application for standardized modelling languages and (b) simple quantitative methods for the assessment of crop yield variability and the optimization of within-field management zones.

1.4 - What counts in SSCM decision support?

Farm decision-making is by definition an uncertain process. In general terms, farm management, as traditionally carried out by farmers, has been defined as "the process by which resources and situations are manipulated by the farm manager in trying, with less than full information, to achieve his [or her] goals." (Dillon 1979). This simple understanding suggests that new ways to "manipulate" farm resources will only be accepted if focused on the farm manager goals, effectively increasing the amount of information for decision making. The process by which the farm is managed goes beyond the scientific correctness of biophysical models, requiring the basic adoption question to be answered in a simple and effective manner.

Challenges in the development of SSCM decision tools are bigger when extracting simple, but relevant, responses from larger amounts of information and related processes. One of the priorities cited is to couple several data types and sources, analysis tools, and domain specific knowledge (McBratney *et al.*, 2005), while aiming to enable continuous learning and adaptive management (Walker, 2002). New PA technology needs to address farm decision processes embedded in the scientific assessment process, which should attend to human, environmental, and economic aspects as further discussed in this section.

The proper design of SSCM decision processes can be related to both the modelling of crop management knowledge and the associated software development approach, where different management processes may require the use of distinct approaches. Underlying IT methods should account for linguistic and behavioural abstractions of process-centred developments that also consider farmers learning and adaptive management. These semantic models may serve as complementary assets of agronomic, spatial, and quantitative models (Priami &

Quaglia, 2004) composing a knowledge framework focused on the support of farmer' decisions (Keating *et al.*, 2002). Open evolutionary software architectures seem appropriate to integrate several development initiatives. Ramsin & Paige (2008) have suggested the suitability of this approach using object-oriented technology towards knowledge-driven environments supporting SSCM decisions. This view is also supported in bioinformatics by Sorger (2004), stating that networks and open access to models will be more critical than open access to databases.

The review so far has shown that much of the requirements for a pragmatic tool supporting SSCM decision processes would involve system development technologies which have not yet been extensively investigated by the PA community. Surprisingly, few attempts have addressed system modularity and interoperability or data flow optimization (Saraiva *et al.*, 1998; Murakami *et al.*, 2007; Nash *et al.*, 2006). SSCM decision support conceptually involves the integration of modules for adaptive reasoning and management support (Robinson, 2005). This pool needs to consider the integration of as many procedures as necessary to cover core representations of the agronomic knowledge to support the acquisition, management, sharing and reuse of farm management knowledge. Finally, Web service technology can serve as a media facilitating inexperienced users and enabling dynamic customization of models for a specific management context. This system architecture may characterize a knowledge support for learning and increasing flexibility in management. The main aspects influencing this customization process are further detailed in the next sub-sections.

1.4.1 - Social & human aspects

As discussed, the vision of PA as an information intensive practice is changing to a point where a more vertical coordination and control of farm assets (Barry *et al.*, 1992) is suggested. This involves a multilevel process flow (Fountas *et al.*, 2006) that needs to consider new approaches of composable systems (Sørensen, 2008). The shift to an increasing mix of traditional concepts and semantically related IT (Rosskopf & Wagner, 2005) reassembles the idea in which PA is simply traditional agronomic and whole-farm management by means of advance of technology with a subsequent increase in management knowledge. It is suggested here that PA has evolved to be a farming approach that relies in data-intensive operational agronomic practice, information-intensive tactical field planning, and knowledge-intensive farm strategic management.

Barry *et al.* (1992) highlight important linkages between vertical coordination and financial structure in agricultural management using classic economic and firm structure theories (Jensen & Meckling, 1976; Williamson, 1979; Grossman & Hart, 1986). This theoretical management approach highlights farm manager centred systems, increasing concerns about issues related to user computer literacy, risk perception, technological adoption, learning and adaptive management, and participation in system developments.

Practical flow management models as suggested in Fountas *et al.* (2006) have been previously standardized through semantic-oriented service frameworks (Nakamura *et al.*, 2002), reinforcing the modelling of tacit farmer's production knowledge. Initial SSCM developments using integrated control and simulation technology for knowledge-base farm management (Sørensen, 2008) agrees with recent standards from military command-control systems, as suggested in Tolk (2006) for "Grid computing" PADS (further discussed in **Section 1.5.3**). There autonomous software agents capable of simulating learning and human reasoning are applied to facilitate human-computer interfaces in real time monitoring-analysis-action activities.

Computer use & literacy

It is suggested that farm managers may have gained a better understanding of the potential benefits of technological adoption (Rosskopf & Wagner, 2005) due to a greater proliferation of on-farm personal computers and Internet access to shared resources (Gelb *et al.*, 2005). Öhlmér (2006) argues that even if the general computer literacy has somewhat improved, it has not affected the ability to understand the information content. It is also well accepted that farmers have become more aware of issues relating to direct economic benefits (Rosskopf & Wagner, 2005; Fountas *et al.*, 2005).

Major barriers to computer ownership may still be related to the belief that the use of computer systems would not justify investments, as given by early surveys (Taylor *et al.*, 1991). Farmers appear to invest more in standard applications and field recording programs (Ascough *et al.*, 2002; Hayman, 2003; Offer, 2006), believing that learning a specialized agricultural software is difficult and time consuming (Offer, 2006; Öhlmér, 2006). In addition, the technology has not been regarded by farmers as becoming more user friendly in the last decade (Rosskopf & Wagner, 2005), also indicating that a long term lack of technical training has mostly prevented them from adoption (Taylor *et al.*, 1991; Gelb *et al.*, 2005)

In 2005, a total of 60 percent of U.S. crop farms had computer access, but only around half of them (33%) used a computer for farm business (NASS-USDA, 2005). Although Ascough II *et al.* (2002) suggest that computer adoption rates have steadily grown in the last two decades and now equals the general population use in the US Great Plains, recent overall US figures shown a slower increase in ownership, 2% in relation to 2003, has been seen (NASS-USDA, 2005).

In Australia, an increase from 5% to 75% of computer ownership on grain farms over the last two decades (Hayman & Easdowne, 2002) may explain better figures reported by Linacre (2006) on ownership of computers for business operations. 56% (72,828) of the 129,934 Australian farms with an Estimated Value of Agricultural Operations (EVAO) of $5,000 or more used a computer as part of their business operations in 2005. From this total, 53% (69,362) of farms had used Internet access, 22% being connected through broad band access. Impressive Australian numbers do not show however that a slower growth in adoption from 2003, in that year accounting for 54% (71,936) of farm computer ownership with 46% of the total connected to the Internet (ABS, 2003).

In Brazil, Lowenberg-DeBoer & Griffin (2006) show a evidence that computer use in farm offices is lower than in the US, Australia or Argentina. A PA market survey in São Paulo State found that adoption rates are even lower and slower, only accounting for a 1% growth in three years (from 13% in 2001 to 14% in 2003 of farms having a computer). Finally, global figures show that software applications are primarily used for taxes, record keeping, word processing, and spreadsheets (Rosskopf & Wagner, 2005), while tools of applied research methods show a general low ownership and use (Ascough *et al.*, 2002; Hayman, 2003; McBratney *et al.*, 2005).

Low adoption, risk perception & awareness: Does PA pays off ?

The continual development of new agricultural technologies has always required farm managers to stay informed of the latest advances and decide whether or not to adopt them. As in traditional farming techniques, low rates of SSCM technological adoption are mostly related to the risk of adoption of an unproven technology that may fail to meet management expectations or warrant return of investments (Tozer, 2009). On the other hand, the lack of awareness or the misperception of risk on the adoption of a profitable new technology may lead the agribusiness to a considerable disadvantage in the medium to long term (Foog, 2003). However, the unclear message about PA profitability may have increased a critical perception of the usefulness and the accessibility of DSS tools, which are classic concerns for user acceptance of computational tools (Davis, 1989). Therefore, issues involving the use of DSS as a routine management tool in SSCM may involve several sources of perceived risk.

Botteril & Mazur (2004) suggest that frequent mismatches between perceived risk and measurable probabilities of risk do not consider important factors influencing how people understand and respond to risk. Botteril & Mazur (2004) also describe numerous factors influencing how risk is perceived that were used to investigate the idea of farmers tending to be averse to risk, concluding that it is not clear how different rural management risk perceptions are from the rest of society due a dearth of research on these groups and on the influence of other socio-demographic factors.

Specific to the adoption of SSCM technology, Adrian *et al.* (2005) also report that limited research has been conducted on potential users' perceptions and attitudes toward PA technologies. As result of their survey, a multivariate analysis on structural factors has shown that factors such as: attitudes of confidence, perceptions of net benefit, farm size and farmer educational levels have positively influenced the intention to adopt the technology, where perception of usefulness has mostly influenced perception of net benefits. Davis (1989) defined perceived usefulness as the belief that using a particular technology will enhance the potential user's job performance, and perceived ease of use as the belief that using a particular technology will be free of physical and mental effort.

Intensive field monitoring technology may have increased the perception of farming as a risky business because of clear evidence of the spatial and seasonal variability on crop yields, in addition to market uncertainties and stronger environmental regulations (Tozer, 2009). Still, in very simple terms, a DSS can be understood as any type of practical solution that can facilitate a decision-making processes in face of high management uncertainties utilising any additional source of information. Consequently, common risk analysis in agriculture may not involve proper agronomic and field operational aspects and mostly account for econometric evaluations and policy programs such as: i) credit and portfolio risk analysis; ii) individual farm risk program, iii) crop insurance risk program; iv) farm policy analysis; and v) econometric modelling.

In contrast, the improved crop information provided by PA technology may support models for risk assessment forecasting in potentially poor growing seasons. The perception of PA usefulness and resulting net benefits may increase if areas of likely low yield potential can be mapped and removed from production, minimizing potential financial losses. Such assessments would compose decision-support systems guiding management actions of lower production or capital risks across the whole farm analysis (Tozer, 2009).

The characterization of general PA decision-making aspects that may support new risk analysis in a way to favour the awareness of technological adoption includes: i) decisions in a continuous information environment where consequences are generally not known when the decisions are made but can be more precisely estimated; ii) better understanding of variability of prices and yields as major sources of risk in agriculture; iii) short term changes in equipment, legal and social concerns, and the human factors induced by changes of new technological and research standards.

Learning, adaptive management & soft system approaches

After historical evidence of low technological adoption rates (Lowenberg-DeBoer & Boehlje, 1996; Matthews *et al.*, 2008), the improvement of training and learning methods addressing the technology transfer of DSS to farm managers and agronomic advisors has been an increasing concern (Loevinsohn, 2002; Seppänen, 2002; Robinson, 2005; Mackrell, 2006; Llewellyn, 2007; Cox *et al.*, 2008). Loevinsohn (2002) outlines research methods to enable adjustments of farm management decision processes. Seppänen (2002) describes how methods creating tools for learning are applied to organic vegetable farming, suggesting the construction of non-deterministic pathways for specific activities. Robinson (2005) suggests a variation on the action learning cycle (Kolb, 1984) that emphasizes the strengths and benefits of research and farmer cultures, and seeks to minimize the negative impacts of each culture on the other. Mackrell (2006) presents an ontological study on the knowledge of Australian women cotton growers on family farms, associating their management roles with agricultural DSS. These case-specific contributions illustrate the variety of human related aspects abstracted through soft and adaptive system solutions.

A broader overview is given in McCown *et al.*, 2006, who discuss the historical experiences with the relative failure of farm management models, and summarize lessons on how to make theoretical models relevant to farmers. Following this context, McCown & Parton (2006) exemplify the relevance of three system approaches to actual farm management economics, being: i) crop and animal production simulation models; ii) farming system research; and iii) soft-system intervention to facilitate farmer learning.

Soft-systems methods can yield research and farm management advantages (McCown *et al.*, 2006). These participative appraisals aim to discuss, acquire and model tacit information from differing perspectives in order to improve information systems (Cox *et al.*, 1993; van Beek & Nunn, 1995). They have been suggested to evaluate the required functionality of DSS for land managers (van Beek, 1995) and agricultural management (Hamilton, 1995; Matthews *et al.*, 2002). However, simplified applications of this concept have been mostly conducted by means of workshop-based activities, in which business and academic groups are to produce qualitative indicators that don't fully contribute to identify system required functionalities. This is the case in which they have been applied to homogeneous land use units (van Beek, 1995) or plant growth process models (Matthews *et al.*, 1999; Cox *et al.* 2008; Bellocchi *et al.*, 2009).

If linked to SSCM technology through research cooperation programs, soft-systems methods may represent a valuable and extended source of both, technical information supporting farm manager's learning, and farm management knowledge models guiding the insertion of quantitative analysis in practical farm management. In this last case, either the use of soft-systems approaches to evaluate the outputs from intensive field monitoring, or vice-versa, will address requirements in which decision trees supporting SSCM should mix scientific knowledge with best management practices to actually improve management actions (McCown, 2002a).

The term "adaptive management" has become a fuzzy concept due to it being increasing used to refer to different actions related to several objectives. Nyberg & Taylor (1995) and Sit & Taylor (1998) address possible misinterpretations and suggest that the key procedures of adaptive management fall in the following order: acknowledgement of "best" practices; careful selection of practices to be applied, implementation of a plan of action, monitoring of key indicators; analysis of the outcomes in relation to original objectives, and incorporation of previous knowledge into future decisions.

Under a systems perspective, Díaz-Salís *et al.* (2009) give a simple definition where adaptive management is a strategy composed of a set of decision rules that are clear and meaningful to farmers. Sets of managerial decision rules may embed specific agronomic knowledge and when structured into decision trees, map an effective information flow to aid management. Kuhlmann & Bordesen (2001) suggest that adaptive management blends methods of investigation and discovery with deliberate manipulations of managed systems, as a hybrid of scientific research and resource management. This approach may be also associated with concepts of knowledge-based systems in the technological field of Artificial Intelligence (AI), especially when considering the aspects suggested by Kuhlmann & Bordesen (2001) of a cyclic feedback of new knowledge for continuous improvement of policies and field practices. The principles are that observations and evaluations on the ways that human interventions affect managed systems are expected to provide knowledge gains about system interactions and productive capacities. This matches the processes for the adaptive management cycle with the SSCM suggested in McBratney & Whelan (2001) when describing key components of the SSCM technology cycle.

In practical terms however, adaptive management has somewhat different goals from research. It differs in scope and nature from typical research experiments, and consequently involves more than just technological research transfer (Sit & Taylor, 1998). But now scientists can play a more effective role in this management approach, which is not new (Walters 1986), by means of improved technology to incorporate research knowledge into the core of farm management processes. However, if the promise of this concept is to be realized, it is local resource managers and advisors who must become the "adaptive managers" (Sit & Taylor, 1998).

User participation in technological development

In developing process models, there is a tendency to by-pass the perceptions and awareness of farmers to adopt these technologies, and whether other attitudes than economic benefits play roles in the adoption decision (McCown, 2002; Adrian *et al.*, 2005). More participatory approaches considering the user influence in agricultural decision support are not new, and have been suggested in Baker & Curry (1976). Other reports aim to explain the role of farmer participation in the information system (Hartwick & Barki, 1994) and to evaluate users' attitudes in knowledge-based DSS (Hochman *et al.*, 1994). The user perspective of the relevance of the internet for agribusiness is introduced in Ivanic *et al.* (2001).

Lynch & Gregor (2004) investigates areas of decision making theory that reinforce the user interaction during system development. Lynch & Gregor (2004) have used concepts of participative decision making introduced by Locke & Schweiger (1979) to predict improvement in system quality and planned organizational change, when investigating the relationship between process outcomes for 38 decision support systems in the Australian agricultural sector. Results have shown strong patterns between the user influence in system design and the impact of agricultural DSS. As an example, the avocado management support tool introduced by Mulo *et al.* (1998), and followed in Newett *et al.* (1999) and Vock and Newett (2001), in which the type of user participation was seen as consensual since the conceptual design phases and has resulted in a significant change of focus in the nature of the system.

It may also be argued that a wise strategy could be to adopt software engineering tools that can assist the efficient reuse and customization of experimental system developments, rather than trying to involve farmers in early phases of technical analysis. The standpoint of minimizing system redesign through a user's interaction during all stages of the development process may be considered relevant in reducing software investments and increasing levels of software quality, but it wouldn't avoid the need for continuous system maintenance and adaptation in the long run. For the long term sustainability of DSS tools, system development approaches and architectures must be able to cope with the typical dynamics of real life management decision processes. In the theory of unstructured decision processes, strategic decision making is suggested to be cyclical, informal, flexible, and modified and clarified as the decision process progress (Mintzberg, 1978).

1.4.2 - Environmental & economic aspects

Several aspects of farm accountability have been considered and mostly adopted from the already available management decision tools usually in the form of less expensive spreadsheet systems that handle standard data (e.g. budgeting, payroll, financial balance, machinery maintenance, stock and logistic) rather than in new PA econometric models (Ancev *et al.*, 2004; Stoorvogel *et al.*, 2004). The availability and popularity of this type of farm office support tool has no equivalent in terms of environmental assessment and valuation methods. Farm management decision process modelling is not new, but it has been traditionally related to accountability, property, land tenure, infrastructure, and socio-economic attributes. Typical designs lean to either general aspects of managerial activities and operational calendars (Gauthier & Néel, 1996; Bett, 2004), or detailed record keeping of farm management interventions (Shaffer *et al.*, 2000), and do not consider attributes relative to management in the SSCM context.

New DSS contributions to the economic aspect of farm management are now well advanced in Web agent technology (Sierra, 2004; Koumboulis *et al.*, 2006). These contributions already consider a well recognized opportunity offered by online markets and the key importance of agricultural exports in many economies (Ivanic *et al.*, 2001; Hargreaves & Hochman, 2004; Abdinnour-Helm *et al.*, 2005; Fernandez & Trolinger, 2007; Masiello-Riome *et al.*, 2008). The commodity market chain often involves much inefficiency as the earnings are shared by a multitude of traders and processors, and producers may receive the smaller share of the final consumer price (Sierra, 2004). Electronic commerce can allow producers to reach global markets at reduced transaction costs, and electronic markets and online auctions offer excellent ways of achieving and improving this type of commerce (Masiello-Riome *et al.*, 2008).

Information is a key product from PA technology, and does play an economic role in productive crop systems. The technology is now becoming available to monitor input/output of farm resources at an increasing resolution. Ultimately, data gathered on production output would ensure that only sustainable techniques are adopted within progressive research, educational and political frameworks. However, the evaluation of environmental aspects in farm decision making is a major knowledge gap in the realization of the proper site-specific management paradigm (McBratney *et al.*, 2005). At present, the necessary characterization of the expected production variability over space and time is pending, compromising evidence on the positive impact of site-specific practices. This may have restricted the evolution of analysis technology. According to Kuhlmann (2006) the proper knowledge on crop yield variations requires the evaluation of probability distributions of non-controllable yield factors, so that suitable support tools which clearly lead to economic advantages can be developed. Understanding the cause/effect and the evaluation of environmental impacts in money metrics at very detailed level will probably take more commitment from research institutions and the agricultural industry. At present, spatio-temporal methods for agricultural investigations have been mostly undertaken in regional risk analysis, such as the econometrics of pricing crop insurance contracts (Ozaki *et al.*, 2008) and the environmental management of pest incursion of wheat (Eliston *et al.*, 2004).

The PA models may suggest a more realistic response based on continuous high-resolution field data and simpler automated analysis of less complete or precise set of predictors. This analysis reflects the ultimate goals in PA decision support with claims for "greater simplicity on the far end of complexity" (Cox, 1996; Hayman, 2003; Blackmore, 2007). In this context PA models have the potential to address simple indices which are often used for agricultural and environmental impact assessments. Indices supporting decisions may be difficult to build due to limited thematic knowledge and the establishment of universal benchmarks.

Biere (2001) suggests that good information is critical to good business management which can properly integrate financial data for logistical decisions. Biere (2001) introduces an activity-based method which provides the information needed to make decisions concerning activities within the firm, where benchmarking is suggested as a means of obtaining information on performance functions. Benchmarking has become increasingly important as margins decline in information markets. Index benchmarking from intensive field data may enhance the whole-farm management effectiveness and its associate agronomic, economic, environmental, and logistical benefits.

Keating & Carberry (2008) suggest PA technology as one of the few feasible options to break away from the current efficiency frontier, supporting the creation of new production systems which can increase returns for little added risk. PA related knowledge may provide a means for base line analysis of emerging opportunities in environmental aspects, i.e.: biofuels, farming carbon, forest-based carbon sinks, soil carbon sinks and farm resource stewardship; and trends such as: climate change and shortage in water supply.

1.4.3 - Information and knowledge: system development aspects

The computational support for the integration of field monitoring data has not evolved as expected by Whelan *et al.* (1997). To date, the overwhelming amount of gathered data has found no support from analysis technology (McBratney *et al.*, 2005; Matthews, 2007). Advanced IT methods applied to SSCM information flow have mostly addressed wireless data communication standards (Lutticken, 2000; Wei *et al.*, 2005; Nash, 2006) and control of monitoring devices (Blackmore *et al.*, 2002; Arguenon *et al.*, 2006).

This field level technology standardization has been considered good as a modular design for new products (Zhang *et al.*, 2002) and efficient as a data exchange platform for sensors, controllers, and software packages from different manufacturers (Stafford, 2000). However, this approach has not fully supported so far the development of decision models that are relevant to farmers (McCown, 2001a; McCown & Parton, 2006), being only applied in crop simulation models (Rivington *et al.*, 2007; Florin, 2008).

Alternatively, conceptual frameworks have been recently designed for more flexible and integrated characterization of management influencing factors, from strategic stakeholder to field operational decision flow (Bett, 2004; Fountas *et al.*, 2005; Rivington *et al.*, 2007). From a survey analysis on distinctive business innovation patterns, Miles (2008) suggests that farm management can be understood as a small-scale, technology-based and knowledge-intensive business, in which examples are limited. He concludes that in relation to knowledge system designs, only a few business segments conform to the model in which innovation is largely organized and led by formal research and development (R&D). Thematic conceptual frameworks can be further implemented through a series of available semantic-driven technologies (Gauthier & Néel, 1996; Saraiva *et al.*, 1998), supporting customized representations of continuous storage of local knowledge. Currently standardized system development architectures have a greater potential to suits several requirements for improved socio-cultural and environmental considerations in farm management (Linch *et al.*, 2000; Mackrell, 2006), and for intelligent software for agricultural decision support (Kosai & Hoshi, 1989; Gauthier & Néel, 1996; Matthews *et al.*, 2002; Öhlmér, 2006). Web services may add facilitated search and accessibility of technical and managerial data (Fensel *et al.*, 2004).

Improvements in system design

Challenges in the development of SSCM supporting tools involve constant technological update, while enabling a continuous integration of many knowledge assets (*e.g.* agronomic, economic, ecologic, soil, field operation, farm management, spatio-temporal analysis). Improvements in system design are here understood as relating to requirements for increased communication by means of standardized protocols, notations, and modelling languages.

System design methods are associated with models of software and management processes, giving a common language for system abstraction and knowledge sharing across domains. Several authors suggest that the use of unified languages in design facilitates the integration of scientific knowledge and farm management processes by means of knowledge management systems (Jones *et al.*, 2001; Hervé *et al.*, 2002; Moore *et al.*, 2005; Papajorgji & Pardalos, 2005). However, Papajorgji (2007) points to the limited use of modelling methods in agricultural research, which can be related to claims of segmented developments (Matthews, 2007). As a result, the analysis of several specific aspects of crop management requires from farmers and agronomic advisors a fair amount of study and several pieces of software. In addition, the lack of model integration, sharing and re-use (Papajorgji & Shatar; 2004) may have limited the improvement of knowledge and the design of methods of analysis for large, heterogeneous, and distributed datasets. To minimize the knowledge gap which indirectly influences the low rates of technological adoption, some authors have considered the creation of metadata specifications and standard protocols to support the use and exchange of information for crop models (Hunt *et al.*, 2001; Bostick *et al.*, 2004), agricultural DSS (Hunt *et al.*, 2006), and SSCM (Bramley & Williams, 2001; Abuzar *et al.*, 2003; Wei *et al.*, 2005).

In fact, no conceptual framework design has been suggested to characterize basic components of management decisions in SSCM, such as considering quantitative analysis of crop spatio-temporal variation within object-oriented architectures. This technological gap is subject of further investigation in this work and encompasses a large number of aspects in both software development and quantitative methods.

Considering the user perception previously discussed (**Section 1.4.1**), it can be stated that the DSS for PA should be more than a collection of narrow scope decision support tools. However, a comprehensive list of distinct DST requirements for PA (Robert, 2000) was followed by persuasive suggestions that the traditional "integrated DSS package" concept may need to be broken down into simplified and more specific solutions (McBartney *et al.*, 2005). Still, this suggestion may be preserved for cooperative knowledge-based designs via modular composability techniques. The composability of information artefacts of specific scope into an integrated knowledge support environment is suggested as a common topology in different categories of generic DSS (Power, 2000). Another question that may still remains to be considered is the parsimony of models being composed.

To achieve the required modularity in SSCM decision tools, solution designs should also be considered within an open architecture that uses strong semantic representations. The term open architecture is used to refer to a system which can be dynamically built by off-the-shelf components and conforms to approved standards, allowing customization of solutions and easy connectivity between distributed devices and programs (Papajorgji; 2005).

Improving the information value chain

The shift from a technology drive to an adaptive management of opportunities suggests a vertical coordination of agricultural firms (Barry *et al.*, 1992), with a balance between human, economic and environmental factors. Improvements in the information value chain are here understood to be related to requirements of a vertical information flow between different management levels by means of system interoperability and semantic Web technology. Another dimension of farm management multiscale analysis is suggested by Cox *et al.* (2008) for decision frequency on various time scales, from a single day activities to seasonal field or whole farm decisions.

The information flow across different scales of decision-making (e.g. plant, field, farm, plant growth stage, and season) may be supported by new methodological solutions for data, system, and model interoperability, platform independent solutions, and ontological mapping which have received limited attention in applied PA research. Moore *et al.* (2007) suggest a hierarchical framework for simulation of agricultural and environmental systems. In a similar fashion Numrich *et al.* (2004) reinforces techniques to embed decision-support, control and simulation systems for training and testing integrated knowledge management tools. Layered concepts for improvement of the information value chain are suggested by Numrich *et al.* (2004) as:

- Data Quality - describes the information within the underlying control systems;
- Information Quality - tracks the completeness, correctness, currency, consistency, and precision of the available data items and information statements;
- Knowledge Quality - deals with procedural knowledge and information embedded in the control system (e.g. templates, assumptions, and rules), and it is the first component related to the common model of the business operation; and
- Awareness Quality - measures the degree of using the information and knowledge embedded within the cognitive domain of the control system.

Open developments using semantically rich frameworks are suggested to diminish the existing mismatch between data, information, and knowledge of farm management processes in commercial DSS tools and scientific methods of analysis (Rosskopf & Wagner, 2005; Sørensen, 2008). The improvement of the information flow between management scales may be facilitated by intelligent software agents (Gil, 2006), which can emulate typical management behaviours across different data aggregation levels. Intelligent software agents are also suggested to help understand the decision assumptions and use this knowledge to compose services in support of the immediate needs of users (Tolk, 2006). Following these concepts, Nakamori *et al.* (2007) proposes a system for online fresh-food demand management and forecasting based on knowledge integration from three distinct information systems, being: "purchase behaviour", "demand forecasting model", and "managerial knowledge".

Knowledge intensive management

Knowledge intensive assets as a "new factor of production" are suggested in Starbuck (1992) to overcome the relative importance of capital and labour as business inputs and outputs. Improvements in knowledge intensive management are here understood to be related to requirements for the exchange of ideas and specific knowledge pools between different farm management actors (e.g. farmer, agronomic advisor, operators, and scientists) by means of knowledge-based technology (e.g. engineering, management, shearing and reuse). The concept of knowledge intensive firms is not exclusive to current technologies for knowledge management (Schreiber *et al.*, 2001) and knowledge creation (Tieju *et al.* 2007), which is actually based on the classic epistemological foundations refered to in Starbuck (1992) (e.g. Polanyi, 1958; Kuhn, 1962; Collins, 1974). Different contexts for analysis and assessment perspectives have contributed to the notion of an integrated knowledge system complementing tacit, scientific, operational and managerial knowledge assets.

Knowledge management is a traditional concept in computational problem-solving tools related to AI research, which has accounted for several contributions on generic evolutionary development technologies such as: knowledge sharing (Gruber, 1995; Farquhar *et al.*, 1996); Web-based learning (Atolagbe *et al.*, 2001) and coordination (Terai *et al.*, 2003); evolutionary components (Oussalah, 2002); ontology mapping (Fensel *et al.*, 2001; Gennari *et al.*, 2003; Corsar & Sleeman, 2007) for adaptive control (Wang *et al.*, 2007); and autonomic management (Huebscher & McCann, 2008).

In agriculture, KBS are computer tools supporting farmer's behaviour, learning and knowledge management, which can be applied for self management of adaptive human-computer interactions according to individual usage characteristics and functional preferences (Pinheiro & Furtado, 2003). Cortés *et al.* (2000) use AI techniques for the definition of environmental DSS based on an architecture suggested in Radermacher *et al.* (1994), which combines several subjects such as AI, GIS, simulation modelling, and user interactions. Other related resource management cases include: agent-based GIS for land-use and land-cover change (Berger, 2001) and forestry ecosystems (Twery *et al.*, 2005); modular neural nets integrating natural phenomena forecasts (Solomatine & Siek, 2006); interaction of agents in fresh food management (Nakamori *et al.*, 2007); and metadata ontology for agricultural e-commerce management (Fu *et al.* 2007).

Finally, the reuse of abstract models is a major step towards cost effective and quality assured KBS developments. To enhance flexible reuse, these models can be broken down into reusable components, containing artificial problem solving methods and ontologies of domain models (Schreiber *et al.*, 1999).

1.5 - What counts for the effective development of SSCM decision tools?

1.5.1 - Generic DSS typologies

The concept of DSS is very broad, encompassing several definitions, process approaches, and uses due to the wide range of domains involved (Alter, 1980; Power, 2000). A DSS can take different forms and be built in many different ways not relevant to this study. Therefore, a specific summary on DSS typologies which are specifically related to SSCM decision support aspects is presented in this section. A general and synthetic DSS definition that reflects key considerations in this thesis can be stated as: a DSS is a computerized system for assisting and validating decisions made by a user, rather than automating decisions.

References to DSS are usually related to computer applications that perform such a required supporting role. In relation to the identification of cognitive processes, DSS relates to an outcome of a mental process leading to the selection of a course of action among several alternatives (Mintzberg, 1978). Decision processes involve a final choice in the form of an action or an opinion. Choice between alternatives based on the analysis of estimates involves supporting the monitoring, estimation, evaluation and/or comparison of alternatives. Different processes involve different choice analysis such as: complex choice, choice under uncertainty, choice of incommensurable commodities, spatial choice, temporal choice, choice of competing decision makers, and where the paradox of choice may be promoted by overloads of information and tasks.

For Arnott (2004), DSS constitute a class of computer-based information systems, including knowledge management systems, which support decision-making activities. It is clear that different knowledge domains emphasize distinct aspects of the decision process. A play on the DSS acronym may illustrate this aspect, giving: “Dss” for the decision cognitive viewpoint; “dSs” for the methodological support viewpoint; and “dsS” for the system engineering viewpoint. Perhaps, it may suggest the lack of a balanced “DSS” development that potentially affects the relevance of available tools to farmers.

A growing contribution of DSS applications, concepts, principles, and techniques can be seen in agricultural production. Keating *et al.* (2003) surveyed systems analysis and interventions that have been applied to farming systems, typifying them as:

- Economic decision analysis using production functions;
- Dynamic simulation of production processes;
- Economic decision analysis using simulation of production processes;
- Decision support systems; and
- Expert systems.

Bett (2004) describe decisions by farmers as complex ones involving two stages: one is whether to adopt or not, and secondly, to pick the optimum level of the technology. To decide whether to adopt or not involves phases of knowledge, persuasion, decision, implementation, and confirmation; where adoption relates to the current level of use and intensity of use of a technology. Griffin *et al.* (2004) have reported PA technology trends related to decision support as considering yield monitors, variable rate applications, yield mapping, soil mapping, remote sensing, auto-guidance, and on-the-go proximal sensing.

Problems in decision making take a generic form when considering human aspects as previously discussed (**Section 1.4.1**). Functional aspects influencing the perceived DSS usefulness were compiled from Stone & Hochman (2004). They consider that DSS are most likely to deliver relevant information to farmers if they:

- provide information with evident, defined, high and measurable value;
- integrate analytical methods scientifically validated to impart that information;
- provide information for farmers own decision, rather than explicit answers;
- address discrete matters rather than comprehensive or whole-system issues;
- possess transparent logic, if not autonomic computational processes;
- are used to acquire rather than implement new skills; and
- require as little direct use as possible.

Perhaps a great challenge to DSS development is how they are delivered in conformity with new technologies and research areas, the important points being suggested in Newman *et al.* (2000) are:

- Demonstrations that process simulation can deal credibly with real agriculture,
- Strategic decision-making using evolutionary computation for action reports;
- Software in conformity to emerging influences of soft systems approaches,
- Significant validation of integrated simulation and DSS for policy development,
- Development of quantitative methods via a WWW in an expedient manner; and
- Reliance on machine learning techniques for increased access to large databases.

Boonstra (2003) defines generic decision processes related to operations resource management that are often influenced by:

- limited ability of people to process information;
- disagreement among stakeholders;
- change, uncertainty and indistinct objectives;
- psychological barriers of individuals to adapt information and act rationally; and
- a tendency towards incrementalism and arbitrariness in decision-making.

Contributions defining conceptual structures of decision making often follow the description of a typical process pathway. The generic decision making process is mostly recognized as composed of five steps as: i) recognition of the problem; ii) collecting information (data gathering & interpretation); iii) determine a solution (system modelling and design); iv) selecting and engaging a solution (building a method, modelling and implementing a software); and v) evaluating the solution (hands on prototyping, automated procedures, simulation of scenarios, sensitivity analysis). To a certain extent, these steps preserve close relation with the cycle of process for realization of site-specific management as suggested in Whelan (1998). When described in terms of crop simulation models, a DSS is often understood in three broad phases of action, those being intelligence, design, and choice phases. In this case, the intelligence phase may involve field trials and data gathering, the design phase in the modelling activity itself, and the choice phase concerns to the selection of criteria, the search for alternatives and the forecast of results.

A taxonomic approach based on 25 strategic decision processes to describe decision pathways is given in Mintzberg & Waters (1985) using a structure of 12 elements: 3 central phases, 3 sets of supporting routines, and 6 sets of dynamic factors. Mintzberg & Waters (1985) proposes a generic model to describe classes of interrelationships, suggesting 7 possible types of path configurations through the model. Three central phases are: i) identification phase (e.g. decision recognition routine, diagnosis routine); ii) development phase (e.g. search routine, design routine); and selection phase (e.g. screen routine, evaluation-choice routine, authorization routine). The three sets of supporting routines involve decision control routines, decision communication routines, and political routines. Dynamic factors are defined as: interrupts, scheduling delays, feedback delays, timing (delays/speedups), comprehension cycles, and failure recycles.

More specific to system related categorizations, Adelman (1991) suggests DSS as a diverse class of computer technology integrating database information and analytical modelling methods that consider general elements related to AI. Power (2000) follows this concept categorizing five dominant technology components as communications-driven, data-driven, document-driven, model-driven, and knowledge-driven support systems. These components have been proposed within an expanded framework (Power, 2000) to classify a large number of software packages and systems. The expanded framework aims to help the understanding on how to integrate, evaluate and select appropriate means of decision support. Power (2000) further highlights the aspect of knowledge-driven DSS by means of Web services. Fields of research listed as subfields of AI foundations (**Table 1.1**) have been discussed in Russell & Peter (2003) as directly associated to elements of knowledge-driven DSS (Power, 2000; Russell & Peter, 2003)

Table 1.1: Subfields of AI research and issues related to knowledge support.

Field	Start	Issues	Methods
Philosophy	428 B.C.	Can formal rules be used to draw valid conclusions? How does the mental mind arise from a physical brain? Where does knowledge come from? How does knowledge leads to action?	Dualism; Materialism; Empiricism; Induction; Logical Positivism; Observation Sentence; Confirmation Theory.
Mathematics	c. 800	What are the formal rules to draw valid conclusions? What can be computed? How do we reason with uncertainty?	Algorithms; Incompleteness Theorem; Intractability; NP-Completeness; Probability (in terms of possible outcomes).
Economics	1776	How should we make decisions so as to maximize payoff How should we do this when others may not go along? How should we do this when the payoff may be far in the future?	Utility Theory; Decision Theory (Combination of Probability & Utility Theories); Game Theory; Operational Research
Neuroscience	1861	How do brains process information?	Neuroscience; Neurons; Neural Networks. Economics
Psychology	1879	How do humans and animals think and act?	Behaviourism; Cognitive Psychology; Cognitive Science.
Computer Engineering (Hardware & Software)	1940	How can we build an efficient system?	Microprocessors; Language Compilers; Data Management; System Analysis and Design; System Interoperability; Parallel Processing; Network Protocols.
Control Theory & Cybernetics	1948	How can artefacts operate under their own control?	Control Theory; Cybernetics; Objective Functions.
Linguistics	1957	How does language relate to thought?	Natural Language; Computational Linguistics; Knowledge Representation.

1.5.2 - Designs methods & implementation architecture

Modelling notations and languages are key constructs to proper system development practice, being the core aspect of novel computation theories (Turing, 1937). However, incorporating a modelling activity as a necessary step in any system development is often disregarded in many projects. Semantic modelling concepts related to object-oriented architecture and new service-oriented approaches suitable for agronomic applications, which have been discussed (Papajorgji, 2007) and adopted as common specifications (Moore *et al.*, 2005) in a systems approach, are summarized in this section.

Limited experimentation in evolutionary software development approaches has been conducted as a standard for analysis of data intensive monitoring. Therefore, a stronger formalisation of the modelling approach is suggested, which considers a development framework concerning parameters directly influencing the quantitative characterization of spatio-temporal production variation. System design modelling methodologies and coding notations are central to system development (Papajorgji *et al.*, 2000). There is an evident need for more systematic data handling and information management when modelling components of agricultural DSS (Papajorgji & Pardalos, 2005; Matthews *et al.*, 2008). Previous developments in system biology discussed in Priami & Quaglia (2004) suggest that a stronger object modelling formalism yielded a better organization and understanding of behavioral properties of cells (e.g. chemical, physical, functional). However, agronomic process modelling is mostly done through unstructured procedures (Papajorgji *et al.*, 2004), in which greater priority has been recently given to soft-system participative approaches. These solutions have proven effective, but localized, technology transfer infrastructure that facilitates farmers and scientists learning, although they are difficult to replicate in large scale (Matthews, 2007).

In computational linguistics the definition of a language consists of both syntax and semantics (Jacobson, 1986; Booch, 1994; Nierstrasz *et al.*, 2005). Linguistic extensions for GIS applications have added uncertainty components to spatial modelling (Molenaar, 1998). A semantically rich framework may better assist researchers in problem solving for agronomic and spatial reasoning knowledge gaps (Gauthier & Néel, 1996; Öhlmér, 2006). It is understood that system designs and developments using a semantically rich modelling notation may facilitate knowledge sharing, information flow, data processing and code maintenance to better cope with a continuous change of requirements in crop management processes (Papajorgji & Pardalos, 2005). For this reason, basic computational concepts relative to the object-oriented programming (OOP) and new service oriented approaches are the subject of a more in depth literature review (**Chapter 2**).

1.5.3 - Recent technological pathways

Reports from the United Nations on "E-commerce and Development" (UN, 2003-2006), suggest the agribusiness sector is among three priority markets to consider electronic commerce technology and semantic Web-services, particularly in developing countries. Internet facilities have been indicated as the most important source of information for farmers and agronomy consultants in agricultural journals and extension service reports (Rosskopf & Wagner, 2005), but knowledge sharing analysis activities are limited.

Rosskopf & Wagner (2005) suggest agriculture is a knowledge-intensive business, where farmers are often not used to managing their knowledge in a very structured way. New technologies can help farmers to achieve better knowledge management, potentially enhancing their productivity and efficiency.

Another emerging approach is Agent-Based Modelling (ABM), which is defined in Janssen (2007) as the computational study of social agents as evolving systems of autonomous interacting agents. Adaptive management agents may support how a macro phenomenon emerges from a micro level behaviour among a heterogeneous set of bio-physical interacting agents (Holland, 1992), which describe typical behavioural rules and interactions. Agents may find navigation means through Global Information Grids (GIG). The GIG technology, or simply grid computing, is a globally interconnected, end-to-end set of information capabilities, associated processes and personnel through which information is collected, processed, managed, stored and disseminated on demand (Numrich *et al.*, 2004).

The functionality offered by a hybrid solution made from a composable shell of ontotological Web services, intelligent agents, and knowledge management can support the facilitated use of integrated analytical tools (Ahuja *et al.*, 2002; Ahuja *et al.*, 2005) with a farmers practical and intuitive thinking embedded (Öhlmér, 2006). According to Fogg (2003) a user knowledge-centred technology should involve aspects of cognitive science which are useful to create persuasive technologies for the purpose of influencing peoples attitudes, perceptions or behaviours. This last aspect may be relevant when considering the exchange of scientific and tacit knowledge for sound decision making.

Web services

According to Berners-Lee (2007), the success of the Web can be understood as result of three critical factors: i) unlimited links; ii) open technical standards for continued innovation; and iii) network layers enabling independent innovation for transport, routing and applications. From a technical perspective, the World Wide Web (WWW) is a collection of electronic pages written in standard HTML format (Hypertext Markup Language), where pages can be universally linked using the URI standard (Uniform Resource Identifier) and the HTTP (HyperText Transfer Protocol) network transfer protocol (Berners-Lee, 2007). Its separation into development layers allows simultaneous and autonomous innovation to occur at many levels of user interfaces, making great use of the open system design.

A universal link, the Uniform Resource Locator (URL, an URI type), allows anyone to connect with another and so promoting the free exchange of ideas and the creation of a wide variety of new services. Better scientific data integration may happen through the use of open Web links between commercial and academic initiatives around the world, as knowledge assets are mostly spread out across countless databases, spreadsheets, documents, and proprietary formats. Specific to agriculture, initiatives known as e-Agriculture were listed as priority action lines at the World Summit on the Information Society (WSIS'06), so reinforcing information and communication processes rather than technologies and tools (Masiello-Riome *et al.*, 2008; Mangstl, 2008). To determine the scope and priorities for these initiatives, Masiello-Riome *et al.* (2008) analyse results of an online global survey on action lines for e-Agriculture with emphasis on market access and overall information flow. Mangstl (2008) reports e-Agriculture issues, priorities, and commitments from the Food and Agriculture Organization (FAO) perspective. Mangstl (2008) core focus is the exchange of commercial, managerial, and scientific knowledge assets, where knowledge-based Web-service developments are considered priority investment for market chains, farm/production management information systems, and research and innovation.

Service-Oriented Architecture (SOA) provides standards to build cost-effective knowledge-integration infrastructures, creating composable system solutions (Kreger, 2003; Tolk & Pullen, 2003). From an enterprise point of view, SOA is a system development approach to organizing information resources to meet changing needs of the business by building interoperable, robust, and reusable services that models the underling application functionality (Bloomberg, 2007; Baer, 2007). In simple terms, SOA involves the use of Web architectures to efficiently support business diversity by the integration and management of different decision knowledge assets (Kreger, 2003; Pullen *et al.*, 2005; Bloomberg, 2007). Concepts of Knowledge-Intensive Firms (KIF) were introduced in Starbuck (1992), as expanding economy concepts of capital- and labor-intensive organizations which do not encompass data-intensive management aspects. Starbuck (1992) defines the idea of learning by knowledge-intensive assets as a simple stack of diversified expertise that does not imply technology-intensive management. In this sense, diversity also means that many of these management assets don't concern the same language or problem definition.

It is now clear that a proper balance between diverse aspects in crop management analysis requires information system developments that consider the dynamic composability of individual problem solutions (Papajorgji, 2005), while ensuring the transparency and reuse of their particular processes, plus secure interoperability of knowledge assets (Priami & Quaglia, 2004; Baer, 2007). Implementing SOA depends upon exposing information and processes as self-contained services that can communicate and interoperate with each other (Baer, 2007). It involves techniques for Service-Oriented Analysis (SOA) and Design (SOAD), which grew out of efforts in collaboration among heterogeneous systems (Zhao & Cheng, 2005) that are closely related to object-oriented architectures.

Semantic Web

Lately, ontology mapping has emerged as a prime technique to model system semantics for the development of representation languages and ontologies (Bell *et al.*, 2007). Ontology mapping makes use of markup languages for defining a semantic system structure using terms, the definitions of those terms, and the specification of relationships among those terms (Sini *et al.*, 2008). It is a recent computer solution to simplify and improve knowledge reuse via the Web. The use of ontologies to build a semantic Web aims to alter the way humans may benefit from Internet use, according to Bell *et al.* (2007), from an active user interaction with passive information extraction to a somewhat passive interaction with active (or autonomic) information extraction and analysis.

In a great effort to make new IT approaches available to the whole agroindustry, the FAO has already indicated the importance of semantic representations and invested in semantic Web frameworks such as the AGROVOC repository (Sini *et al.*, 2008). In the FAO context, Web-services containing glossaries of terms are already available as distributed databases (ftp://ftp.fao.org/gi/gil/gilws/aims/references/flyers/ontologies_en.pdf), and advantages for using Web ontologies are detailed in Fisseha *et al.* (2001). Positive points can be summarized as: i) navigation by semantic links; ii) data management indexed by key attributes; iii) user's query via controlled vocabulary; iv) adaptive query supported by domain natural language; v) cross-relational information retrieval; and vi) display of semantically related concepts.

It can be argued that much of the PA enabling technology has been born from operational military technologies (e.g. GIS, GPS, Remote Sensing). This may suggest that the next steps towards the interoperability of SSCM decision support components could also mirror new military command and control research initiatives. Better integrated farm management may require the consideration of primary standards now being investigated for command-control in grid computing environments. Page *et al.* (2004) argues that for the military strategic domain, simulation composability has arisen as a longstanding standard of interoperability. Page *et al.* (2004) also support the view of Petty & Weisel (2003), where interoperability covers the technical aspects, as for system development, and composability the conceptual aspects, as for integrated simulation analysis. Page *et al.* (2004) support this following categorization when dealing with issues of integrated and intelligent simulation system:

- Integrability contends with the physical/technical realms of connections between systems, which include hardware and firmware, protocols, etc.
- Interoperability contends with the software- and implementation details of interoperations, including exchange of data elements based on a common data interpretation, etc.
- Composability contends with the alignment of issues on the modelling level. The underlying models are purposeful abstractions of reality used for the conceptualization being implemented by the resulting simulation systems.

Semantic Web and grid computing researchers are now building common ontologies to bridge associations between different semantic and declarative knowledge representations. The resulting capabilities could provide a new generation of cognitive grids and distributed intelligent systems applied to learning, planning, self-repair, memory organization, meta-reasoning, and task-level coordination (Deelman & Gil, 2006; Gil, 2006). Dumitrache (2008) summarises the ability to share data, information, and knowledge, concluding that trends in advanced monitoring control techniques include intelligent agents as well as hybrid systems formalism.

Agent Based Models (ABM) & grid computing

Agent and Multi-Agent Based Modelling (ABM and MABM) have emerged from software engineering techniques to overcome issues of semantic developments in AI. A knowledge engineering review on AI theories (Wooldbridge & Jennings, 1995), which considers cognitive, operational, decision-making, and game-theory frameworks previously used in automation problems (Smith & Davis, 1980), reports the design and construction of intelligent agents through three main branches: agent theory, architecture, and languages (Huesbcher & McCann, 2008).

The basic properties of hardware or software agents were first identified by Wooldbridge & Jennings (1995) as being: i) Autonomy - agents operate without external intervention, having control over their actions and internal state; ii) Social Ability - agents interact with others via an agent-communication language; iii) Reactivity - agents perceive their external environment and respond in a timely fashion to changes; and iv) Proactiveness - agents do not simply respond to their environment, being able to exhibit goal-directed initiative.

These techniques have extended semantic concepts from object-oriented approaches towards automatic reasoning frameworks for intelligent agents (Inchiosa & Parker, 2002; Buccella *et al.*, 2008), enabling the behavioural representation of objects to be modelled through interaction strategies and promoting semantic objects into autonomic agents (Jenings, 2000; Jackson, 2002). They have recently inspired autonomic computing concepts aiming to decrease user involvement in human-computer interactions (Horn, 2001; Huesbcher & McCann, 2008). Here the term "autonomic" comes from biology, referring to the human nervous system taking care of our unconscious reflexes (Huesbcher & McCann, 2008), and it can be understood as the automatic adjustment of vital organs to constant changes in the external environment (e.g. size of the pupil, rate and depth of respiration, dilatation or constriction of blood vessels).

Systems adaptation relies on self-managing capabilities to effectively respond to unpredictable situations (Luck *et al.*, 2004). These self-managing capabilities are given by intelligent software agents autonomously planning and pursuing their actions and goals to cooperate, coordinate, and negotiate with other agents (Luck *et al.*, 2003). The main streams of ABM developments are currently used in Web browsers, retrieval mechanisms, and personal assistants. Pushing technology relies on intelligent "watch" agents (Lister *et al.*, 2006), which have been used to track user behaviour for personal digital assistants (Kumar *et al.,* 2002; Silva & Rocha, 2003; Kunjithapatham, 2004). Agent languages are often available in visual programming environments for multi-agent experimentation (e.g. Swarm in Objective C; Cormas in Small Talk, Repast and Ascape in Java).

Present applications of this technology have been spread across several knowledge domains including eCommerce, grid computing simulation; mobile communication; system agents for learning, adaptation, and discovery (Zambonelli & Parunak, 2003). In relation to agriculture, some examples are given by Parker *et al.* (2001) in understanding structural adjustment in regional agriculture in response to shifts in policy incentives; Elliston *et al.* (2004) in regional disease incursion management; Koumboulis *et al.* (2006) regarding a DSS for possible scenarios of trading commodities in agribusiness; Arguenon *et al.* (2006) in prototyping of Precision Viniculture (PV) harvesting robots; Sengupta & Bennett (2003), Evans & Kelley (2004), Alexandridis & Pijanowski (2007), and Buccella *et al.* (2008) in GIS for land-change using spatial, temporal, and economic behavioral models. These results show the ABM evolution from an agent design metaphor to agents as a source of technologies of next generation computing (Luck *et al.*, 2004).

Autonomic agents can play a fundamental role in generic “grid computing” applications. Grid computing is by definition and integration of services across distributed, heterogeneous, and dynamic 'virtual organizations' from disparate resources in both ebusiness and e-science (Foster *et al.*, 2002). Grid workflows are defined in Prodan (2007) as a collection of off-the-shelf activities or components, interconnected through control and data flow dependencies. In simple terms, it can be understood as "utility computing" promoting "peer-to-peer" interactions. Foster & Kesselman (1999) suggest computational grids as a solution for inexpensive access to high-end computing capabilities, since they provide a parallel processing architecture in which CPU resources are shared across a network, and all machines function as one large supercomputer.

Due to the nature of PA technology and SSCM decision-making, challenges in DSS developments should be faced using innovations and opportunities which have been suggested by several authors (Ahuja *et al.*, 2005; Kitchen, 2008) to address modular and composable knowledge management. The ABM approach can potentially support farmers to better access and manage increasing quantities of available information, dynamically responding to changing circumstances in crop production. Some degree of autonomy in PA software components could bind complex analysis into easier to interact decision tools, requiring less technical training for farmers when trying new scientific tools. Autonomic software agents could be very useful in accounting for quantitative, agronomic, and managerial analysis; if underpinned by a knowledge management system of crop management, spatial-temporal reasoning and agronomic assets (Berger, 2001).

Computational complexity

The computational complexity of algorithms implemented for statistical assessments is never a technological trend, but a fundamental issue to be constantly considered when dealing with tools for managing large datasets (Mather, 1999; Kundu & Ubhaya, 2001), such as those involved in intensive crop management (Walker, 2002). Therefore, the development management tools bearing quantitative methods may improve software performance as long as an awareness of the memory and CPU time costs of new algorithms is maintained.

Nonlinear approximations with high dimensional input data remains a nontrivial problem (Mather, 1999). An ideal algorithm for such tasks needs to eliminate redundancy in the input data, detect irrelevant input dimensions, keep the computational complexity low, and, of course, achieve accurate function approximation and generalization. This problem has often imposed random sub-sampling techniques aimed at faster process response and more practical user interactions. Perhaps, this solution diminishes the analytical opportunity given by new trends in intensive monitoring, such as smaller robots (Blackmore, 2007) and multi-sensors platforms (Lobsey *et al.*, 2007).

Sub-sampling techniques are observed in Vesper (Whelan *et al.*, 2001), as well as in the majority of the geostatistical packages available. A common approach for polynomial optimization problems in goestatistical tools is the Lenvenberg-Marquardt method (LM) for non-linear least squared regression. Typical algorithms for this method usually assumes the worst-case computational complexity in the order of $O\ (\mathrm{m}.n^{\mathrm{k}})$, where: n is the dimension of the input vector (number of observations); k is the degree of the correlation function to be fitted; and m is the number of lags estimated by the empirical variogram.

In the case of yield monitoring, the number of observations per field commonly exceeds 50,000 yield observations. Datasets of over 20,000 observations already justify awareness of algorithm complexity (Mather, 1999). To support efficient LM algorithms for dense datasets, new heuristics have been recently available with a reduced complexity of $O(n^2.(\mathrm{m}.n^2))$ in Stan & Kamen (1999) and $O(n.(\mathrm{m}.n))$ for neural networks (Kim *et al.*, 2006). As an example, Kundu & Ubhaya (2001) proposes an algorithm for regressive non-linear curve fitting that reduces the LM complexity to the order of $O(n)$ for second order polynomials.

1.6 - Discussion and concluding remarks

There is a strong need to convert the art and craft of SSCM analysis and decision knowledge into a real scientific-based, farmer-oriented, and system-optimized tool. It is also clear that some steps forward have been made in the evolution of agricultural decision tools, perhaps just matching the improved understanding of factors accounting for effective crop management with renewed and more sophisticated requirements. Unrealistic expectations in the technology may have misled farmers' perceptions about which analytical tools would be factually available. In the 80's, "the computer" would solve issues using well structured data bases; in the 90's, "the system approaches" would solve problems using integrated GIS and crop simulation; in the 2000's, "the information flow" would help using system interoperability and Web services. Currently, expectations from semantic services and agents supporting a knowledge intensive agribusiness may be relying in a more mature and flexible IT approach focused to emulate human reasoning and to facilitate user's learning.

The body of this research addresses common aspects of computational tools and quantitative methods supporting agribusiness decision making for the adoption of site-specific management technology. These concern questions directly related to a farmers risk perception for the opportunity on the return of investments in new technology. It is suggested that a proper system design may be related to semantic abstractions of crop management processes and the associated software functionality. Still, issues involving the development of SSCM decision tools may be related to a limited compliance in research with a minimum set of effective software engineering techniques. The challenge for SSCM supporting tools is to couple several data types and sources, analysis tools, and domain specific knowledge, while continuously enabling adaptive change.

After 15 years of a new technology supporting SSCM, promises and expectations on the availability of field intensive monitoring, broadly known as PA, have not proven themselves as fast as new agribusiness trading standards have been imposed on farmers. Although important and valued improvements were introduced in terms of data gathering and spatial referencing and control at the within-field level, fast advances on specific hardware and firmware for robotic operations do not match with software functionality to facilitate data storage, information flow and knowledge acquisition and farm management DSS. As for operational processes, rudimentary data storage structures generated by individual sensor devices under different manufacturer's proprietary formats do not supply the required data interoperability and model composability.

The low adoption of some SSCM technology observed to date, mostly related to data use and interpretation, has contradicted forecasts of the exponential spread of this sustainable sound management approach. Although within-field intensive data from one field survey may give us a good insight to the contributing factors of final production variation in a crop-season, it often doesn't stand by itself to support next season or long term management decision processes. Negative impacts may have been promoted by ambiguous conclusions affecting the perceived usefulness of the technology as a support to decision making. The investment risk can be considered high as intensive monitoring benefits are still difficult to calculate, having estimated net returns varying from US$18 to US$48 per hectare. Inconclusive returns from high investments at initial adoption phases may have contributed to loss or isolation of a great number of single data surveys from different fields, crops and seasons, making conclusive analysis difficult or even impossible. Therefore, the availability of datasets may still limit the determination of thresholds for the opportunity of adoption. These facts have potentially delayed an increasing knowledge on new agronomic and managerial relationships revealed by intensive data gathering. Results in this research may also be limited by a lack of minimum number of samples characterizing the same crop over several seasons and diverse crops of one season, homogenously distributed across different farms and regions. Therefore, decision support methods addressed in subsequent research chapters concern to farmers at different phases of technological adoption (i.e. initial, intermediate, and advanced phases).

The literature review presents a clear discussion of DSS concepts and development approaches that involves different levels and aspects in farm management, overlapping perspectives from distinct disciplines, and computational solutions of dissimilar typology. In general, the development of IT tools is characterized by isolated research projects mostly focusing on stand-alone solutions for a specific operational process, whether or not supporting data integration requirements relevant to tactical management decisions. Successful results from individual short-term research implementations usually fade overtime due to a lack of maintenance, in contrast to a proper system development process that has already been recognized as essentially participative (with farm managers) and cyclical (evolutionary versions).

The overall conclusion for main issues involving the development of SSCM decision tools is that limited developments have been resilient to a minimum set of software engineering requirements for the type of application. Software engineering requirements are understood as a set of techniques involving three basic system development dimensions: i) user requirement engineering (e.g. crop management process models); ii) platform independent and modular system design (e.g. abstraction of system components and behaviour); and iii) code development technology (e.g. IDE's, API's, open software).

Little or no importance has been given to making proper use of system analysis and design techniques for system developments, communication protocols, semantic representations, and metadata documentation. While it is understood that the use of few fundamental concepts would greatly simplify system integration and modelling composability towards an easy to use tool box of scientifically sound analyses, also allowing farm managers to interact with simulation outcomes and to include their knowledge of their particular production system. Although commercial tools are already resilient with industrial software development standards, their solutions are still mostly based on a general purpose modelling formalism that can support specific standalone tools, not taking into account domain-specific knowledge and spatial analysis capabilities.

In support of crop yield characterization and interpretation processes, the available software lacks minimum development standards that could sustain information flow. For strategic decision processes, the modelling of conceptual frameworks have so far disregarded to consider new Web service technologies dealing with dynamic interactions between heterogeneous and distributed data structures. Open computational developments would provide to individual end users a means to support particular reasoning for their needs for pragmatic management. Perhaps, the availability of such environments may still be dependent on further maturity in software methodological solutions to enable easier information interoperability and knowledge composability.

Chapter 2

Methods for development of SSCM decision tools

Summary

The contemporary software literature shows that issues in system developments are many and often common to all fields of application, but appearing more critical in some areas of scientific developments, such as for agricultural research. This chapter complements the review in Section 1, with a review of system development aspects for decision support tools for PA. It briefly reports on a wide range of decision support applications closely related with differential management decision-making, including more recent Web related technologies. In addition, this review tries to identify present development standards and foresee potential pathways in software design which could improve the promptness and quality of tools directly available to farmers in support of decision-making processes in SSCM.

Aspects of the evolution in system architectures are given in relation to open system developments, where new potential approaches are discussed for their contribution to a new generation of SSCM decision tools. Additional references on basic computational concepts are presented in **Appendix 2**. The main aspects of Object-Oriented (OO) and SOA approaches are introduced and suggested as milestones towards knowledge support systems for SSCM decisions. Findings are considered according to whether or not short comings could be attributed to issues in current system development standards. First, which aspects of existing tools could be attributed to system development issues? Second, how much adherence is there to current industry standards on open developments? Last, which requirements of PA DSS could be matched by the use of Web-based technologies?

A technical survey on the implementation and the design aspects specific to PA DSS developments is conducted. While the response was limited, sufficient information is provided to characterize common patterns in the commercial solutions available for SSCM, where OOP and SOA are used during implementation phases regardless of relevant methods for Object-Oriented System Design (OOD). Future directions point to service-oriented and knowledge-based systems, but show little or no concerns with aspects of potential areas such as the semantic Web or ABM.

2.1 - Human-computer interactions

Advances in human-computer interactions have been mostly characterized by an unbalanced evolution between hardware and software components (Baxter *et al.*, 2006), many times referred to as the "software crisis" over decades (Dijkstra, 1972; Mangold, 1996; Baker, 2006). Initial issues have been associated to software coding (Naur & Randell, 1969), systematic analysis and design methods (Dijkstra, 1972), requirement engineering and system engineering considerations (Impagliazzo, 2004).

General software development issues have further influenced specific knowledge domains. Several authors have for long pointed out general failures involving cost, timely delivery and product quality in the development of scientific information systems (Sobrinho, 1992). The speed, security and quality standards already realized for transaction systems (e.g. internet banking, ATM), have hardly ever been matched by scientific implementations (Tian *et al.*, 2006; Wilson, 2006).

Particular issues in research developments for agriculture (Sobrinho, 1992), natural resources (Strebel *et al.*, 1994), and distributed resource models (Wright *et al.*, 2000) are usually reported as a consequence of either weak problem definitions or complex mathematical computations. This type of inefficiency has been credited many times to method-less developments (Strebel *et al.*, 1994; Cox, 2006).

In agriculture, the usefulness of tools could be maximized with the adoption of basic system design and development methods. This approach could facilitate the upgrade and interchange of interdisciplinary models (Wright *et al.*, 2000), assist intensive data integration (Kelly *et al.*, 2001; Lima *et al.*, 2003), and enable proper spatial reasoning for PA tools (Cook & Bramley, 2001). On farm decision support has been mostly focused on the prototyping of mechanistic models (McCown, 2002a; Papajorgji *et al.*, 2004), usually resulting in a simulation tool of short-lasting usefulness (Walker, 2002; Russell & Norvig, 2003).

Much of the up-coming PA technologies have been closely related to, or directly derived from, research agendas, often inheriting general aspects of poor software development as suggested by Martin (2000). The imbalance between system components seems to have stronger effects in multi-parametric applications such as land-use planning and farm management decision-making. Therefore, failures in agricultural DSS developments (Newman *et al.*, 2000; Poluektov & Topaj, 2001; Walker, 2002; McCown, 2002; Stone & Hochman, 2004; Nguyen *et al.*, 2007; Matthews *et al.*, 2008) are likely to be not exclusive to this domain.

Research can potentially benefit from using system design methodologies and programming architectures that computer scientists have been developing over the past 30 years. Some applications have already shown positive returns, such as stochastic modelling of molecular networks (Priami & Quaglia, 2004), interoperability of biophysical and economic models (Antle & Stoorvogel, 2001); web-services for analysing and filtering yield monitor data (Murakami *et al.*, 2007), and agent-base modelling of field-robots in grape harvesting (Argenon *et al.*, 2006). Additional solutions are also expected from new interface prototyping concepts (Ramsin & Paige, 2008).

Still, faster chips, bigger memory devices, and sophisticated algorithms haven't been enough to consolidate computational science and provide affordable, accessible, and pragmatic development solutions. Challenges are still centred on well designed software solutions for knowledge acquisition and adaptive learning in decision support processes. Present approaches of open developments and cooperative architectures (Binstock, 2005; van Delden & Engelen, 2007; Tolk, 2006) reinforce that early requirements in software development (Naur & Randell, 1969; Brooks, 1987) have yet to be fulfilled (Binstock, 2005).

Decision support systems are no exception to the way in which computer systems can be developed. Human-computer interactions are made through compiled, interpreted, or translated executable programs which are binary versions (software) of a physical system implementation (source code). This development stage translates the abstracted program functionality (system design) by means of formal languages (programming languages) in which systems are written. These programming languages translate natural-language-like source codes into binary executable programs. They are notational systems for computation encrypting human-readable into a machine-readable form (Louden, 1993). One way to classify programming languages using a scale of levels of human-computer interactions is suggested in Wood (2002), where a high-level language permits a communication that is closer to natural languages such as English or Portuguese. In contrast, low-level programming describes an operational control that is closer to the binary machine language (**Figure 2.1**).

A software system is intrinsically complex from a number of aspects (Mangold, 1996; Cesare *et al.*, 2007; Langr, 2008). Object-Oriented Programming proposes software developments as collections of self-contained "components". The main concept is the object class which is a template from which actual objects can be created. It is a general tool that can be useful to model domain-specific problems ranging from system interaction and control protocols to agronomic processes and quantitative methods for data analysis and interpretation.

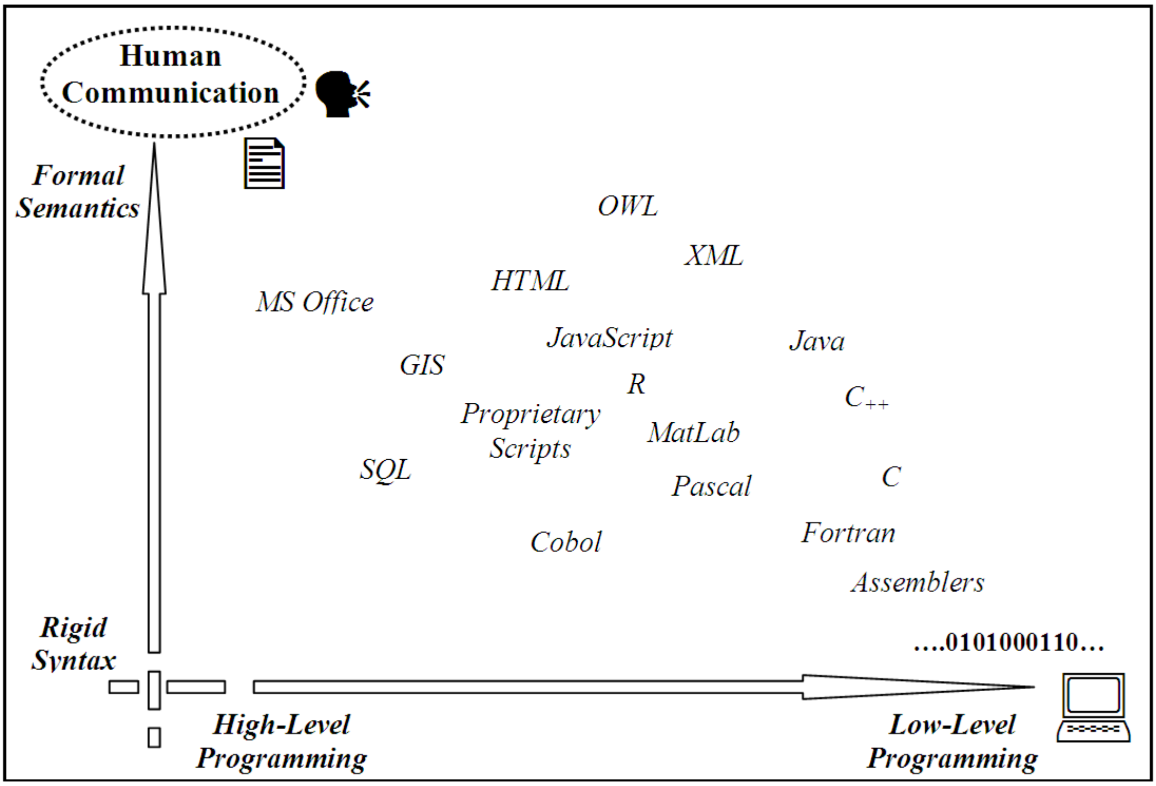


Figure 2.1: Levels of communication in human-computer interactions (after Wood, 2002).

2.2 - Object-Oriented applied to PA

The development of several applications closely related with SSCM decision support have for long shown the usefulness of the object-oriented concept in addressing farm management inputs and methods for crop production monitoring and simulations (Gauthier & Néel, 1996; Saraiva *et al.*, 1998; McCauley, 1999; Acock *et al.*, 1999).

A direct contribution of this technology is the capability to incorporate legacy crop models to new developments, which offers interfaces that facilitate user interactions with quantitative crop simulations (Thorp *et al.*, 2008). They introduce an application of precision agriculture for field management optimization that integrates field monitoring data with a DSS for agrotechnology transfer, namely DSSAT, (Hoogenboom *et al.*, 1994). A previous OOP application reusing the same legacy system has coupled GIS and DSSAT functionalities, showing flexibility in the evolutionary reuse of software components. Other examples are given in: McCauley (1999) coupling a cotton expert system with GIS for spatially variable simulation outputs; Shaffer *et al.* (2000) with a general framework for whole-farm legacy simulation systems in Fortran and Basic.

Evolutionary development is another aspect illustrated with the work of Cox *et al.* (2006a), which re-engineers the Whopper Cropper (Nelson *et al.*, 1999) from a crop decision aid to a discussion support system (Hayman, 2003). It has been integrated in sustainable agricultural research with a graphical interface facilitating diagnostic analyses from a database of pre-run APSIM simulations, the Agricultural Production System Simulator (Keating *et al.*, 2003).

Specific to SSCM, most of the developments characterize the stronger attention given to operationl processes over strategic decision processes, such as: cotton plant mapping (Plant & Kerby, 1995); field monitoring and operational management from multi-sensor data (Saraiva *et al.*, 1998; Shrestha *et al.*, 2003; Sung *et al.*, 2004; Zhang *et al.*, 2007a; Nash *et al.*, 2007), also through open Web services (Murakami *et al.*, 2007); an operating system for precise irrigation (Hans, 2003); image segmentation for multi-scale analysis mapping banana plantations variability (Johansen & Phinn, 2007, Lanthier *et al.*, 2008); weed detection (Schulthess *et al.*, 1996); control of liquid fertilizer applications (Ulson *et al.*, 2002); automation of off-road equipment (Blackmore, 2002; Ampatzidis *et al.*, 2006); erosion prediction (Ascough II *et al.*, 2005).

In relation to farm management, agricultural solutions are given for: modular crop simulation for potato growth (Hodges *et al.*, 1992); agricultural systems (Van Evert & Campbell, 1994); farm agro-ecosystem knowledge management and decision support (Gauthier & Néel, 1996); generic user interface for on-farm crop simulations (Acock *et al.*, 1999); field level GIS for integrated DSS (Wang & Tim, 2000); DSS for farm management (Recio *et al.*, 2003; Ali et, al., 2004); a forage growth model (Andales *et al.*, 2005); multiple-crop production simulation (Fleisher, 2001; Beck *et al.*, 2002); international DSS for crop nutrient management (Li *et al.*, 2006). Finally, other agronomic related applications have focused on: greenhouse environmental control (Gauthier, 1992); plant competition dynamic simulation (Rossiter & Rija, 1999); a virtual plant growth morphogenetic simulation (Honghao & Fanlun, 2005); and analysis support class libraries for numerical estimates (Fila *et al.*, 2003) and spatial pattern analysis and block interpolations (Runquist *et al.*, 2001).

2.3 - Web services supporting farm decision-making

The access to, and processing of information of many types, and from distributed sources, led the search for technologies allowing applications to interoperate across programming languages, platforms, and operating systems. The World Wide Web Consortium (W3C) defines web services as “a software application identified by a URI, whose interfaces and bindings are capable of being defined, described, and discovered as eXtensible Markup

Language (XML) artefacts" (Bell *et al.*, 2007). In simple terms, a service-oriented architecture is a collection of distributed services across the Internet that communicate with each other, sharing business logic, data and processes. In this cooperative architecture a service provider can also be a service consumer. A summary of concepts of this technology is presented in **Appendix 2** for further references.

PA related applications are grouped into 5 main areas to depict distinct aspects using SOA technology. The main areas are GIS, soil and climate, infrastructure for agriculture and biologic modeling, farm management and crop simulations, and SSCM. An overall analysis shows that a great part of the development effort has been directed to the design of meta-infrastructures for applied research, focusing on the use and the extension of the XML into new application-specific layers. In modelling and design of infrastructures, significant attention is given to standards for open community communication networks, perhaps at a broad agribusiness scale.

Another general fact is the greater number of reports of climate solutions, as compared to soil applications. In relation to farm management and crop simulations, there is a lack of spatial considerations that could offer appropriate within-field variability analysis. In GIS, most of the legacy development characterizes the use of proprietary solutions, only more recently adopting open-GIS standards for specific tools available at the field scale. Finally, site-specific developments are limited to the storage, management and networking of continuously monitored data. They are conducted at a conceptual level, reflecting the lack of domain specific knowledge representing decision-making process flow. There are no reports on the specific development of web service methods used by most of the commercially available software claiming to support decisions in SSCM. Aiming to cover this information gap, these products are subject of the development survey form further discussed in **Section 2.6**.

2.3.1 - GIS

Contributions including the methods and standards of Web GIS services for land management and spatial reasoning can be useful when applied to integrated farm decision-making developments. Different services are offered (**Table 2.1**) for integration of agronomic knowledge with GIS (Bian *et al.*, 2004) and spatial models (Nölle; 2004), including specific tools based on JavaBeans for visual model design and automatic Java code generation (Takatsuka & Gahegan, 2002). **Table 2.1** is first sorted by the scale of application, from broad to fine resolutions, and then chronologically where SOA solutions come in last.

Table 2.1: Web GIS services related with agriculture.

Article	Application	Scale	SOA	Implementation
Takatsuka & Gahegan (2004)	Geo-scientific Design & Analysis	Generic	No	Java; JavaBeans
Nölle (2004)	Agricultural Geo-service	Generic	Yes	GML; WMS; WFS
Aloisio *et al.* (1999)	Radar Imagery & Web GSI	Region	No	Java; XML; HTML
Steward *et al.* (2001)	Agribusiness Performance	Region	No	ArcGIS; SDE; Oracle Spatial
Button (2001)	Yield Management Web GIS	Region	No	GIS; Data Server
Ellis & Searle (2001)	Land Management DSS	Region	Yes	Applets; DHTML; Open Map Server
Bian *et al.* (2004)	Agronomic Knowledge DSS	Farm	No	ArcIMS; SDE; JSP
Nash *et al.* (2007) Sorensen (2008)	PA Web GIS Suite	Field	Yes	GML; WMS; WFS; WCS; WPS

Open development standards are well applied and based on the Open Geospatial Consortium (OGC), also extending the use of the Geography Markup Language (GML; Cox *et al.*, 2002) for the modelling, transport and storage of site-specific field information (Nash *et al.*, 2007) using technologies like the Web Map Service (WMS), the Web Feature Service (WFS), the Web Coverage Service (WCS), and the Web Processing Service (WPS). These have been adopted as specifications of a knowledge-based management information system (Sorensen, 2008) for the Web service suite proposed by the FutureFarm Consortium© (Nash, 2007).

Although experiments have shown the functionality of Web GIS services, Nash *et al.* (2007) have recognized among other authors (Egenhofer, 1993; Newman *et al.*, 2000; Tu & Abdelguerfi, 2006) that the ability to efficiently handle Web-based geospatial data, as required for PA decision making, requires more specialized developments than current standards for business transactions.

2.3.2 - Soil and climate

Computational initiatives to improve the accuracy and the accessibility of weather data for agriculture have been promoted by several governments in the form of information portals on the Web. However, most of the reports do not characterize typical applications of SOA methods nor domain specific XML extensions. Solutions for soil and climate are presented in **Table 2.2**, and two main points can be observed. First, is a common integrated and evolutionary development perspective between soil and climate Web services from different development groups in Australia (McGraw *et al.*, 2001; Milford *et al.*, 2001; NRMS, 2004), Brazil (Fileto *et al.*, 2005; Evagelista *et al.*, 2005; Otavian *et al.*, 2005), and the USA (Steiner *et al.*, 2005; Fernandez & Trolinger, 2007; Fernandez & Trolinger, 2007a). In particular they have targeted architectures for broad-scale solutions like the Australian Silo (Bureau of Metheorology, 2001) and the Brazilian Agritempo (Assad *et al.*, 2004). The reason why there is no particular sorting criterion in this table, other than grouping some solutions is to illustrate this aspect.

Table 2.2: Web soil and climate services related with agriculture.

Article	Application	Scale	Spatial	SOA	Implementation
Gerakis & Baer (1999)	Soil Texture	Generic	No	No	Pearl
Arauco & Sommaruga (2004)	Climate & Environmental	Region	No	Yes	XML; J2ME
Melkonian & van Es (2007)	N Management in Maze for Weather	Field	No	No	FTP; SQL; HTML
McGraw *et al.* (2001)	Soil Information	Region	No	No	Oracle Spatial
Milford *et al.* (2001)	Soil Web GIS	Generic	Yes	Yes	Java; Open GIS
NRIMS (2004)	Natural Resources Information	Region	No	Yes	Pelr; Java; XML; Open GIS Server
Fileto *et al.* (2005)	Soil & Crop Suitability	Region	No	Yes	Java; XML
Evangelista *et al.* (2005)	Climate GIS Server	Region	Yes	Yes	Java; JavaBeans
Otavian et. al (2005)	Soybean Rust Climate Risk	Region	No	No	Aplets; Servlets; XML; HTML
Steiner *et al.* (2005)	Climate Data for Crop Similation	Region	No	Yes	C#; SQL; ASP; XML
Porter *et al.* (2005)	Evapotranspiration (ETo) Network	Region	Yes	Yes	SQL; JavaScript; Perl; Java; JSP
Yang *et al.* (2007a)	ETo for Rice Development	Region	Yes	No	WheatherInfo; HTML; XML
Yang *et al.* (2007b)	Integrated Information: Soil	Region	Yes	No	HTML; XML
Wilson *et al.* (2007)	Integrated Information: Climate	Region	Yes	No	HTML; XML
Fernandez & Trolinger (2007a)	Irrigated Cotton Simulation	Field	No	No	WheatherInfo; CottonLogic; HTML

Implemented services have been improving fast, as the use of code reuse and modelling template techniques have increased in adoption. Results show a slow but increasing value of information to farmers through integration of dynamic climatic services (*e.g.* risk warnings, database and maps query, time series). Some applications have already provided over 6 years of direct assess of data interoperability to farmers (Fernandez & Trolinger, 2007a), others real-time climatic map interpolation and simulation of water limited yield (Evangelista, 2005), but none of the field level applications offer proper spatial capabilities for SSCM. Although, these other services could potentially make direct use of the soil information in McGraw *et al.* (2001), specific interface programs would need to be implemented for its proprietary data structure. A similar example can be made between Fileto *et al.* (2005), Evangelista *et al.* (2005), and Otavian *et al.* (2005), where the solution in Otavian *et al.* (2005) can not be used to improve Soybean suitability analysis in Fileto *et al.* (2005) via automatic binding.

2.3.3 - Agriculture and biological modelling

Priami & Quaglia (2004) report the extension of several mark-up languages in biosystem modelling, which mostly focus on domain specific declarations intended to facilitate the independent, distributed, and cooperative exchange of databases, algorithms, processes, and simulations. Developments such as a formal language defining the semantics of biological processes (Glossa; Kazic, 2000) and the System Biology Markup Language (SBML; Finney *et al.*, 2000) (**Table 2.3**) support the information infrastructure necessary to describe biochemical networks (Hucka *et al.*, 2003).

This type of XML-extended language usage is intended to provide foundations for cooperative modelling networks (Lloyd *et al.*, 2004), being also related with ontology mapping techniques, which are further discussed in **Section 2.4**. They are characterized in **Table 2.3** with their underlined acronyms and sorted by scale of application. In this case, scale is divided into two blocks: agribusiness portals and generic modelling tools. Agribusiness applications are most related with public assess to data warehouses, with the agricultural XML Schema aiming at efficient and effective electronic communication throughout the grain and oilseed supply chain (AgXML©, 2006). A XML Schema is a typical markup document expressed in terms of constraints on the data structure and its content.

Table 2.3: Web service infrastructures for agronomic and biological modeling.

Article	Application	Scale	SOA	Implementation
Bostick *et al.* (2004)	Crop Model Data Exchange Server	Agribusiness	No	HTML; ASP; JSP
Gingle *et al.* (2006)	Cotton Diversity Database	Agribusiness	No	HTML; ASP; JSP
Bedggood & Sutton (2007)	Grain Crop Variety Trials	Agribusiness	No	HTML; SQL Server
AgXML Org. (2006)	Grain & Oilseed Information Network	Agribusiness	Yes	XML; AgXML
Sini (2006) Sini *et al.* (2008)	Agricultural Thesaurus	Agribusiness	Yes	PHP; JSP; XML; AGROVOC
Ramachandran *et al.* (2004)	Earth Science Metadata Structure	Generic	No	XML; GML; ESML
Murray-Rust (1995)	Chemical Reaction Modeling	Generic	Yes	XML; CML
Proteometrics Inc. (1999)	Macromolecular Structures	Generic	Yes	XML; BioML
Kazic (2000)	Biosystem Modeling	Generic	Yes	XML, Glossa
Finney *et al.* (2000)	System Biology	Generic	Yes	XML; SBML
Lloyd *et al.* (2004)	Numeric Cellular Analysis & Simulation	Generic	Yes	XML; MathML; CellML
Pullen et al (2005)	Composable Simulation Models	Generic	Yes	XML; SOAP
Moore *et al.* (2007)	Modeling Protocol	Generic	Yes	UML; XML; SDML

Another contribution is the definition of a common modelling protocol based on UML for agricultural and environmental systems (Moore *et al.*, 2007). This protocol includes the Simulation Description Markup Language (SDML) that also underlies the APSIM modelling suite (Keating *et al.*, 2003). Moore *et al.* (2007) conclude that once models are developed in compliance with open common protocols, researchers can better respond to challenges in cooperative work. Finally, the FAO agronomic thesaurus (AGROVOC; Sini, 2006) is an important institutional support to Web service infrastructures, now evolving to a collaborative services concept for the ontological Web (Sini *et al.*, 2008), further discussed in **Section 2.4**.

2.3.4 - Farm management and crop simulation

Research for this section reinforced the reuse of legacy systems via new ways to interface farmers with complex simulation and quantitative assessments (Hayman, 2003). Main crop-simulation based DSS (e.g. DSSAT; APSIM) have been extended in their practical use and understanding directly to agronomy advisors and farm communities. However, fewer adherences to SOA standards at field level (**Table 2.4**) would suggest a less cooperative development approach between extensions of the same parent system (e.g. solutions from Hargreaves & Hochman, 2004; Cox *et al.*, 2006a; and Hunt *et al.*, 2006a to APSIM).

Another restrictive aspect for the integration between crop simulation and SSCM tools is the lack of spatial representation and reasoning in mechanistic models at field level. The majority of simulation services offering some degree of spatial reference are for region or farm scale, still mostly relying on proprietary software. Thysen *et al.* (2002) evaluate practical applications from Jansen *et al.* (1998, 2000) and Hensen *et al.* (2001), suggesting that the Pl@nteInfo® solution shows the feasibility to build adaptive and real-time Web decision support. Legacy algorithms from the CROPGRO-Soybean simulator (Boote *et al.*, 1989; Boote *et al.*, 1997) have been re-used by Welch *et al.* (2002), considering the user participation in the proper use of OOP. Welch *et al.* (2002) suggest a easy-to-use field-level solution which is non-spatial, standalone and proprietary, which strongly contrasts with the majority of open development solutions shown in **Table 2.4**.

Table 2.4: Web service for farm management and crop simulation.

Article	Application	Scale	Spatial	SOA	Implementation
Jensen *et al.* (2000)	Plant Protection Web DSS	Region	Yes	No	HTML; JavaScript; Perl; SAS
Hansen *et al.* (2001)	Pest Management in Potato	Region	No	No	C_{++}; ASP; SAS Server
Wharton *et al.* (2008)	Pest Management in Potato	Region	Yes	Yes	Perl; PHP; XML
Van Ouwerkerk (2004)	Farm Web DSS	Farm	Yes	No	JavaScript; ASP; ArcGIS
Welch *et al.* (2002)	Soybean Crop Simulation	Field	No	No	Visual Basic; DSSAT
Paz *et al.* (2004)	Soybean Crop Simulation	Field	No	No	Visual Basic; ASP; DSSAT; HTML
Hargreaves & Hochman (2004)	Farm Management	Field	No	No	NetMeeting; APSIM; Soft Systems
Cox *et al.* (2006a)	Farm Management DSS	Field	No	No	APSIM; C_{++}
Hunt *et al.* (2006a)	Farm Management DSS	Field	No	No	APSIM; PHP; ASP

2.3.5 - Site-specific crop management

Table 2.5 shows that in contrast to individual early adopters of open development methods (Saraiva, 1998; Lütticken, 2000), Web services addressing site-specific management are still pretty much at conceptual levels. An exception is given in Murakami *et al.* (2007) which presents an application of the Precision Agriculture Markup Language (PAML) for an online procedure embedding domain knowledge in analysis of yield monitor data (Mollin *et al.*, 2002).

Murakami *et al.* (2007) is the result of an evolutionary development approach, as chronologically grouped in **Table 2.5** (from Saraiva, 1998 to Murakami *et al.*, 2007). A few commercial tools claim Web service capabilities, but technical documentation is not fully available. These have become the subject of a survey reported in **Section 2.6**.

A strong point in the SSCM contributions is the apparent step-wise development providing formal XML extensions for PA information infrastructure (e.g. PAML and AgroXML). AgroXML (Nash, 2008) is developed specifically for the agricultural domain, using GML standards for high resolution spatial information. However, the small number of direct solutions for SSCM only addresses field monitoring processes, and don't deal with quantitative assessment or conceptual design of decision-making processes.

Table 2.5: Web service for site-specific crop management.

Article	Application	Scale	Spatial	SOA	Implementation
Lütticken (2000)	Farm Information Network	Generic	No	No	Java
Saraiva (1998)	Object Model for SSCM Data	Field	No	No	UML
Blackmore *et al.* (2002)	Behavioural Model of	Field	Yes	No	UML
Murakami *et al.* (2002)	Site-Specific Data Infrastructure	Field	Yes	No	UML; Java; XML; Mosaico
Murakami *et al.* (2007)	Yield Data Management	Field	Yes	Yes	Java; eMosaico; XML; <u>PAML</u>
Nash (2007)	Site-Specific Information Flow	Field	Yes	Yes	XML; GML; <u>AgroXML</u>

2.4 - Towards a semantic support for PA

Over twenty years of evolution in the decentralized Agris System reference (Salokhe, 2004) has built the conceptual infrastructure for an Agricultural Ontology Service (AOS). This service, proposed by the FAO (Fisseha *et al.*, 2001) to address the provision of a semantic search, now uses the existing knowledge contained in vocabulary and thesaurus systems (AGROVOC; Liang *et al.*, 2006).

The AOS aims to allow integrated development of domain-specific terminologies and concepts that may better support information management across the Web. Mapped vocabularies indexing the AOS are: i) the AGROVOC Thesaurus; ii) the Agris/Caris Classification Scheme (ASC); iii) the FAO Technical Knowledge Classification Scheme (TKCS); iv) the FAO TERM SUBJECTS; v) the Ag-Event Application for exchange event metadata; and iv) the Chinese Agricultural Thesaurus (CAT). It can be downloaded freely in several formats for non-commercial use, and it is used around the world for indexing and retrieving data from agricultural information systems.

Specific agricultural ontology services are proposed for: i) agribusiness metadata description (Fu *et al.*, 2007) formalized by a Resource Description Framework (RDF) and supporting knowledge management for agricultural e-Commerce; ii) agricultural sustainability in the State of Amazonas, Brazil (Brilhante *et al.*, 2006), using indicators of sustainable development described in XML and Web Ontology Language (OWL); and iii) plant ontology mapping (Goumopoulos *et al.*, 2004) supporting collaborative work towards the automation of crop management and glass-house scenario simulation. Plant ontologies such as the PLANTS system and the Plant Ontology Consortium (POC) project are available for research application describing: i) botanical terms; ii) morphological and anatomical structures; iii) organ, tissue and cell types; and iv) plant growth and structural development stages.

The uses of semantic GIS services, which are also relevant to PA, have been reported in several contributions. Venancio *et al.* (2006) describe the OntoCarta development relying on open-source public domain tools (*e.g.* Java, XML, GML) to build a semantic Web GIS resource using Protégé (Noy *et al.* 2002). OntoCarta helps map navigation and geo-object interoperability, being part of the ontological workflow proposed by Fileto (2003) to compose a semantic Web for the Brazilian agriculture (POESIA). In this framework, interpolated maps are automatically generated by interoperability between other resources re-used or implemented in the same framework, such as: machine learning (Weka; Witten & Frank, 2000), climate (Agritempo; Evangelista *et al.*, 2005), soil (Agrissolos; Fileto *et al.*, 2005), and soybean infestation (Otavian, 2005).

Contributions making a combined use of XML and RDF to other specific GIS applications are reported by Fonseca *et al.* (2002), Córoles *et al.* (2003), and Bell *et al.* (2007). Buccella *et al.* (2008) provide a comprehensive survey of current approaches for ontology-driven GIS analyses and compare methods for ontology integration. They conclude that a series of considerations are still to be solved when mapping GIS ontologies. These considerations have also been reported for generic geo-services (Egenhofer, 1996; Newman *et al.*, 2000; Tu & Abdelguerfi, 2006; Buccella *et al.*, 2008), and site-specific investigations (Nash *et al.*, 2007). They are now listed by the OGC as guide lines for the evolution of its open standards (*e.g.* GML, WMF, WFS).

Although adding clear advantages for representing reasoning capabilities, other authors have raised additional questions (e.g. "How the quality of an ontology can be evaluated and validated?"; "How to determine its completeness?"; "Does it represent the real world or some specific view of it?"). These questions reveal the truly preliminary development stage of semantic Web technologies (Guarino & Welty, 2004; Buccella *et al.*, 2008).

In relation to semantic Web representations applied to SSCM, one has to rely on early efforts for metadata protocols of field intensive monitoring (Bramley & Williams, 2001; Abuzar *et al.*, 2003). Although these contributions had for some time shown the importance of agricultural metadata models for PA, only recently have system related investigations been reported on the ontology mapping of site-specific monitoring processes (Arguenon *et al.*, 2006; Nash, 2007)

2.5 - Other advanced tools facilitating direct access to farmers

The use of intelligent agents is present in several reports of applied GIS domains. The evolution of the general methods and positive results of applied research should be motivation for more attention to these technologies as a potential means of offering facilitated user interfaces and semi-autonomic data analysis to support SSCM. The idea behind the use of this technology is not to offer a "smart black box" solution that would put the user rationale aside, but actually to facilitate farmers' accessibility in the way that they could infer individual management knowledge and validate their decision-making. In this sense, autonomic pieces of software could transparently organize and process raw data, as well as to bring insights from complex simulation models and scientific knowledge.

This evolution of generic methods for development of intelligent software agents is well reported: intelligent decision support (Petrov & Stoyen, 2000); distributed model base management (Tolk & Pullen, 2003; Li & Peng, 2004); distributed grid simulation (Pullen *et al.*, 2005); reconciling heterogeneous information assets (Lister *et al.*, 2006); and autonomic computing (Huebscher & McCann, 2008). Extensive reviews on specific applications of these methods are given in Parker *et al.* (2001) for urban land-use; Evans (2007) and Buccella *et al.* (2008) for current agent approaches in spatial simulation; Brown & Xie (2006) for spatial dynamic modelling; and Heckbert & Smajgl (2005) for urban monitoring systems.

The use of agents for GIS in urban, environment, and forestry studies are introduced in: Gimblett (2002) and Janssen (2005) with considerations in human-environment systems; Parker *et al.* (2001) and Berger (2001) with implementations in land resource use change and policy; Castle & Crooks (2006) with semantic Web GIS for geo-object simulations; Smajgl (2004) modelling the use of common-pool resources; Elliston *et al.* (2004) with a crop disease incursion management integrated with agricultural production and economy models; Golden *et al.* (2005) with ecological forecasting; and Cortés *et al.* (2000) and Thomson *et al.* (2007) with knowledge-based aids in forest disease and biodiversity management.

Applications at a broad agribusiness scale have been reported at a more incipient level. Evans & Kelley (2004) simulate the distribution of land use preferences at household level and observe that individual preferences are weighted differently as a function of scale. Folorunso *et al.* (2006) focused on the impact of the E-commerce in agribusiness where agents help farmers with their transactions online. Other agents are also considered for structural changes in farm land and mediating factors of cooperation and collaboration between best individual strategies of farmers. Wada *et al.* (2007) use a dynamic agent model for shifting cultivation in Laos as a function of demand and supply of crops. In their approach, villages are treated as decision-making agents, in their own right, using a scale-sensitive procedure to validate the model across differing spatial resolutions.

The use of agents in PA accounts for very few reports mostly related with operational requirements (Ribeiro *et al.*, 2003; Blackmore *et al.*, 2004; Blackmore *et al.*, 2007) or conceptual architectures for auto-steering and agricultural robot behaviours (Blackmore *et al.*, 2002; Blackmore *et al.*, 2004a; Gracía-Pérez *et al.*, 2008). Agents are mostly recognized as dedicated processors (firmware) which are components within major mechatronic architectures (Blackmore *et al.*, 2007). A formal use of the agents in association with ontology mapping for control of several agricultural robots is reported in Arguenon *et al.* (2006). Their work focused in the cooperative behaviour of vineyards robots under different and synchronized tasks, concluding that optimal choices towards the development of harvesting systems can be identified and modelled using agents.

2.6 - A survey on methods for development of SSCM decision tools

The survey presented in this section aims to identify current implementation standards and evaluate potential pathways in software design that could improve the efficacy and drive the evolutionary development of PA software tools. It is not intended to be comprehensive in terms of software development techniques or extended to generic GIS tools. Questions are directed to current and emerging system approaches, with the aims: to compile a contact list of PA software developers; to summarize common patterns in the development of PA tools; and to identify trends in DSS architectures which can be applied in SSCM decision processes.

2.6.1 - Previous surveys on PA decision support tools

Several publications on software tools to support farm management have been reported in surveys on different aspects of farm mapping solutions and SSCM decision support. Ess *et al.* (1997) evaluated commercially-available software for grain yield mapping mostly related to a GIS perspective. One of the first comprehensive lists of software solutions for PA is introduced by Swayer *et al.* (1999). They compare the usefulness and practicality related to operational aspects of twenty-five (25) farm management tools involving GIS and econometric functionalities. They were evaluated on their capability to support decision processes in business management (*e.g.* finance, labour, machinery inventory, and production traceability), yield mapping, generic GIS, and agricultural applied GIS. An updated overview of farm mapping software is given in Fitzpatrick & Neale (2008), examining the range of available tools and functions that seem useful to assist landholders and natural resource managers. They suggest a decision matrix to assess primary producer needs and the ability of specific mapping tools to meet their needs and expectations.

A significant improvement on software functionality and interactivity could be observed between early reports (Swayer *et al.*, 1999) and recent reviews (Fitzpatrick & Neale, 2008). However, this relative evolution has not been reflected in technological adoption, nor has serious attention been given to new Web-based developments.

The report by Swayer *et al.* (1999) was considered relevant as a reference, because it considered indicators of decision support capabilities in the analysis. They have also evaluated functionalities for spatial data interoperability and customized management related to five overall decision processes, namely: *economic analysis, fertilizer recommendation, lab links, fertilizer blending calculations, and prescription mapping*. However, their survey is limited as related to system development and implementation architectures (*e.g.* OS compatibility, data format compatibility, interoperability, and open standards). Therefore, a new survey form (**Section A2.5**) has been developed on the basis of elementary system development questions, aiming for both an updated summary of existing decision support tools for SSCM processes and aspects of evolutionary development.

2.6.2 - Existing PA DSS software

Most of the agricultural software industry does not clearly report their associated development approaches and implementation techniques in the form of general information, mainly focusing on the marketing of functionalities. To diminish the information gap on adopted methodologies in system development, existing PA DSS have been identified, and a list of 35 DSS developers was targeted with the survey form on methods for DSS developments (**Section A2.6**). This list did not intend to be comprehensive or conclusive, and it did not consider tools constrained to communication protocols, servo-mechanic data gathering control, or merely accounting spreadsheets. The list in Swayer *et al.* (1999) has been revised and extended with other references and agronomy related Web sites (AGanswers, 2005; Farm Chemicals, 2000; Payne, 2005; The Geospatial Resource Portal, 2005).

2.6.3 - The survey form on methods for development of decision tools

Gaining views on efforts and experience developing software applications in PA is important to evaluate present implementation standards and foresee potential pathways in software design. Results of the development survey form introduced in **Appendix Section A2.6** are used in formulating a conceptual system framework to serve as a reference for near-future improvements in applied software (**Chapter 3**). It is not intended for any individual evaluation or comparative matrix to be compiled as result, as only summary information will be used for reference. The underlying motivation for this survey is to identify and report common requirements to promote better standards of software accessibility, modularity, composability and reverse engineering. It is expected that identifying these requirements could help the development of more pragmatic tools for decision support in the adoption and operation of site-specific management, if they are matched with both commercial implementation and knowledge-based modelling research.

2.6.4 - Summary of the survey responses

Effective responses to the survey were limited, where 15 out of the 35 DSS developers argued to be excused from the survey because of intellectual property policies in the company, no matter how generic the questions. No response at all was gained from 10 companies (30%) including some of the big technology providers, with an additional 7% (3 companies) not being located at addresses appearing on Web links. Individual responses are not to be published for respect of the privacy of the collaborators.

Seven developers (20%) have completely fulfilled contributions from which very general, but clear results can be drawn. It answered questions such as: “Does PA speak object-oriented languages?” and “Do PA developments conform to present industry standards?”. All companies have reported the present adoption and the intention of future investments in OOP, SOA, and KBS. Although, little or no concerns has been shown in relation to potential areas like the Web semantics or ABM.

In contrast with some of the current tendencies in the software industry (**Appendix Tables A2.2** and **A2.3**), none of the developers supporting SSCM decision making are using Java Standard Development Kit (SDK) or other complementary Interactive Development Environments (IDE). They mostly use more traditional code standards (**Appendix Section A2.1**) such as C_{++} (4 out of 7) and Visual Basic (5 out of 7), even if Web standards appears to be increasing through investments in JavaScript and XML (2 out of 7) and particular attention to .NET solutions (**Appendix Table A2.1** and **Section A2.4**). However, the adherence to object-oriented concepts appears to be a definitive standard for programming (OOP, 7 out of 7) and design (OOD, 5 out of 7), and also the use of IDE tools (**Appendix Section A2.3**) applying the object concept (3 out of 7).

In relation to user’s participation in development and the use of Web services to improve communication, the great majority have shown concerns and diverse means to communicate with users (6 out of 7), mostly focused on farmers (5 out of 7), research (4 out of 7), and agronomist/consultants and technology providers (3 out of 7). Active communication with users was reported by 4 companies through diverse means with an average of 3 companies for each type of media in question 4 of Section C of the survey (**Appendix Section A2.5**).

In contrast with all the other companies, one was completely reserved in terms of user interactions. They do not directly consider user requirements, rather relaying in extensive amounts of domain knowledge for development, only reacting to longstanding customers requirements. Although unusual in this survey, this practice does not necessary represent any by-passing of farmer's knowledge, rather being understood here as an up-to-date engineering-centred strategy that values the importance of knowledge intensive as a resource management as discussed in **Section 1.4.3**.

Finally, answers from Sections B and C have further characterized that little interchange between technology providers exists (3 out of 7) potentially explaining frequent reports of poor data interoperability between complimentary software solutions. Results from question 8 of Section B of the survey show that all the decision support modules that are expected to be required are in fact available (e.g. GIS, variogram analysis, economic analysis, prescription mapping, proximal sensing, image processing, and analysis of management zones), however they are not all offered in one software solution . The overall conclusion of the survey indicates trends in object-oriented design patterns and Web-based developments in support to site-specific differential management.

2.7 - Concluding remarks

An overview on the evolution of human-computer interactions is presented as a means to understand natural system limitations when developing supportive tools for site-specific management decision processes. The literature review is used to illustrate some of the methods and tools that have been successfully used so far and to investigate potential architectures that can match the requirements of DSS for SSCM. Current Web paradigms are introduced as milestones for the development of a new generation of knowledge support artefacts that can aid integrated, educative, and adaptive farm management. Their application to PA related knowledge domains is presented and results are discussed.

The chronology in this rationale is to suggest that many of the existing limitations in the functionalities offered by SSCM decision support tools are related to historical system development issues, and not based on the failure of specific agricultural DSS solutions. Due to the extensive character of the evolution in software development, only introductory aspects relevant to the context of this study are discussed. It is suggested that more in-depth research in applied object-oriented architectures and Web services may contribute to the maturity and effectiveness of PA software developments.

The object approach has proved to persist as a basis for new open developments towards knowledge-based Web services for PA, but strong evidence is given to the importance of systematic adoption of basic design methods and interactive development technologies. Evolutionary software development techniques have shown successful applications in support of broad agricultural and whole-farm analysis, but have not been well investigated in relation to differential crop management decision processes. The majority of tools directly available to farmers has little adherence to basic modelling standards and implementation architectures which could facilitate code re-use, data interoperability, and distributed and cooperative services.

Given PA DSS requirements (Robert *et al.*, 2000; Lynch *et al.,* 2000; Robinson, 2005; Matthews *et al.*, 2008), it is suggested that the technological tool box matching the required functionality has only recently improved to the level of providing composable and integrated software solutions. Web-based technology has already shown potential application in farm-level PA, but developments addressing the integration of site-specific data from multi-sensor platforms have also indicated that some aspects in this technology are yet to mature into scalable evolution.

Results of the survey on methods for DSS developments (**Section 2.6.4**) have shown that object-oriented and service-oriented technologies have mostly used an integration of C^{++}, IDE and .NET solutions as a current and interoperable approach, which offers a straight forward technical solution with an easier maintenance syntax structure. None of the currently available tools that could be classified as a decision support system can be characterized by a development which would consider the use of semantic mapping or autonomous agents for intensive knowledge management. These appear to be areas of greater attention in other disciplines also related with GIS and intensive data monitoring, such as for grid simulation in urban planning and conflict management or forestry management of population variability. It is shown that great attention is being given to the involvement of decision makers (i.e. farmer, agronomist/consultant, and researcher) using traditional and new functional modelling notations. The limited response has not compromised a representative result from the survey, even if it could not bring a comprehensive overview of current developments. Importantly, the identification of system development characteristics as reported in Section 2.6.4 is of great support to the better understanding of all phases involved in the development of more pragmatic tools supporting the adoption and operation of site-specific management.

PART II

Methods Supporting Decisions on the Adoption of SSCM

Chapter 3

A framework for assessing the opportunity in SSCM

Summary

The literature review in Part I has suggested that there is no practical software supporting crop management for within-field production variability. This systemic problem can be linked to two main causes; the lack of consideration of quantitative spatial assessments and the limited adherence to semantic system design methodologies. Simple quantitative methods for spatial and temporal assessments of crop variation need to be standardised by a large sample of intensively monitored data for different crop systems. Semantic design frameworks need to be abstracted and refined in order to support evolutionary open development approaches and provide the basis for integrated knowledge-based farm management.

Although object-oriented and Web architectures can potentially improve this situation (and have been used for agriculture) limited experimentation has been conducted to match autonomic analysis of intensive field monitored data with knowledge on crop management processes. A stronger modelling approach is proposed in this work with a conceptual framework for understanding the domain of differential crop management decisions and presenting the parameters and methods directly influencing the opportunity for adoption of SSCM technology.

Standard system design methods and tools, upon which object-oriented architectures can be created and reused, are applied according to common steps for the adoption of open component developments. The proposed framework design for methods supporting management decisions uses an innovative method of application of the Unified Modelling Language (UML), designing the quantitative assessment of crop variation and the associated opportunity for delineating potential management zones. ULM diagrams used were the Use-case Diagram, the Object Class Diagram, and the Sequence Diagram. These conceptual descriptions are expected to serve as a platform independent template, allowing future refinements in the abstracting of objects, their state (attribute values), their behaviour (functional methods), and their relationships. The new method of application has offered easy means of visual design and object class documentation, and the resulting Platform Independent Model (PIM) can be further implemented using integrated development tools of any programming language or operational system.

3.1 - Introduction

This chapter introduces an innovative method of application of the UML. A conceptual design is carried out using methods to support management decisions in the context of quantitative assessments of spatial aspects of within-field crop production variability. The UML models considered aim to characterize the main processes involved in decisions related to methods for differential crop management which are addressed in following research chapters.

Quantitative methods are strongly suggested for supporting the control of sustainable agricultural systems (Day *et al.*, 2008), and potentially enhancing the value of information for field management decisions when conceived through systemic approaches. This central role of system analysis in developing innovative farming systems has long been recognized by international groups; ICASA (Bouma and Jones, 2001) and EFITA (Gelb and Parker, 2006), promoting a better overall system understanding and re-use (Harsh, 2006) and for the design of integrated farm decision support tools (Öhlmer and Nott, 1979; Kozai and Hoshi, 1989; NRC, 1997; Ahuja *et al.*, 2002; Öhlmer, 2006).

The parsimony of analysis considering spatial and temporal aspects of within-field crop variation has also been suggested as a basic decision hypothesis for the opportunity of adoption of SSCM technology (McBratney and Whelan, 2001). However, the literature review in **Chapters 1 & 2** have also shown that there is no simple and effective system solution fully supporting this central assessment in the adoption decision process. This lack of effective tools directly available to farmers has been strongly associated with a limited adoption of SSCM technology (McBratney *et al.*, 2005). Many software products are still reflecting ideas in which the standalone coupling of geo-data layers, descriptive statistics, and accountability tables would suffice to support SSCM. Tools are lagging behind in analysis and interoperability features based on both quantitative methods (Rus *et al.*, 1993; Bouma, 2002) and/or on-farm action research (McCown, 2001a; Lynch and Grecor, 2004) approaches.

Several decision-making frameworks have been suggested, used, and expanded within distinct knowledge domains (e.g. business management optimization, empirical analysis, knowledge engineering). A common point to all domains is the inherent complexity of decision processes, which are generally composed out of issues related to human, computational, systemic, and scale of management factors. Farm management decision support is no exception, whether considering aspects associated to operational crop production or to strategic adoption of PA.

In SSCM, the task of developing effective tools is not easy and an evolutionary and participative development approach (Papajorgji, 2005), which is better matched by open software platform developments (Murakami *et al.*, 2007), is required. Open and modular implementations are likely to address the multidisciplinary complexity involved in agronomic decisions (e.g. soil, climate, plant, infestations, environment, machinery, and adoption of new technology), and the incipient nature of SSCM research which still contains several decision knowledge gaps (Robert, 2000; McBratney and Whelan, 2001; McCown, 2002a; Dobermann *et al.*, 2004; Robinson, 2005; Matthews *et al.*, 2008).

Although object-oriented and Web-based architectures have been considered in some SSCM related tools, there is an evident need for more systematic data handling and information management when abstracting components of agricultural DSS (Matthews *et al.*, 2008). Most experimental projects focus on fast code implementation for expert model validation and give little or no attention to practical aspects of system design and interface prototyping (e.g. requirement engineering, code documentation, stakeholders' participation, algorithm optimization). There is an great amount of research and operational data (e.g. crop simulation and yield monitor data) being produced in relative isolation and distinct formats, leading to duplicate efforts (McCown, 2002; Wilbanks and Boyle, 2006; White and van Evert, 2008).

Model design can help to document and make expert abstractions and algorithms reusable, and supporting the integration of fragmented information assets. It enables shared analysis and the use of data from disparate sources (Bouma and Jones, 2001; Ahuja *et al.*, 2005; Papajorgji, 2007; White and van Evert, 2008). Formal mechanisms for documenting and distributing research information, model abstraction, and system design also merit attention. They should meet the same rigor, quality, and reproducibility standards as imposed on scientific laboratorial methods (Wilson, 2006); in order to ensure accessibility and reuse.

It is argued that the use of standard methodologies for platform independent designs and modeling notations is, at this point, more relevant to model incipient SSCM techniques. Due to present levels of underdeveloped knowledge about the role of individual factors and relationships for integrated SSCM decision processes, a full system implementation is likely to mislead proper abstraction of objects, compromising the degree of future re-use and class specialization.

Design methodologies can now better support not only software implementations, but also the communication between topical expertise and business management requirements. Movements like Science Commons (Wilbanks and Boyle, 2006) also reinforces design strategies and tools for faster and efficient scientific research in order to speed the translation of data into discovery, unlocking the value of mathematical analysis and domain-knowledge models that to be accessible and benefit more people.

The standard use of a minimum set of design techniques in PA decision making could grant a better understanding of site-specific concepts, crop management processes and methods of analysis. This would facilitate translations between functional, managerial, and legacy knowledge. In the long run, information has more value when it is widely shared than when it is closely held (Thompsom and Sonka, 1997). This particular description is reflected in one of the first initiatives towards Web-based solutions for PA, the Cyberfarm management assistance (Sonka and Coaldrake, 1996). In contrast, current DSS are still segmented and isolated; overloading a farm manager with manual computer work and lacking integrated analytical capabilities. Wilbanks (2008) suggests that the Internet should be viewed as a platform for facilitating the free circulation and sharing of physical tools of science.

Contemporary IT developments have reinforced the need for semantically rich models, in which Web services are now evolving to support advanced distributed simulations (Tolk, 2006) using Grid computing (Tolk & Pullen, 2003; Numrich *et al.*, 2004). A new generation of design methods offers techniques that can enable machine-based reasoning through semantic-enriched information and provide intelligent support to users (Omelayenko *et al.*, 2003). Still, limited attention to knowledge management technology is regarded to the applied academia (Tian *et al.*, 2006), as observed in agronomic research. From CommonKADS (Breuker & van de Velde, 1994; Schreiber *et al.*, 1999) to ontology (Corsar and Sleeman, 2007) and Agents and Grid computing (Gil, 2006; Huebscher & McCann, 2008), different designs all point towards knowledge intensive assets as a new factor in production and business competitiveness. All these designs use UML models as a common basic concept.

Accordingly, the use of a few basic diagrams from the UML method is further explored in **Section 3.3**, to address the assessment of spatial production variation. The new method of application has proved to facilitate conceptual abstractions and implementation designs, and to offer a standardized mean to document and preserve the modelling rationale underlying proposed solutions. It is also expected that this novel PA application of the Model Development Approach (MDA) can offer a conceptual framework design that will support prototype implementation and method experimentation within this research as well as a reference for near-future improvements in applied software (**Section A3.2**).

3.2 - The Unified Modelling Language (UML)

Unified Modelling Language is a general visual design language for specifying and developing complex systems, especially large object-oriented projects. The purpose of the UML is to facilitate analysis and design of any type of application, providing a language-, methodology-, and platform-independent modelling notation. In formal definition, "UML is an evolutionary general-purpose, broadly applicable, tool-supported, and industry-standardized modelling language for specifying, visualizing, constructing, and documenting the artefacts of a system-intensive development process" (Alhir, 2003). It is an industry standard for modelling that can be used to analyse and document systems of any type and combination of business logic, management process, hardware, operating system, programming language, or communication network. The language enables and promotes the capturing, communicating, and leveraging of knowledge of system development actors (users, domain specialists, analysts, and programmers) (Richards & Castillo, 2007). It has been applied to software and non-software systems and domain specific methods and processes, capturing architectural knowledge (semantics) and system flow (syntax) (Alhir, 2003).

The UML tools, such as the NetBeans 6.1 used for the framework design in **Section 3.3**, have evolved so far that modelling is no longer simply an academic design exercise that is forgotten after the implementation phase starts. There are a large number of open source UML-based tools freely available (http://java-source.net/open-source/uml-modeling). One of the most common functionalities of these tools is automatic code generation. Originally meant for low level software engineering, most of them convert diagrams into executable object classes. Some of these integrated development tools offer reverse-engineering, analysing an existing source code to construct a set of UML diagrams. Although reverse engineering can be useful for understanding the vast undocumented code legacy, it does not fully provide information related to business organizational aspects (e.g. the Use-case, Component, Activity, and Collaboration Diagrams). Several Integrated Development Environments (IDE) can execute UML models in a way that deploys and validates the designed application.

There are claims of overloading methodology and design constructs in the UML method (Richards & Castillo, 2007). However, the great deal of functionality encompassed in the language does not require nor dictate any type of minimum required diagram set or model documentation. Although involving a comprehensive set of techniques, the use of a limited set of UML diagrams is understood to suffice as a modelling methodology capable of abstracting SSCM decision processes.

3.2.1 - The UML applied

The use of the UML is related to the general understanding that separating software design into multiple perspectives helps to improve the overall abstraction of a system, reducing complexity and supporting design decisions. It is understood that simplified design diagrams can be used to bridge gaps (e.g. how to integrate variability assessments in practical decision-making processes) between business requirements (e.g. the assessment of within-field crop variation) and available technology (e.g. easily accessible SSCM decision support tools).

In Australia, Moore *et al.* (2007) describes a common modelling protocol that is explicitly a hierarchical framework view for biophysical system simulations, and uses UML diagrams and XML schemes. This formal protocol specification (Moore *et al.*, 2005) proposes PIM models using UML class diagrams that describe the relationship between components of modular simulation system developments such as the APSIM suite. The design specified in Moore *et al.* (2005) makes extensive use of UML class and sequence diagrams to describe a protocol of template structures and message synchronization between components of agricultural simulation models. Several sequence diagrams detail all the possible dynamic flows of events and messages during a simulation process.

Other UML uses in agriculture can be generalized into two groups based on spatial analysis or process simulation models. For spatial reasoning, examples include a GIS for agro-environmental management (Martin & Vigier, 2003), a spatial information system supporting common resource agricultural policy (Hasenohr & Pinet, 2006), the monitoring of fertilizer applications (Pinet *et al.*, 2006), and the analysis of spatio-temporal patterns (Miralles, 2006). Mechanistic model applications are for dynamic plant growth simulation (Drouet & Pages, 2001), soil-water balance model (Papajorgji & Shatar, 2004), and agricultural systems (Papajorgji & Pardalos, 2006).

For SSCM, UML models have had limited investigation, and then mostly for continuous monitoring information infrastructure. The first set of models was introduced by Saraiva (1998) using the Use-case and Class Diagrams characterizing georeferenced data flows in the domain of PA. Blackmore *et al.* (2002) proposes a State Diagram designing behavioral transitions of autonomous tractors, a Class Diagram describing the structure of data flows and an hierarchical chart for inheritance of expert system functions for system control. Murakami *et al.* (2002) introduce a metamodel Package Diagram illustrating the modular composition of an infrastructure for field monitoring information systems. It is further detailed with class diagrams and information flow frameworks representing inheritance and interaction relationships between objects abstracted for intensive field sampling. Murakami *et al.* (2007) follow their previous work, extending the use of a UML Class Diagram that represents the system structure for a specific XML scheme (PAML) for storage and management of field data for Web services. Nash *et al.* (2007) shows a design extending the XLM to the agroXML for a similar domain of field monitoring information flow. Their approach also extends the use of UML models in SSCM; introducing an Activity Diagram for data flows of a Use-case Diagram of site-specific soil sampling, where the information about concurrent processes and knowledge on the business workflow can represented. Common conclusions from these contributions are that UML diagrams depicting knowledge from integrated system requirements and business processes are affective and the need for formal investigation of the use of applied UML design methods is warranted.

3.3 - A framework for supporting the adopting of SSCM technology

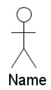
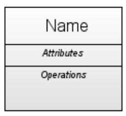
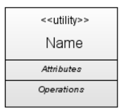
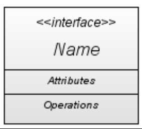
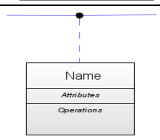
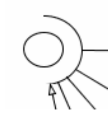
In the context of system development methodologies, this research considers the application of design methods in conforming to recommendations of the Object Management Group (OMG). Results from the DSS development survey (**Section 2.6.4**) are considered in formulating a conceptual system framework, which is fundamental for knowledge representation of a multidisciplinary problem domain. Object classes and/or class interfaces from legacy UML designs for SSCM operational processes and crop simulation are also considered in system analysis (Saraiva *et al.*, 1998; Blackmore *et al.*, 2002; Papajorgji & Pardalos, 2006; Murakami *et al.*, 2007; Nash *et al.*, 2007).

Open development tools were used for empirical prototyping of object classes and public API's, aiming to evaluate source code management and automatic generation. Focused on Web compatibility, the Java standard development kit (J2SE) and the NetBeans integrated development environment (IDE) were used for project management, UML models, source code editing and compilation. It is expected that the use of these tools could support a semantic representation of conceptual and practical aspects of management processes with facilitated code generation.

A conceptual framework level of development has been addressed as a basis for a modular and evolutionary development approach towards a knowledge-system suite to assist farm management. This framework design is centred on the generation of platform independent designs, where code generation and refinement is considered only as an academic prototype investigation to evaluate the use of interactive development environments. It is argued that the use of standard methodologies to generate PIM is more relevant to present levels of the applied knowledge domain than comprehensive system coding development. A summary of UML notations for different elements and relationships used in this chapter are given respectively in **Tables 3.1 & 3.2** according to standards given in Booch *et al.* (2006) and NetBeans IDE (2008).

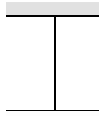
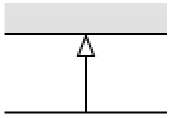
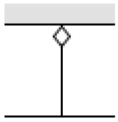
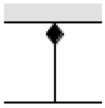
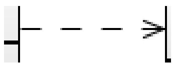
A Class Diagram is introduced as a metamodel describing several aspects influencing precision farming management processes (**Figure 3.1**). This metamodel framework summarize the wide range of knowledge domains considered for integrated farm management and highlight the strategic aspect of the opportunity for SSCM. Methods defined for object classes associated with the adoption of SSCM technology, the "SSCM Opportunity" and "Spatio-Temporal Reasoning" classes, are detailed on this top level system structure in order to introduce the kind of functionalities and relationships that will be further modelled in the next subsections using a Use-case Diagram, three Class Diagrams, and one Sequence Diagram.

Table 3.1: UML diagram design elements with their notation and description.

Elements	***Notation***	***Description***
Use-case Class		Describes the system functionality using multiple scenarios of a specific flow of user transactions.
Actor		A coherent set of user roles during system interactions.
Object Class		Any regular object class abstracted in your system design.
Utility Class		A utility class represents a type that has no instances, as a set of global variables and procedures that have been grouped in the form of a class declaration.
Class Interface		A stereotype of class offering only public operations, but no attributes or method bodies.
Association Class		Class information (e.g. attributes, operations) about a specific association shared by two elements.
Assembly Connector		A connector between elements that provides the services that another element requires, which is defined from a required interface to a provided interface.

*** sources:** Booch *et al.*, 2006 and NetBeans, 2008 (www.netbeans.org).

Table 3.2: UML diagram design relationships with their notation and description.

Relatioships	***Notation***	***Description***
Association		A general association relationship between two elements.
Generalization		The relationship between a subtype element and a supertype element in which a supertype must possess the same attributes of subtypes.
Aggregation		The relationship between two elements where one of these classes plays a more important role within the relationship.
Composition		An especial type of aggregation in which all child elements are dependent on the parent element.
Usage		A dependency in which one element (the client) requires the presence of another element (the supplier) for its correct functioning or implementation.
Dependency		The relationship between two elements whose definitions depend on one another in such a way that changes to one can result in changes to the other.
Realize		These relationships are used in two places: between interfaces and the classes that realize them, and between use-cases and the collaboration that realize them.
Extend		A dependency between Use-case and Object Classes in which the client extends the behavior of the source.

* **sources:** Booch *et al.*, 2006 and NetBeans, 2008 (www.netbeans.org).

A Use-case Diagram (**Figure 3.2**) is used to understand specific design refinements for strategic decision-making for SSCM, which conforms to the class metamodel. This diagram depicts the general context of within-field production variability assessment to aid the adoption of SSCM technology. This Use-case Diagram shows human-computer interactions between system actors and system functionalities that generalise the behavioral sequence of transactions for the system assessing the opportunity for technological adoption. Further decomposition of the integrated farm management classes into more specific model components is accomplished describing objects, their state (attribute values), their behaviour (functional methods), and their relationships (e.g. hierarchy, dependency, association, inheritance, generalization, refinement). Object classes are abstracted within a categorical hierarchy of system models, these being the assessment of the opportunity for SSCM adoption

(**Figure 3.3**) by means of a variability index (**Figure 3.4**) that uses quantitative parameters from a spatial variography analysis (**Figure 3.5**).

3.3.1 - The integrated farm management metamodel

It is understood that a full range of methods and tools in system development and knowledge engineering can supply open and interoperable architectures better supporting the maintenance and interchange of concepts, models, modules, and source code. This suggests that tools directly available to farm managers from different knowledge domains could be integrated through a customizable suite of individual knowledge management solutions (**Figure 3.1**). A specific farmer would select and interact with different software artefacts according to his tacit knowledge on what information could support his specific farm context and individual decision processes. Information could be supplied by standardized repositories of validated scientific models, making use of interfaces capable of autonomic routine functionalities (e.g. georeferencing, data exploratory analysis, evaluation of geostatistical parameters, monitor data management) for facilitated interactions. A knowledge management system controlling individualised management databases could interact with information from past management practice performances (predictions and decisions vs. actual outcomes) that includes a particular set of quantitative indices, simulations, spatial analysis, time series, agronomic evaluation and prescription, economic-environmental assessments, and on-line semantic Web services.

It has been shown that software engineering has recently evolved to a point where the supply enabling technology for the development of the suggested knowledge suite functionalities is also possible. Still, a closer parity between available decision support tools and practical requirements involved in SSCM decision processes is dependent on applied designs which can depict the way in which mathematical analysis of spatio-temporal and agronomic factors and relationships could be added to the flow of management decision processes.

These designs are better implemented through standardized notations and integrated development technologies, which are already applied in SSCM for field monitoring workflow (**Section 3.3.2**). No research has been found on the application of those methodologies specific to decision processes for evaluating the opportunity for adoption of SSCM.

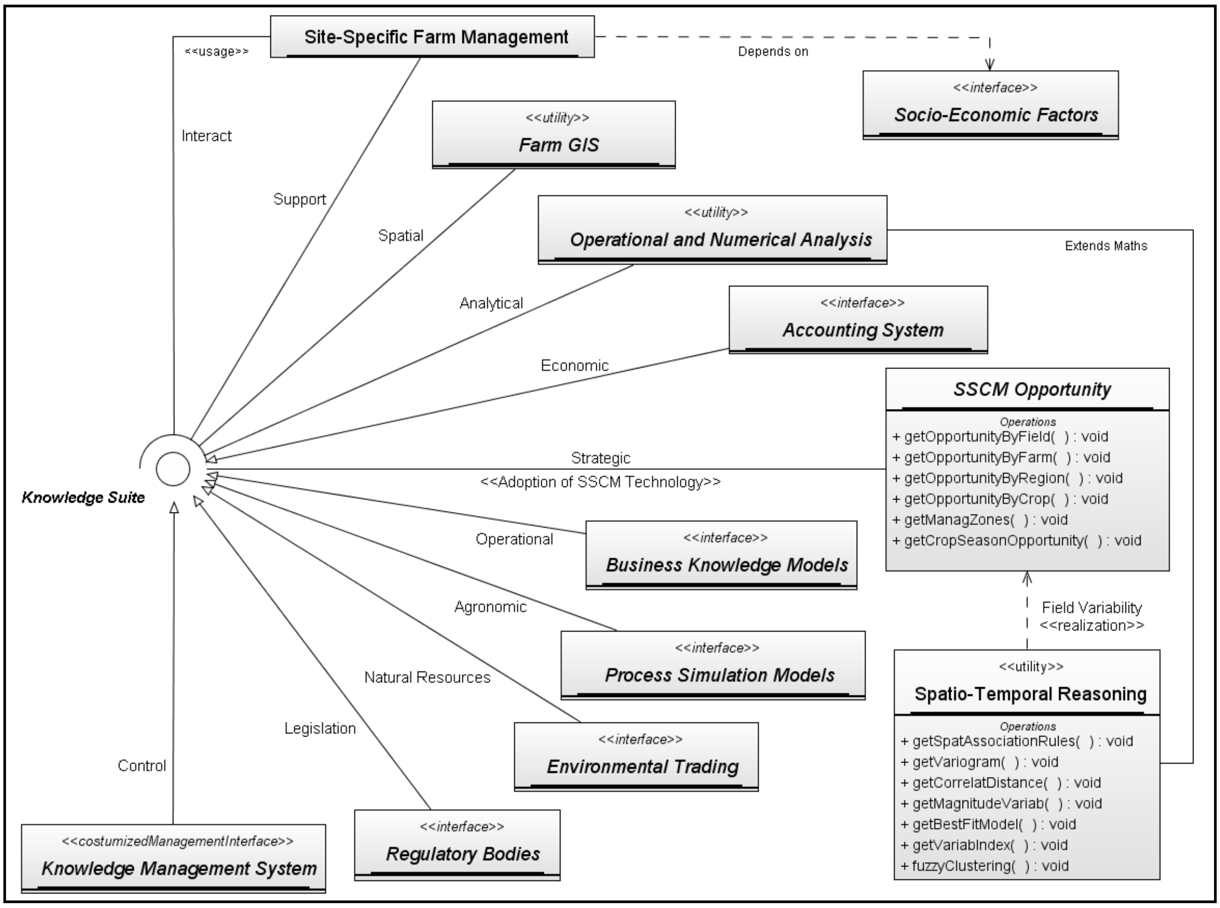


Figure 3.1: Conceptual metamodel of domains supporting integrated farm management.

The metamodel of typical aspects influencing farm management (**Figure 3.1**) highlights the strategic adoption process which is detailed in the framework introduced. The framework design is based on the hypothesis that an opportunity index for SSCM assessed by simple quantitative measures for spatial crop variation, should consider geostatistical parameters and site-specific agronomic knowledge.

3.3.2 - A preliminary design for decision support on the opportunity to SSCM

Use-case diagram

A Use-case Diagram is a scenario view modelling that encompasses a solution tailored to the user perspective. Use-case Diagrams depict the functionality of a system using Actors and Use-cases. Actors are external to a system and represent roles for "users" of a system. Use-cases are interactions or dialogs between a system and actors, including the messages exchanged and the actions performed by the system. Use-case classes are used to model and represent units of functionality or services provided by a system to users, being denoted as ellipses.

Figure 3.2 shows a system model for knowledge support in differential crop management decisions. It considers a farm manager actor, a system actor for quantitative characterization of the spatial-temporal variability, and a knowledge management actor. The farm manager actor (*Farmer*) is a decision-maker user who has to ensure an optimal crop-season management given measures of within-field variability provided by the system. Strategic decisions regarding the potential for within-field management zones are undertaken by the farm manager actor based upon analysis of variability indices for the opportunity for adoption of SSCM technology: the *Assess Crop Variation* Use-case Class. Final decisions, their associated indices and predictions, and practical economic and ecologic outcomes are to be stored in a knowledge management actor, which offers access to historic management information and analysis assets. This abstract actor (*Knowledge Support Suite*) would also implement self-learning algorithms supporting knowledge extraction from autonomic mining of field and crop intensive monitoring datasets. Additional knowledge management functionality could facilitate future decision reasoning by considering historical decisions and associated outcomes, although these are not further detailed in this framework.

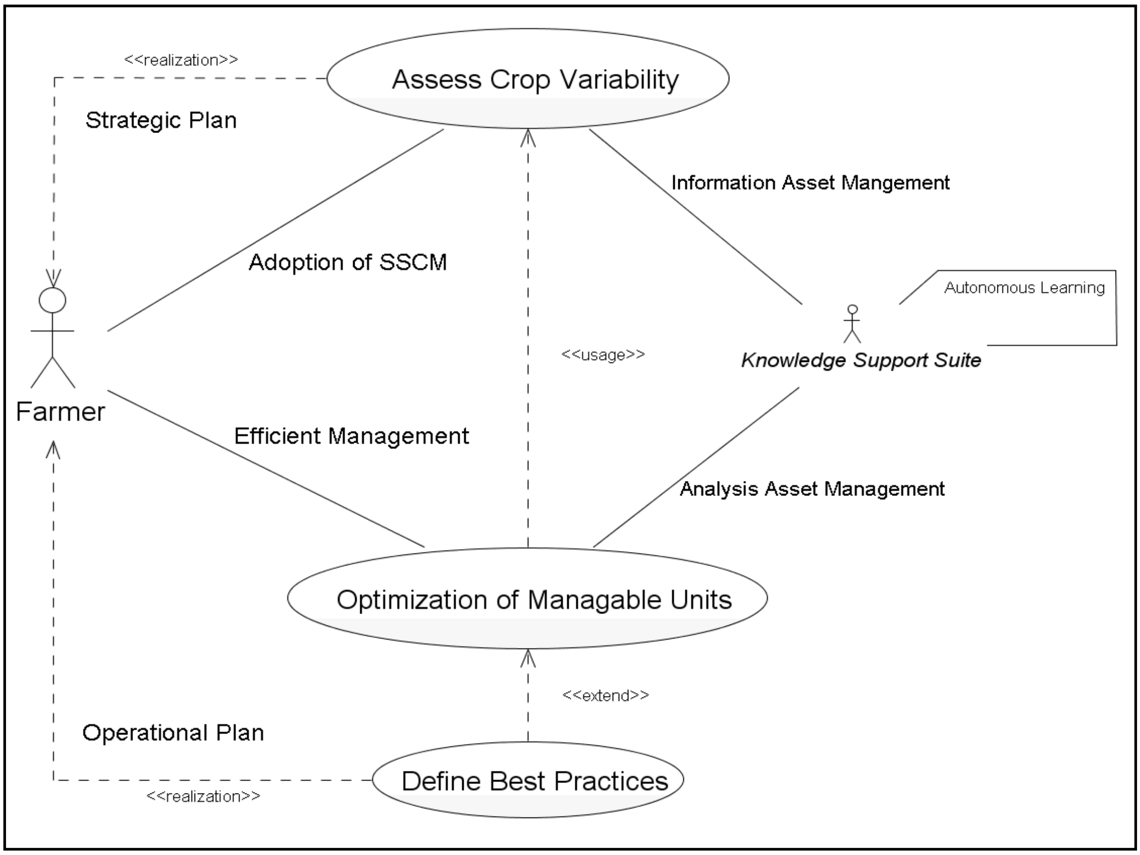


Figure 3.2: Use-case diagram for actors assessing and implementing the adoption of technologies for site-specific crop management (SSCM).

The other Use-case Classes, *Optimize Management Units* and *Define Best Practices*, describe functionalities relating to an optimal operational plan for efficient farm management. The relationships between Actors and Use-case Classes define user actions (e.g. *Efficient Management*, *Adoption of SSCM*) and the realization outcomes (e.g. *Strategic Plan, Operational Plan*). Use-case relationships have been defined through functional interactions (e.g. <<*usage*>>, <<*extend*>>) associated with the crop variation analysis (*Assess Crop Variability*) as the primary relevant evaluation to further consider the delineation of spatial units for best differential management practices. The <<*extend*>> relationship implies that a condition must be satisfied in order to consider the extended Use-case Class, hypothesizing that the best differential management operational plan is dependent on the opportunity of optimizing within-field manageable units. The primary functionality of assessing spatio-temporal crop variation is further investigated by subsequent Class Diagram models, which are introduced in a hierarchical order from generalized to more specific components.

Class diagrams

The Class Diagram shown in **Figure 3.3** basically introduces the overall system structure for evaluating the opportunity for the adoption of SSCM, as related to the *Assess Crop Variation* Use-case Class. Two other Class Diagrams (**Figures 3.4 and 3.5**) further depict more detailed abstractions of class components for executing the same Use-case functionality.

In **Figure 3.3**, a top level Class Diagram introduces seven (7) object classes and their relationships (*Site-Specific Farm Management*, *Field*, *Crop*, *Crop-Season*, *Management Zones*, *SSCM Opportunity*, and *Spatio-Temporal Variability*). This type of structural design is associated with entity-relationship models for database structures. Object classes are represented by rectangular containers of attributes and operations. Attributes store values of object characteristics and operations are functional or behavioural methods of a class that can be used by other object classes through message passing events conforming to different class relationships. Relationships are denoted by different line styles (solid or dashed) and line terminators (e.g. arrowheads, hollow arrow-head, diamond hollow arrow-head) according to the way in which a class participates and communicates with other classes (e.g. association, composition, aggregation, inheritance, generalization).

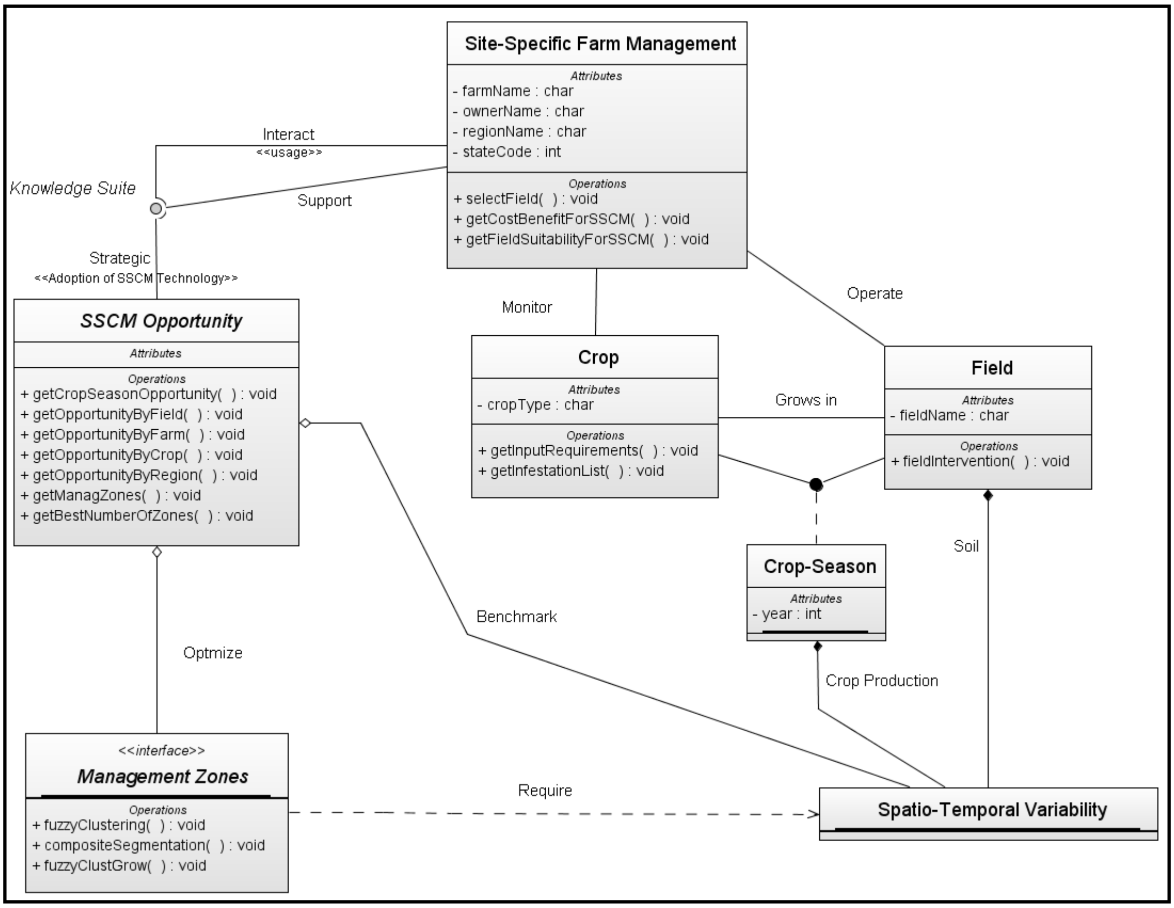


Figure 3.3: Class diagram of object classes and their relationships for evaluating the opportunity for adoption of SSCM.

The *SSCM Opportunity* class is the central abstraction in this diagram. It refers to decision-making processes in a *Site-Specific Farm Management* class for an operational *Field* that grows a *Crop* generating a *Crop-Season* production. *Field* and *Crop-Season* classes establish a composition ("has a") relationship (bold diamond arrowhead notation) with the *Spatio-Temporal Variability* class, where soil and crop production have some level of variation along the geographic extent. The *Spatio-Temporal Variability* class supplies index benchmarks for the *SSCM Opportunity* class from outcomes of variability assessment methods which are detailed in the class diagram for crop variability production indices (**Figure 3.4**). The *SSCM Opportunity* class has an aggregation relationship (hollow diamond arrowhead notation) with the *Spatio-Temporal Variability* and *Management Zones* classes, which denotes that this class is of higher importance and uses return values from message calls to the aggregated classes.

It is also suggested though a dependency relationship that the class *Management Zones* requires methods from the *Spatio-Temporal Variability* class in order to aggregate spatial optimization aspects for the *SSCM Opportunity* methods of analysis. However more specific functionalities and class associations of the *Management Zones* class are not detailed in this framework.

The class diagram shown in **Figure 3.4** details the object classes and methods that are related with the *Spatio-Temporal Variability* class for the quantitative assessment of field variability indices. Additional classes in this diagram are *Continuous Monitoring Data*, *Variography*, *Soil Eca Variation*, *Vegetation Index Variation*, and *Yield Variation*.

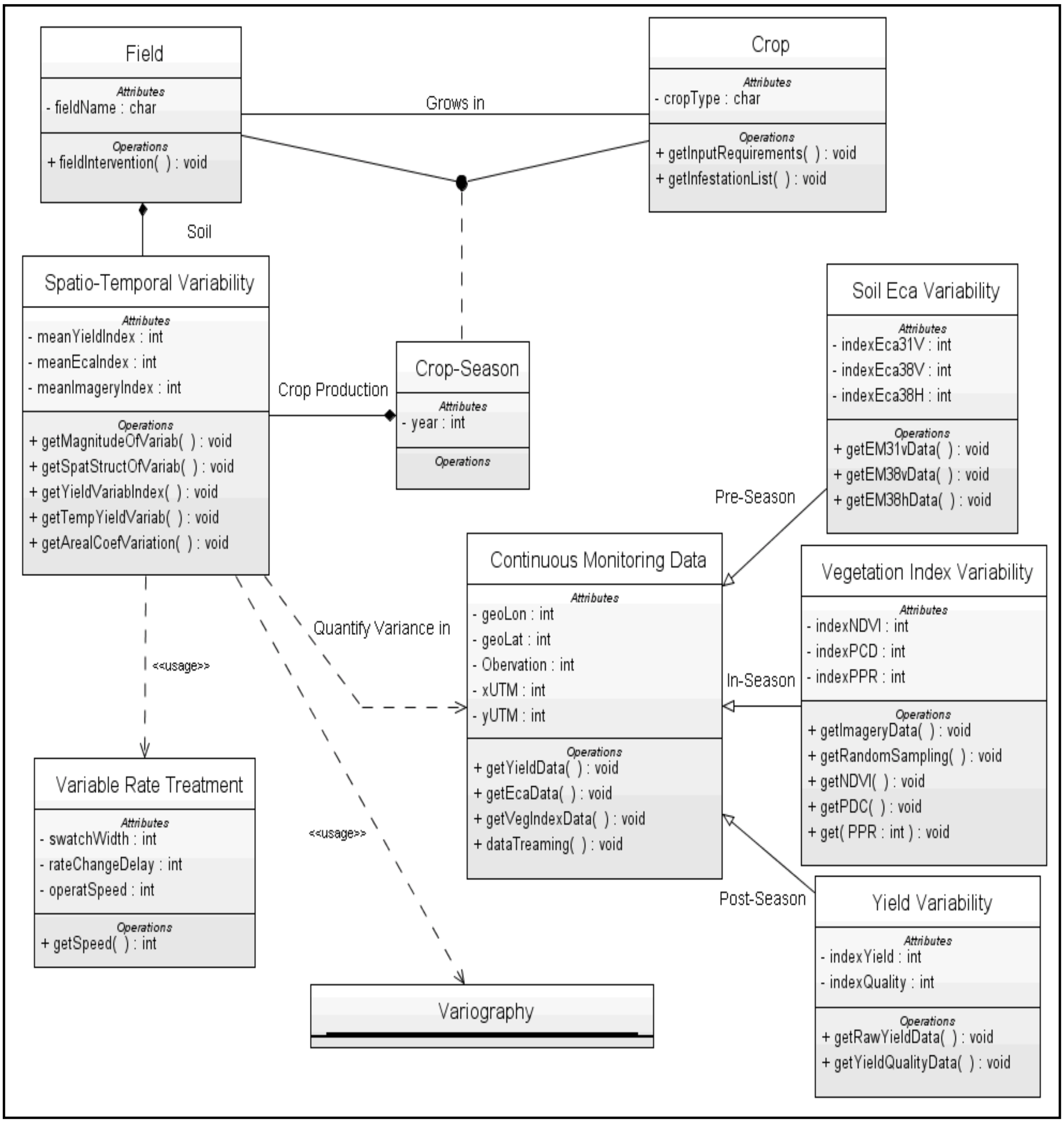


Figure 3.4: Class diagram of object classes and their relationships for assessment of within-field variability indices.

The central class in this diagram, the *Spatio-Temporal Variability* defines methods to quantify the variance in the *Continuous Monitoring Data* class using parameters returned from the variogram methods defined in the *Variography* class. These variogram methods are detailed in the class diagram for the computation of variogram parameters (**Figure 3.5**). Operational aspects related to machinery specifications for differential treatments, which are encapsulated in the *Variable Rate Treatment* abstraction, are also used by methods in the *Spatio-Temporal Variability* class. An inheritance relationship ("is a") denotes (hollow arrow-head) a generalization connection between the *Continuous Monitoring Data* class and the *Soil Eca Variation*, *Vegetation Index Variation*, and *Yield Variation* classes.

It suggests that generalized methods describing the parent class are specialized within the child classes in order to consider specific characteristics for different production monitoring sensors, which are used in different periods of the crop-season (Pre-Season, In-Season, and Post-season relationships).

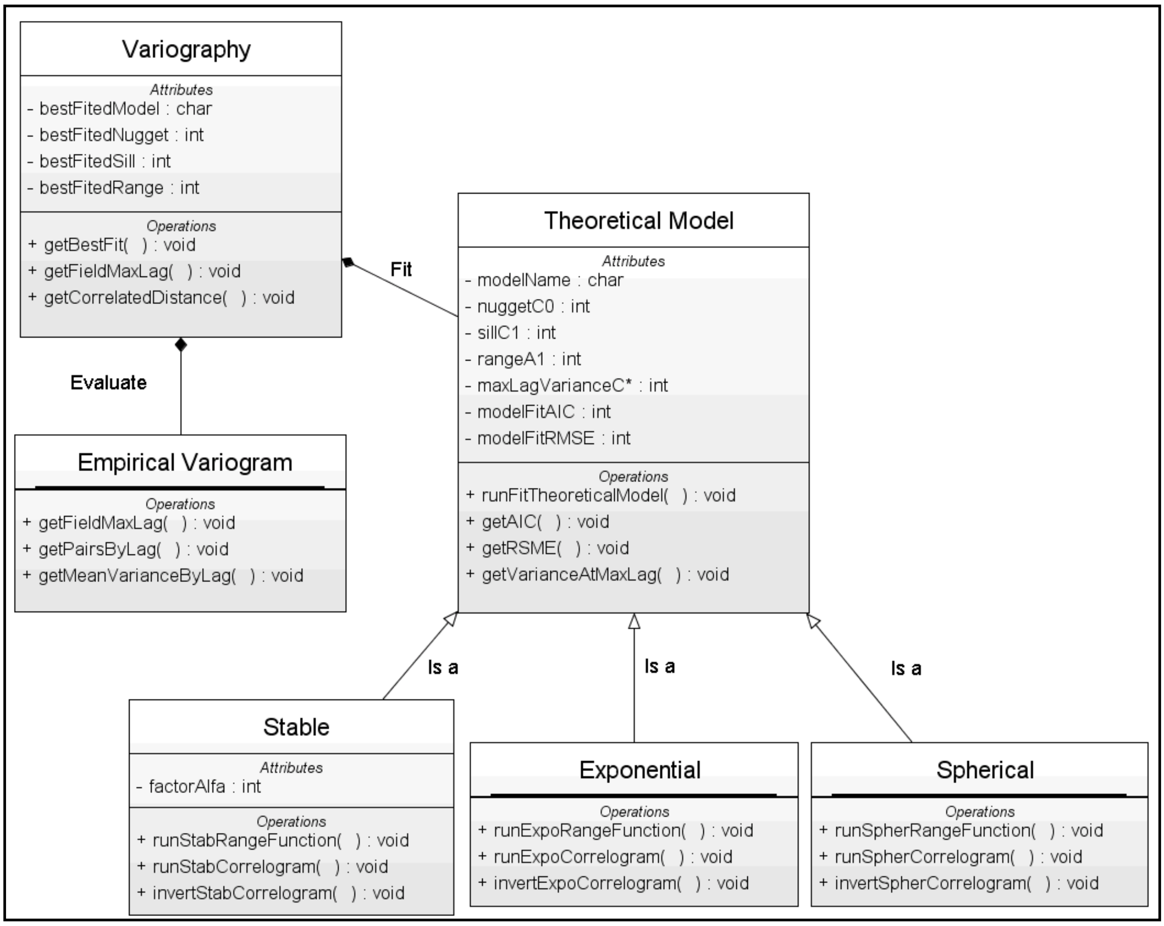


Figure 3.5: Class diagram of object classes and their relationships for variogram analysis and parameterization of field variability indices.

The *Variography* class is the central abstraction in the class diagram in **Figure 3.5**, which introduces two new classes: the *Empirical Variogram* and the *Theoretical Model*. This class diagram depicts standard procedures of variogram analysis. Three types of theoretical variogram models illustrate the inheritance classes which provide generic variogram algorithms to the parent *Variography* class. Specific correlogram functions relative to each model are defined for the *Stable*, *Exponential*, and *Spherical* classes returning different variogram parameters for the *getBestFit( )* method when selecting the best variogram model to be used in other *Variography* class methods.

Sequence diagram

Another design perspective is to represent the process in which an object class communicates with other classes through a time sequence diagram. The sequence diagram shows the messages passing between objects according to the order in which they are created to allow process flow. Message passing between objects is used to invoke a method or require data.

The sequence diagram in **Figure 3.6** shows the process of quantitative assessment of within-field crop variation, illustrating a process that requires the communication between objects from different levels of abstraction (**Figures 3.3, 3.4, and 3.5**). Objects are instantiations with 7 object classes, where a *Farmer* actor selects a field on his farm to consider the adoption of SSCM. The system returns messages with numerical parameters for a benchmark analysis, such as *Yield Variability Index*, *Mean Yield Variability Index*, and *Field Rank* for the adoption opportunity. A spatio-temporal variability analysis requires clean yield datasets from a database of continuously monitored yield data and data distribution from numerical analysis (e.g. *getMeanYield*, *getMeanCVa*, and *getMeanYieldIndex*). The spatio-temporal variability analysis considers the execution of methods within its own *Spatio-Temporal Variability* object class, which are depicted by self-message passing (e.g. *getArealCoefVariation*, *getMagnitudeOfVariation*, and *getSpatStrucOfVariation*). Other interactions for the spatio-temporal variability analysis are creating instances of the *Variography* class in order to obtain returning variogram parameters from *getBestFit*, *getFieldMaxLag*, *getCorrelatedDistance*.

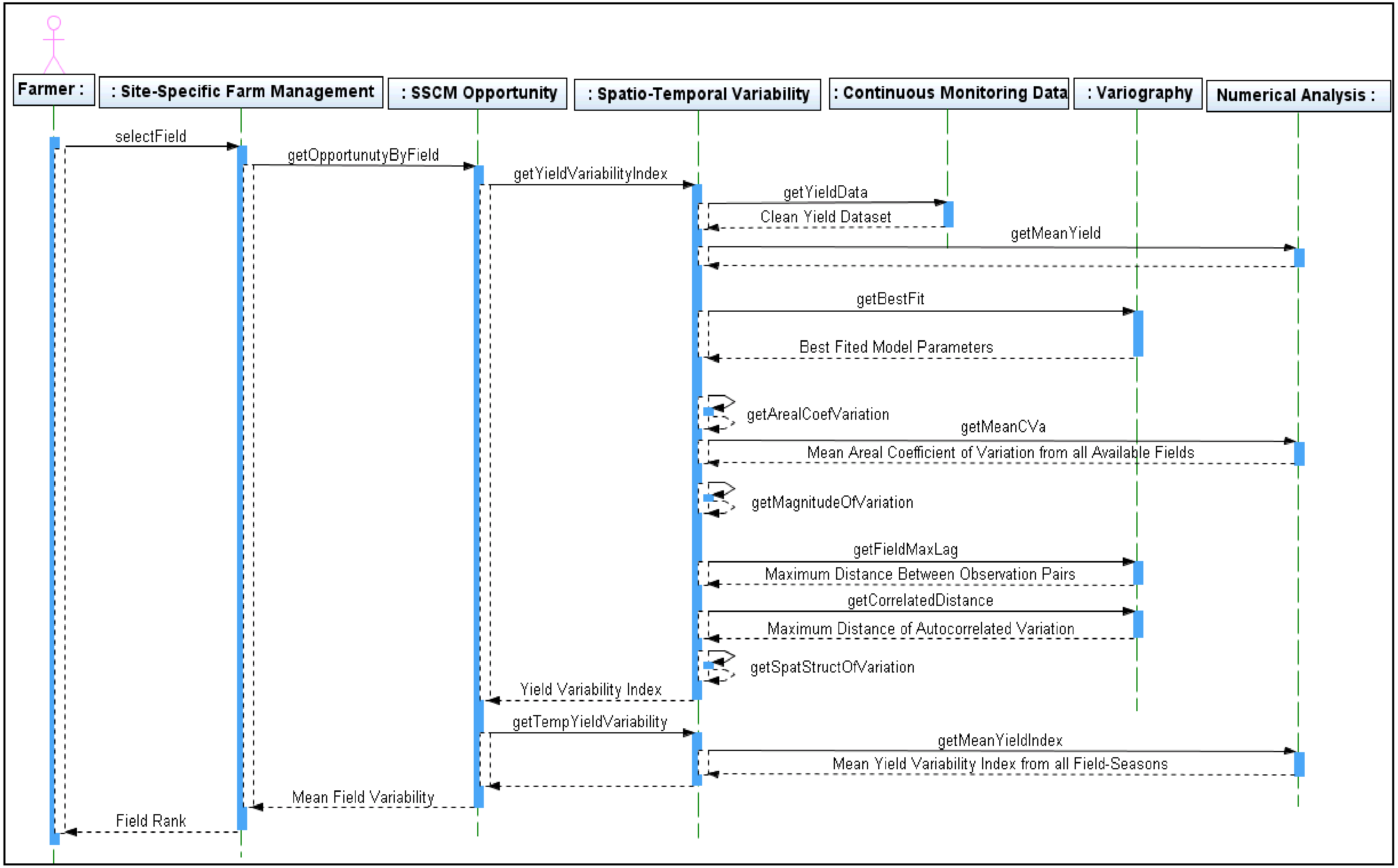


Figure 3.6: Sequence diagram for the process of quantitative assessment of within-field spatio-temporal production variability.

3.4 - Discussions and final remarks

It is suggested that little support for evaluating the opportunity for PA is directly available to farmers. Current DSS overload a farmer with computer work, lack spatial reasoning for quantitative assessments, and do not provide integrated analysis capabilities which couple scientific methods and actual farm business processes.

A platform independent design has been introduced using a new method of application of the UML for a framework of decision support for adoption of SSCM technology. This preliminary design has focused on specific aspect on the assessment of within-field variability, suggesting methods within an integrated farm management metamodel.

It is expected that this model can be broadly used or extended as a template either for design or code implementation, since it is developed using an evolutionary, general-purpose, broadly applicable, tool-supported, and standardized modelling architecture. The reuse of this design to support the development of SSCM tools will also enable the realization of benefits associated with this modelling technology.

The structure and the sequence of transactions performed by functionalities of the *Assess Crop Variation* use-case are depicted through class and sequence diagrams. This conceptual framework supports the quantitative assessment of the production spatial variability based on variogram parameters. The interaction of object classes from the *Optimize Management Units* use-case are also presented at the top level class diagram (**Figure 3.3**), but the specific structure of this system functionality is not further detailed. Several object classes and their relationships have been abstracted into three levels of structural detail, being centred in the *SSCM Opportunity* (**Figure 3.3**), *Spatio-Temporal Variability* (**Figure 3.4**), and *Variography* (**Figure 3.3**) classes.

It is understood that the framework design presented describes structural and functional decompositions of the quantitative assessment of the spatial within-field variation. Although introduced as stand alone structures, object class components abstracted in this design investigation are to be conceptualized as part of a broad and integrated knowledge management suite (**Figure 3.1**), for which UML models are standard basis of more specific knowledge engineering projects. However, it is argued that knowledge gaps on the definition of agronomic methods and their integration within practical management processes may still be limiting the comprehensive use of knowledge management methods. It is believed that a basic conceptual design gap has been properly addressed with the proposed framework, and further issues in the actual quantitative spatial assessments and farm management decision processes are respectively addressed in following research **Chapters 4-7**.

The use of UML diagrams by means of visual and interactive design and development tool (such as the Java NetBeans IDE here used) has proved to favour a free and open development. It is intuitive to use as design tool and effective during experimental prototyping and code reengineering. Still, some class methods are specific to the application knowledge domain and need to be implemented through expert algorithms.

Source codes have been prototyped and are introduced in **Appendix 1** respectively using: i) Java and Splus© script for the *"getArealCoef"*, *"getMagnitudeOfVariation"*, and *"getSpatStructOfVariation"* methods defined in the *"Spatio-Temporal Variability"* object class (**Figures 3.4 and 3.6**); and ii) Definiens Developer 7© process trees for the *"fuzzyClustering"*, *"fuzzyClustGrow"*, and *"compositeSegmentation"* methods defined in the *"Management Zones"* object class (**Figures 3.3)**.

It is observed that some of the abstracted class methods depicted during design (i.e. object classes in the Variography Class Diagram, **Figure 3.5**) have been previously implemented through open development initiatives and are available for download (e.g. degree.org – coordinate transformation and map projections, iamg.org – multivariate geostatistics, SourceForge.net – data mining and clustering). These could potentially be imported and reused in code implementations of the proposed conceptual design, but require a higher level of programming skills.

The new method of application has proved to facilitate abstractions and implementation designs, offering means of system documentation, automatic code generation and to preserve the rationale of the domain-specific methodological solution. The overall UML framework introduced represents a conceptual software structure, which is expected to offer a sole and common repository for numeric algorithms and agronomic rationale presented in following research chapters.

Chapter 4

Measuring crop yield variation to support differential crop management

Summary

The research in this chapter targets the support of strategic investments in SSCM. It aims at the development of methods to be implemented as a module of the DSS conceptual framework proposed in **Section 3.3** (**Figure 3.4**). Questions investigated here are of relevance for decisions concerning the characterization of within-field variability. The basic idea is that a numerical index, rendering the degree of management-responsive crop variability, could provide a simple ranking mechanism to identify fields of greater potential for further investment in differential management. The method addresses the quantification of the magnitude and the spatial structure of yield variation as components of an opportunity index for the adoption of SSCM technologies. Results are standardized over ten years of yield monitor data from three grain grower groups from distinct agronomic regions in Australia. A preliminary approach based on variogram parameters has been revised, and new methods proposed for improved simplicity, functionality and accuracy. The magnitude of variation is calculated using the average field variance and an areal coefficient of variation. The spatial structure is calculated using a maximum length of autocorrelated variation relative to the ability of variable-rate machinery to react. The new method has proven to be more flexible and robust when applied to both stationary and non-stationary yield distributions.

4.1 - Introduction

The stepwise adoption of SSCM technologies is, in many aspects, dependent on the degree of variation observed in production. As a measuring tool, yield monitors have been a leading driver in SSCM technological adoption and likely to show that production differences commonly exist within a crop field and over seasons. In fact, the visual analysis of productivity maps and the use of georeferenced overlays have confirmed the spatial occurrence of variation in crop yield and pointed to some key influencing factors.

As a decision tool, the purpose of gathering yield monitor data is to provide the basic input for logic pathways in differential management. It has been considered decisive in supporting operational improvements (Dillon *et al.*, 2007) and short- and long-term management strategies (Ping & Dobermann, 2005), being of particular importance to the underlying economics as a parameter easily translated into money metrics (Griffin *et al.*, 2004).

However, the additional monitoring and mapping activities have not pragmatically supported farmers in identifying better field management options. From growers' perspectives, over a decade of intensive yield mapping has not fulfilled the potential to manage variability (Jochinke *et al.*, 2006), and there is limited well-documented evidences of PA pay off associated to yield monitoring investments (Lambert & Lowenberg-DeBoer, 2000, Whelan, 2008). As a result, the motivation for yield data gathering could be now under threat.

To date, few studies have been conducted to quantitatively characterize yield variability as an indicator of the opportunity for SSCM. PA research has been mostly focused on different methods for better understanding causes of field production variability. Many techniques aimed to identify and optimize the main contributing factors by addressing the covariance analysis between crop responses and major data layers (Timlin *et al.*, 1998; Cambardella & Larken, 1999; Kravchenko & Bullock, 2002; Eghball *et al.*, 2003; Zeleke & Cheng Si, 2004; Iqbal *et al.*, 2005; Kravchenko *et al.*, 2005; Miao *et al.*, 2006). This cause-effect approach bypasses a summary of nested processes provided by yield variograms, leaving behind the establishment of standard measurement procedures that could quantify the spatial distribution description (Pringle *et al.*, 2003; Taylor *et al.*, 2005).

This lack of standard measures for yield variability could have been a result of limited data availability at the initial phases of PA adoption, when single yield maps can be useful to farmers identifying causes of variation from a previous crop season but of limited value for strategic decisions classifying SSCM adoption suitability (Dobermann *et al.*, 2003).

Although the PA adoption process is subject to a large number of variables, it is known that progress has to be made in the simplicity of methods used to translate monitored data into meaningful information. Crop production systems in Australia are generally characterized by hot climates, scarce rainfall and economic constraints that favour lower-input investments. Therefore, cost-effective tools to quantify crop variability in a manner that will help to identify fields that would justify further investments in differential management are still missing (Whelan & McBratney, 2000; Robertson & Brennan, 2006).

In this context, investigation of a simple index rendering the degree of within-field management-responsive yield variability seems warranted. Once standardized by the available data, such an index could also serve to establish different thresholds of adoption opportunity, made specific to different agronomic regions and management systems. It could also provide a simple ranking mechanism for farm investment planning. The rationale for this investigation is to identify the areas of a farm where the cost of gathering further site-specific data is likely to be best matched by future production improvement. It is suggested that yield variability can be characterized via the two components of magnitude and spatial distribution.

A numeric index is suitable for decision problems directly related to PA adoption questions like "Should I stay with uniform management; or should I go for SSCM?" At early phases in the adoption process, the proposed index could contribute to the justification (or not) of further investments in differential treatment. As a long-term decision tool, it could aid spatial and temporal management plans that would be cost effective.

Motivation to use the theory of regionalized variables is found in the inconclusive results from other yield variance analysis such as fractal (Eghball *et al.*, 1999), temporal standard deviations (Taylor *et al.*, 2003), multiple discriminant (Jaynes *et al.*, 2003), and multi-fractal (Zeleke & Cheng Si, 2004). It addresses the lack of spatial parameters in establishing productivity patterns, as seen in methods based on purely numeric statistics.

Another relevant point for establishing a numeric index is the reliability of input yield data. For some time, literature has been extensively reporting systematic and random artefacts in yield monitor data (Nolan *et al.*, 1996; Arslan & Colvin, 2002; Ping & Dobermann, 2005) and consequent remedial correction algorithms (Blackmore & Moore, 1999; Whelan & McBratney, 2000a, Beck *et al.*, 2001; Molin & Menegatti, 2002). However, only recently more effective and pragmatic tools have been provided for Exploratory Data Analysis (EDA) and clean-up of operational and sensor related problems in yield monitoring, in the form of freeware (Sudduth & Drummond, 2007) and web services (Murakami *et al.*, 2007).

4.2 - Quantifying yield variability with Geostatistics

4.2.1 - Geostatistical analysis

Spatial autocorrelation analysis of the variation present in georeferenced yield monitor data is a key to characterizing and understanding patterns when allocating inputs for the next crop season. The semi-variogram is central to geostatistical representation of spatially correlated data (Goovaerts, 1997). It permits the quantitative characterization of variation for the understanding and assessment of spatial patterns in yield variability.

As variography is a core component of methods considered in this chapter, which is briefly introduced in this section. More comprehensive literature on the variogram models considered here is available for further detailed reference (McBratney & Webster, 1986; Schlather, 2001; Geovariances, 2005; Emery & Lantuéjoul, 2006).

Although the analysis of anisotropy is relevant to variability studies, no directional aspect in yield variability has been considered in order to maintain the proposed simplicity of methods. This simplification has found support in McBratney *et al.* (2002) who noted that yield anisotropy may be imposed by a more intense yield sampling in the harvest direction. In agreement with that, a latter work from McCullagh & Clifford (2006) has presented clear evidences of anisotropy within the harvest orientation to be related with the unequal spacing between rows and columns, when empirically studying conformal invariance to determine the rate of decay of spatial correlations of crop yields. Additionally, Clifford *et al.* (2006) concluded that distinction between anisotropy and convolution properties of yield monitor data are hard to make, as well as the degree and causes of anisotropy.

4.2.2 - Covariance functions

When applied to geostatistics, the covariance is a positive-definite function that characterizes the correlation between two stationary random variables Z_1 (u) and Z_2 ($u + h$), hence is a function of two locations over a pair separation distance (h) denominated “lag”. In this context, available covariance models are the core functions modelling the spatial dependency of a single variable Z_1 (u) and Z_1 ($u + h$), when fitting theoretical variogram models. Therefore, the link between the variogram and the variance is here recalled (**Equation 1**), where the variance ($\gamma(h)$) is calculated for the smallest possible increment:

$$\gamma(h) = C(0) - C(h) \qquad (1)$$

For comprehensive information, an extensive list of covariance functions is giving by Emery & Lantuéjoul (2006) and Geovariances (2005), including descriptions of general equations, suitable applications, valid polynomial dimensions, parameter constrains, and graphs of the function shape given for changes in parameter values.

Relative to the covariance function is the correlogram ($\rho(h)$) which is used in the variogram calculation, being subtracted from the maximum standard covariance value set to 1. The models considered in the final Yieldex (Y_i) method are introduced by their respective correlograms in **Table 4.1**, which are further used in theoretical model fitting. Associated with the concept of incrementation, the integral scale in Russo & Bresler (1981) introduces a method for the computation of the variance as the area of correlation. As further detailed in **Section 4.4**, this method has been replaced by a simple computation of the "practical range" (also denominated as "equivalent range") which directly relates the lag size with the correlation range of the theoretical model (a_1).

Table 4.1: Correlogram models and range coefficients used in the Y_i computation.

Covariance Function	Correlogram [$\rho(h)$]	Range Coefficient [δ]
Spherical	$\rho(h)=1-\left[\frac{3}{2}\left(\frac{\delta h}{a_1}\right)-\frac{1}{2}\left(\frac{\delta h}{a_1}\right)^3\right] \quad \forall(h<a_1)$ $\rho(h)=0 \quad \forall(h\geq a_1)$	$\delta=1$
Exponential	$\rho(h)=\left[1-\exp\left(\frac{-\delta h}{a_1}\right)\right]$	$\delta=2.996$
Gaussian	$\rho(h)=\left[1-\exp\left(-\left(\frac{\delta h}{a_1}\right)^2\right)\right]$	$\delta=\sqrt{3}$
Stable	$\rho(h)=\left[1-\exp\left(-\left(\frac{\delta h}{a_1}\right)^\alpha\right)\right] \quad \forall\ (0<\alpha<2)$	$\delta=\sqrt[\alpha]{3}$
Generalized Cauchy	$\rho(h)=\left[1-\left(1+\left(\frac{\delta h}{a_1}\right)^{-\alpha}\right)\right] \quad \forall\ (\alpha>0)$	$\delta=\sqrt{\sqrt[\alpha]{20}-1}$

4.2.3 - Empirical variogram and theoretical variogram model fitting

This relation is defined by an integral range parameter that is linked to the distance parameter of the basic covariance function (correlation range) and also affects the horizontal axis by normalizing lag distances; hence the denomination of scale factor ($SF = a_1 / \delta$). Therefore, the total variance parameters can be used to establish a practical dimension of correlation. This practical range (R) became a central idea for best fit selection for the Y_i method and it is calculated as the correlation range (a_1) times the coefficient in the scale factor of the correlation function ($R = \delta \times a_1$). To facilitate the understanding and computation of the practical range, the range coefficient (δ) is systematically introduced below with the table of correlograms from covariance functions relevant to Y_i computations (**Table 4. 1**).

The variogram shape of a stationary process is predictable, and its attributes can be recorded and used later in model fitting. The empirical, or experimental, variogram is a plot of variances versus distances between ordered pairs. It is estimated by averaging variances from all pairs of observations within a giving pair separation distance ("lag"; h). This classic geostatistical algorithm has been previously detailed and discussed by several authors (Lantuejoul, 2002) and is represented as in **Equation 2**.

$$\hat{\gamma}(h) = \frac{1}{N(h)} \sum_{i=1}^{N(h)} \left[z(x_i) - z(x_i + h) \right]^2 \tag{2}$$

Typical variogram behaviour shows an inflection point at which the variogram flattens. It is denoted as the "sill" (C_1) and is theoretically equal to the "pure" correlated variance in the data set. The distance at which the sill is reached is called the "correlation range or scale" (a_1) and defines the distances over which there is a predictable relationship in variance. Beyond the sill the data is no longer correlated, and no relationship of variability can be defined. The "nugget effect" (C_0) occurs when the variogram curve intersects the y-axis above the origin, suggesting the presence of random or uncorrelated "noise" at all distances. It is often the result of either sampling problems or occurrence of a variability process at smaller scales than the sampling interval. The theoretical variogram model fitting uses the attributes from the empirical variogram to perform a regressive approximation of theoretical covariance functions. The general fitting parameters are: the "pure" variance of the data (C_1); the correlogram ($\rho(h)$); and the random or uncorrelated noise (C_0), as shown in **Equation 3**.

$$\gamma(h) = C_0 + C_1 \left[1 - \rho(h) \right] \tag{3}$$

The use of a non-linear curve fitting procedure in VESPER (Whelan *et al.*, 2001) applies the Levenberg-Marquardt (LM) method for weighted least squares regressions (Levenberg, 1944; Marquardt, 1963). Vesper is a shareware computer program available for download at the ACPA (www.usyd.edu.au/su/agric/acpa), which is a FORTRAN code for variogram estimation and spatial prediction with error.

4.3 - The preliminary Opportunity Index (O_i) for the adoption of SSCM

4.3.1 - O_i description

To address the lack of field variability measures, Pringle *et al.* (2003) provide a semi-automatically computable Opportunity Index (O_i), assessing manageable within-field yield variation. The approach considers the opportunity of adopting SSCM technology as a function of the variability observed in production of preceding crop seasons and the economic-environmental benefit relative to uniform management. The variability is characterized by a dual aspect in crop yield assessment, the magnitude and the spatial structure of variation.

The O_i formulation derives parametric methods from transitive and nested theoretical variogram models when fitting experimental variograms to yield data and variance trend residuals. This preliminary hypothesis characterizes the index as a function of three main components (**Equation 4**).

$$O_i = \sqrt{M \cdot D \cdot E} \tag{4}$$

Where: M = the magnitude of variation relative to a certain area threshold; D = the spatial structure of variation relative to a management-responsive area; and E = the economic-environmental benefit of SSCM relative to uniform management.

The magnitude of variation (*M)* is quantified as the ratio between the areal coefficient of variation of the field being evaluated and the median areal coefficient of variation from all available sample fields. The areal coefficient of variation (CV_a) is obtained by the double integral of the semivariance from the best fitting variogram model minus the nugget effect. The spatial component (D) is described as the ratio between the maximum average area within which yield variation is autocorrelated (S) and the minimum area at which individual variable-rate machinery can operate (s). The average area of correlation is calculated using the integral scale (Russo & Bresler, 1981). E was assumed constant since there was minimal reliable information on environmental impact and its economic costs at present.

Pringle *et al.* (2003) report a stable index ranging from 2.8 to 47.2, which was basically commensurate with the expected ranking of yield maps. However, discrepancies were observed in fields with very low values of mean yield ($\overline{Y}$) and a very large magnitude of variation seen when coupling the areal coefficient of variation with the spatial trend. This would inflate the magnitude factor (*M*) into large values, giving the illusion of a great opportunity for SSCM when perhaps the yield outcome was just caused by natural adversities occurring non-uniformly over the entire field (frost, water-logging, insect infestation). They also compare O_i results with two alternative assessments of yield variation (i.e. Fairfield Smith, 1938 and Burrough, 1983), showing weak correlations with both. The authors conclude that this approach would be preferable over the previous methods because it offers a more pragmatic computation for broad-acre fields, while being independent of the areal scale of application. Still, further improvements on the preliminary nature of the index components was foreseen as it had been established according to subjective expert interpretations and empirical thresholds over a limited data set trial.

4.3.2 - Previous applications

The O_i has also been used by Taylor *et al.* (2005) to compare the spatial variability of yield data and the suitability to differential management in vineyards across different varieties and regions in Australia, France and Spain. This study identified some trends in the spatial structure of variability, having significant regional location effect but no varietal influence. However, acute trends across any blocks needed to be removed from the data as the trend decomposition process in the technique could not totally remove the influence in the final index results for non-stationary yield distributions. Taylor *et al.* (2005) further explore the analysis of O_i components for the same data set showing greater magnitude of variation in Europe in contrast to greater spatial structure of variation in Australia, suggesting that unique management thresholds are likely to be needed. Their results also show a stable range of index values (from 9 to 16) in comparison to grape indices reported by Pringle *et al.* (2003) (from 2.8 to 33.5). However, the mean value ($\overline{O}_i = 9$) from 29 blocks at Cowra locations differs from Pringle's mean value ($\overline{O}_i = 21$) from 3 grape blocks in the same region of NSW, Australia. Still, comparisons between investigations had reinforced positive aspects of the preliminary approach when applied to different production systems.

O_i methods were used and extended in Tisseyre & McBratney (2007) for a technical opportunity index (TO_i). They introduce a morphological filter applied to interpolated yield maps, taking into account the minimum kernel area that machinery controllers can operate. In this study, considerations of practical accessibility in areas of erosions and dilatations are added to the spatial structure component (*D*). Although supporting a more detailed representation of operational practices, this approach requires additional input data manipulation and skilled interpretations, and also increased the mathematical complexity. Responses from the TO_i were normalised to hypothetical fields ranging from zero (complete nugget effect) to 1 (larger variogram ranges), showing a positive relationship between TO_i values of increasing operational kernels with O_i values of increasing variogram ranges.

Cited in Dobermann *et al.* (2003), the O_i approach is listed among empirical threshold techniques that could be useful for the classification of yield zones. They evaluate the effectiveness of subjective methods in relation to the automation of yield relative percentages, but, unfortunately, they don't actually apply the O_i leaving behind the opportunity to observe O_i outcomes under dissimilar characteristics of field shape and water input (circular central-pivot-irrigated fields under maize-soybean-maize rotation).

4.4 - Applying the preliminary O_i to South Australia (SA)

4.4.1 - Data and O_i methods

A historical data set (1997-2004) of available yield monitoring data was gathered from five (5) farms in South Australia (SA): Brook Park (2 fields); Clifton Farm (3 fields); Faithfield (1 field); Rayville Park (2 fields); and Tingara (2 fields). In all there were 45 broad-acre field-years observations ranging in size from 22 ha to 113 ha. The farms are part of the Southern Precision Agriculture Association (SPAA), which is an Australian non-profit grower's organization built on the information and experience shared and collected amongst farmers focused on the promotion, development and adoption of PA as means for profitable and sustainable farming and environmental preservation. Cultivated grain crops include wheat (*Triticum aestivum,* 21), barley (*Hordeum valgare L.*, 11), faba beans (*Vicia faba*, 6), canola (*Brassica napus*, 5), lentils (*Lens esculenta L.*, 1), and field pea (*Pisum arvense*, 1).

A file folder structure of ASCII (.txt) and JMP 6.0 (.jmp; © SAS Institute Inc., 2005) format files was organized by region, farm, field, year, and crop. Pre-processing procedures were applied in order to remove monitoring artefacts which might compromise proper agronomic information extraction. The trimming procedures used in this investigation have followed steps described in Taylor *et al.* (2007) as part of a protocol for delineating management zones.

The procedures involved are the following:

i) A two step data trimming procedure for the removal of outliers, which was executed in JMP tables. Firstly, a constrainment of the data set to threshold limits derived from previous analysis and participative R&D. In this phase, it is important to preserve the integrity of the associated pair of coordinates. The second step makes use of data distribution parameters to remove outliers, which are above and below the yield mean by 1.5 standard deviations.

ii) A spatial coordinate transformation for easier visual interpretation in absolute distances and geometric overlays of small scale geo-objects. Usually, this phase involves a conversion from radial geographic coordinates, in degrees of latitude and longitude, to planar cartographic projection systems, in metres. This procedure was executed in GEOD, a freeware application for coordinate transformation that is available for downloading from the New South Wales Department of Lands. (www.lands.nsw.gov.au/survey_mapping/surveying/gda/geod_software).

After the trimming procedure, the final number of individual yield points per field varied from a minimum of 7,000 to a maximum of 48,000, caused in fields of similar size by changes in sampling resolutions (e.g. data logging frequency, and harvest speed) from one season to another. An example of sampling variation could be observed during 6 seasons (1999 to 2004) from the field "Road" (113 ha at Brook Park farm), with changes in the density of observation from 177 (in 1999) to 425 (in 2003) points per hectare. This contrasts with both: i) higher data densities during 5 seasons from the field "212c" (25.7 ha at Tingara farm), ranging from 584 (in 2003 and 2004) to 1,128 (in 1999); and ii) lower densities during 7 seasons from the field "41" (41 ha at Rayville Park farm), ranging from 170 (in 1998 and 2002) to 293 (in 2003), or one year from the field "FrontSW" (93.3 ha at Faithfield farm) with 202 points per hectare.

When applying O_i in this research, the objective was to determine index thresholds standardised over 7 years of yield data. Therefore, original S-Plus (S-Plus 7.0 - Enterprise Developer; © Insightful Corp, 2005) script files available from Pringle (2002) were used in order to compute the CV_a, J_a, and trend residual parameters.

Methods in Pringle *et al.* (2003), firstly apply variogram of yield data in Vesper to fit the Spherical, Exponential, Double-Spherical and Double-Exponential models. Best fitting parameters (model type, C_1, C_0, and a_1) are copied from Vesper into S-Plus scripts for individual field computations for CV_a and trend-surface residuals. Variography of residuals uses the same procedure to run the J_a script in S-Plus. Finally, all parameters were copied into Excel for the final O_i calculation.

4.4.2 - Empirical investigation of O_i parameters

Initial results aiming to establish index threshold values have shown inconsistent values for the spatial structure component, which is related with very high values for the final index (**Table 4.2**). The majority of these observations could be related to non-stationary variability processes, in which the use of trend procedures could not avoid large values of the variogram maximum lag (ML) as shown in **Figure 4.1**. Problems with the preliminary O_i method motivated an empirical experimentation process using variogram parameters to search for simpler and less subjective methods of quantifying components of yield variation. The first process considered the inclusion of other theoretical variogram models (Gaussian, Linear with Sill, Stable, Generalised Cauchy, Power and Matèrn) that may explain the unbounded behaviour of many variograms in which crop yield appears to vary increasingly without limit as lag distances increases (McBratney & Webster, 1986). This can be understood as result of either an unexplained smaller scale of variance or nested processes within one another, which is characterized by practical ranges that far exceed maximum distances across the field.

Table 4.2: Unstable O***i*** results for selected fields with occurrences of non-stationarity.

Field	Year	Crop	$\bar{Y}$ *(ton.ha^{-1})*	CV *(%)*	Area *(ha)*	ML *(m)*	O_i
Road	1999	wheat	1.3	24.3	112.8	1,477	141.4
	2000	barley	3.4	14.2		1,466	46.1
	2001	lentils	1.7	34.5		1,467	27.1
	2002	wheat	0.6	110.7		1,472	780.6
	2003	wheat	2.1	16.7		1,476	363.0
	2004	field pea	1.0	14.8		1,470	18.6
Blackflat	1998	wheat	4.4	22.6	42.3	773	19.4
	1999	faba bean	3.5	18.8		769	32.9
	2000	wheat	5.2	15.6		768	7.6
	2001	barley	4.8	19.0		776	264.5
	2002	canola	1.8	25.0		771	19.2
	2003	wheat	4.4	12.3		772	8.9
	2004	faba bean	2.0	16.2		775	29.6
Field 27	1997	wheat	3.9	29.0	50.3	906	477.6
	1999	canola	1.3	34.6		902	32.7
	2000	wheat	4.7	17.8		904	77.6
	2001	barley	4.4	12.4		904	279.8
	2002	faba bean	1.6	37.1		903	599.6
	2003	wheat	3.8	12.0		905	301.1
	2004	barley	1.9	17.2		905	394.1

As the main problem in the O_i response was directly related to variogram fitting to large ranges and non apparent sills, the investigation focused on the spatial structure component. Empirical experimentation was undertaken to investigate the upper limit for the integration of the areal scale of correlation per Russo & Bresler (1981). Considered limits for integration were the variogram range, ML, and areas obtained from correlograms and the variogram of fitted correlation functions.

However, none of the upper limits for integration could respond with *D* values that would increase in proportion to increasing ranges of simulated variograms from different seasons of a single field. Unexpectedly, the integral scale approach relying on trend residuals could not consistently correlate with the intrinsic characteristics of the best fitting variograms (nugget effect, practical range, or function steepness). Many of the complex variogram models included could not provide a good fit to the majority of the available samples and were simply dismissed (i.e.: Double-Spherical and Double-Exponential, Linear with Sill, Power, and Matèrn). Finally, the ranked opportunity from different seasons of a single field did not correspond in any logical way with inferences given by local production knowledge and yield maps.

4.4.3 - The preliminary O_i: results and discussion

Preliminary results using the O_i methods have helped develop a better understanding of a dual aspect in crop yield assessment, the magnitude and the spatial structure of variation. However, the use of trend surface techniques had frequently not accounted for strong structures in variability drifts, with poor model fittings (R^2) ranging from 0.02 to 0.49. Therefore, the approach could not properly describe the residual yield variance, even when using quartic polynomial trend-surface decompositions for the removal of a macro-scale nested effect component in yield variograms (**Figure 4. 1**). Even for samples where the trend surface fitting was significant, the variogram of residuals would still present a strong drift (e.g. Bills 2003). This could be attributed to nested processes at different scales that impart spatial variation on crop yield.

For the samples from SA, 19 index values were considered as outliers out of 23 samples showing strong non-stationary behaviour. Variogram models were accounting for range values much greater than the associated field maximum lag, giving no significance when calculating the spatial structure component and negatively impacting computations of the ‘integral scale’. As a result, O_i values ranged from 7.6 to 780.6 (CV = 107%), while including a 1,000m range threshold for the computation of the areal coefficient of variation. These results greatly contrasted with previous works, where O_i values ranged from 2.8 to 47.2 (Pringle *et al.*, 2003; Taylor *et al.*, 2005; Taylor *et al.*, 2005a). In addition, further issues were identified when high CV_a values were obtained in fields with very low mean yields, consequently building artefact responses in the *M* component of the O_i.

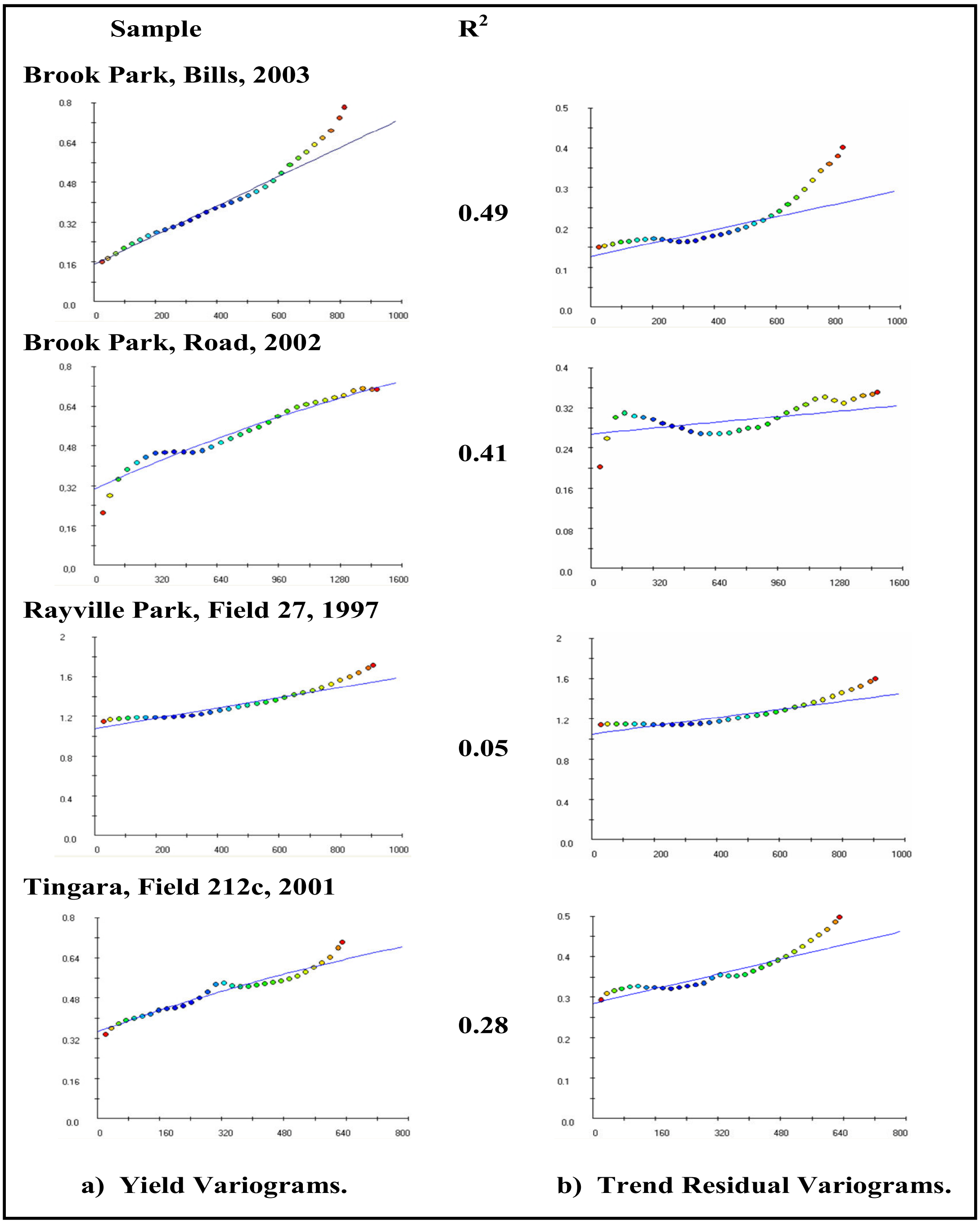


Figure 4.1: Variogram fitting of trend surface residuals as a result from the $\mathbf{O}_i$ method (Pringle *et al.*, 2003).

In terms of computational performance, the original S-Plus scripts (Pringle, 2002) were completely revised, accounting for: i) change in input/output routines allowing buffered readings of multiple field-year for sequential calculations; ii) inclusion of nested theoretical variogram models; and iii) Addition of plug-in S-Plus libraries, GStat and Surf, with optimized algorithms for more efficient spatial trend analysis. Script changes have improved the total computational performance with the optimization of recursive algorithms. As an example, the reduction of CPU time by 82% when computing the spatial structure of variation (from 107s down to 6s for a single field-year sample).

4.4.4 - Problems using the preliminary O_i approach in SA

Results from the *D* component were not significant, having extreme values of correlation distances ranging up to 250 times the average field maximum lag. This component has induced final index values greater than 250 for the 19 samples of strong non-stationary response as detailed in section 4.3. Besides avoiding the actual form of variation, the trend-surface decomposition has only solved variograms of standard stationary behaviour when coupled with the integral scale technique. In addition, the *M* component results were again problematic in the same way as reported in previous applications of the O_i.

Although claiming a solution that is independent of the areal scale of the field, the O_i computation has imposed a sequence of processes which is dependent on proprietary software formats. As result, data import/export procedures further requires from users advanced data management skills. Far from a pragmatic solution accessible to farmers, the overall O_i technique deals with individual field analysis that requires two variogram fitting procedures, for yield and trend residuals, strongly increasing the subjectivity of results. In addition, the original S-Plus script code did not consider optimized algorithms to compute the fourth order trend decomposition procedure, requiring very long CPU time (up to 45 minutes) for individual fields with more than 35,000 observation points.

Due to systematic issues involving the determination of the two O_i components, it was concluded that changes were required in order to standardise procedures that could deal with stationary and non-stationary variability, to reduce the subjectivity of analysis, and finally to improve the computational efficiency and user interface.

4.5 - A new yield variability index: Yieldex (Y_i)

4.5.1 - Australian dataset

In order to ensure a wider scope of yield variability samples for testing the new method, the historical data set previously used for the O_i investigation was expanded with data gathered from another two Australian non-profit grower's organizations involved in PA technology, and additional samples from more recent seasons in S.A. (i.e. 2005 and 2006). The Riverine Plans Inc. is an organization that includes farming systems focused on dry land broad-acre farms in northeast Victoria and southern NSW, with annual rainfall varying from 450 mm to 650 mm. The second organization supplying monitored data is Conservation Farmers Inc. (CFI), which encompasses farms in the northwest of NSW having from 500 mm to 600 mm annual rainfall. The list of grain crop yield maps used in this investigation, with their respective number of field-year samples in brackets, included: wheat (*Triticum aestivum*, 129); canola (*Brassica napus*, 30); barley (*Hordeum valgare L.*, 20); sorghum (*Sorghum bicolor L.*, 13); faba bean (*Vicia faba*, 9); chick pea (*Cicer arietinum L.*, 9); lupin (*Lupinus angustifolia L.*, 3); triticale (*Triticosecale sp.*, 2); lentil (*Lens esculenta L.*, 1); field pea (*Pisum arvense*, 1); and corn (*Zea mays L.*, 1).

A total of 80 fields from farms in the SPAA (5), Riverine (3), and CFI (8) regions have summed up 218 broad-acre field-year samples over a decade of yield monitoring (1996 to 2006). All files were organized and pre-processed as previously described in **Section 4.1**. The implementation of Y_i methods was achieved by the implementation of new source codes in S-Plus scripts and Java classes that can process several fields in a single run. Finally, the consideration of Java classes is a preliminary attempt to create a package for yield variability analysis, aiming to support and explore the use of object-oriented open source libraries.

4.5.2 - Y_i methodology

Although the need to seek more robust methods to deal with non-stationarity was evident, it was also clear that the rationale presented in Pringle *et al.* (2003), quantifying two components of yield variance, should be preserved. In addition, systematic problems of consistency in estimation methods and subjective interpretation of variograms have lead to the aim of a simple automated procedure based on yield data.

The selection of the best fitting variogram was undertaken by means of classical evaluation parameters having an additional consideration for the practical range in relation to the associated field maximum lag. Detailed discussion of evaluation parameters, such as the Akaike Information Criteria (AIC), is given by Webster & McBratney (1989). The new method has a more pragmatic approach, discarding the tailored visual variogram fit in search of a lower AIC. The computation of complex covariance functions is preserved, but only considers Spherical, Exponential, Gaussian, Stable, and Generalised Cauchy models.

Variogram fitting of practical ranges bigger than the maximum lag are discarded, even if presenting lower AIC and Root Mean Square Error (RMSE). Therefore, the best AIC selection is only considered from variograms reaching a sill within the field scale. If all covariance functions failed to limit practical ranges within the maximum lag, the best fit model is given by the lowest AIC from all variogram models, and the spatial structure of variation is calculated by inverting the covariance function to values at maximum lag.

The first Y_i component considers the magnitude of variation. For this component, a areal coefficient of variation was computed by the total average field variance minus the nugget effect, simplifying the double integral calculus in Pringle *et al.* (2003). This average covariance is recursively computed between each single sample location and all the other points within the field.

The second Y_i component regards the spatial structure of variation. It is dependent on the application response which can be easily adjusted if new machinery or commercially available operational standards are to be considered. As explained earlier, the practical range from yield variograms will be used to compute the maximum distance of autocorrelation, thereby, removing the trend decomposition and the spatial correlated 'integral scale' procedures from the technique outlined in Pringle *et al.* (2003).

Finally, a visual validation of Y_i ranks from different seasons of a single field was performed using kriged yield maps plotted with a normalized colour legend which considered minimum and maximum yield values from all field-year samples. Further details on the determination of components and results from the new Y_i methods are given in the following sections.

The magnitude of yield variation

The first step to estimate the magnitude of yield variation (M_V) is to compute the average covariance of the total field (A_C). It is calculated (**Equation 5**) as half the squared yield differences between all pairs of locations, treated as a vector, in the yield sensor data and subtracting the nugget effect (C_0), which represents the random uncorrelated variation which could be caused by measurement or machinery operational error.

$$\mathrm{A}_C = \frac{1}{n^2}\left(\left[\sum_{i=1}^{n}\sum_{j=1}^{n}(\mathbf{x}_i - \mathbf{y}_j)^2 \Big/ 2\right] - C_0\right) \tag{5}$$

When x = (x , y)

In order to allow further comparison of the variation in magnitude between fields with different $\bar{Y}$ values, the A_C is standardized into a new areal coefficient of variation (CV_A) by dividing it by the field $\bar{Y}$ (**Equation 6**). This final factor of magnitude gives a spatially structured coefficient of variation that reassembles the standard coefficient of variation; however it considers the average covariance relative to the entire field area (similarly to block kriging), in replacement of the purely numeric standard deviation from the mean yield.

$$\mathrm{CV}_A = \left(\frac{\sqrt{\mathrm{A}_C}}{\bar{Y}}\right) \times 100 \tag{6}$$

As a final step, M_V is calculated as the ratio between CV_A and an estimate of the minimum CV_A (magnitude) needed to consider differential management practices (**Equation 7**). For simplicity, given present limitations in knowledge and data availability, this is currently assumed to be the median CV_A from the available 218 field-year samples.

$$\mathrm{M}_V = \sqrt{\frac{\mathrm{CV}_A}{q_{50}\left(\mathrm{CV}_A\right)}} \tag{7}$$

The spatial structure of yield variation

The second component of the Y_i is the spatial structure of yield variation (S_V). This addresses the maximum length for average autocorrelated yield variation, here denoted as correlated distance (C_D), and standardizes it against the ability of variable-rate machinery to react, the operational length (O_L), as shown in **Equation 8**.

$$\mathrm{S}_V = \frac{\mathrm{C}_D}{\mathrm{O}_L} \tag{8}$$

As introduced earlier in this section, it was observed from empirical results that an optimal index ranking could be obtained by the use of distinct solutions according to the nature of the best fit model, whether or not showing a practical range within the field maximum lag (**Equations 9 or 10**). Therefore, the maximum correlated distance (C_D) was defined by the distance (h) at which the variance is equal to either:

i) the sill (C_1) plus the nugget effect (C_0) for the other models; or,

ii) 95% of the variance at maximum lag plus the nugget effect (C_0).

Associated equations for distance calculations are described as follows:

- For all variogram models with practical range smaller than the field maximum lag:

$$\mathrm{S}_V = \frac{h}{100} \qquad \text{when:} \quad \gamma(h) = C_0 + C_1\left[1-\rho(h)\right] \tag{9}$$

- For all variogram models with practical range bigger than the field maximum lag:

$$\mathrm{S}_V = \frac{h}{100} \qquad \text{when:} \quad \gamma(h) = C_0 + 0.95\left[\gamma(MaxLag) - C_0\right] \tag{10}$$

In practice, **Equation 9** basically sets the maximum correlated distance (C_D) as the distance (h) equal to the practical range when this value is smaller than the field ML. Otherwise, in **Equation 10**, the value of the best fitted variance at maximum lag is used to calculate the distance (h) by the inverted the covariance function. After the determination of h, C_D is calculated by dividing h by 100 to standardize metres into hectares for the associated length of maximum area of autocorrelated variation.

The variability distribution patterns have to be considered with reference to machinery intervention options. In spatial terms, patterns are assessed in relation to the smallest area unit of treatment applicable. This operational kernel resolution has been already formulated as a function of machinery characteristics (Pringle *et al.*, 2003), of machinery characteristics plus position inaccuracy (Tisseyre & McBratney, 2007), and of variable-rate change along the swath (Dillon *et al.*, 2007). To the extent of this research, the distance limiting the operational length unit (O_L) is based on variable-rate machinery standards as defined by Pringle *et al.*, (2003), being the minimum area (s) as a function of operational characteristics [β = swath (m); ν = speed (m/s); and t = time to alter application (s)] and divided by 10,000 to again standardize it to hectares (**Equation 11**). Typical values of those characteristics for grain crops and grapes are given in Pringle *et al.*, (2003).

$$\mathrm{O}_L = \sqrt{s} = \sqrt{\frac{(\beta\nu\tau)}{10000}} \tag{11}$$

The opportunity index in yield variation

Finally, the Y_i is calculated in **Equation 12** as the square root of the product of M_V and S_V.

$$\mathrm{Y}_i = \sqrt{\mathrm{M}_V \cdot \mathrm{S}_V} = \sqrt{\sqrt{\frac{\mathrm{CV}_A}{q_{50}(\mathrm{CV}_A)}} \times \frac{\mathrm{C}_D}{\mathrm{O}_L}} \tag{12}$$

The diagram presented in **Figure 4.2** summarizes the Y_i method, and also shows the data flow where each specific parameter is calculated.

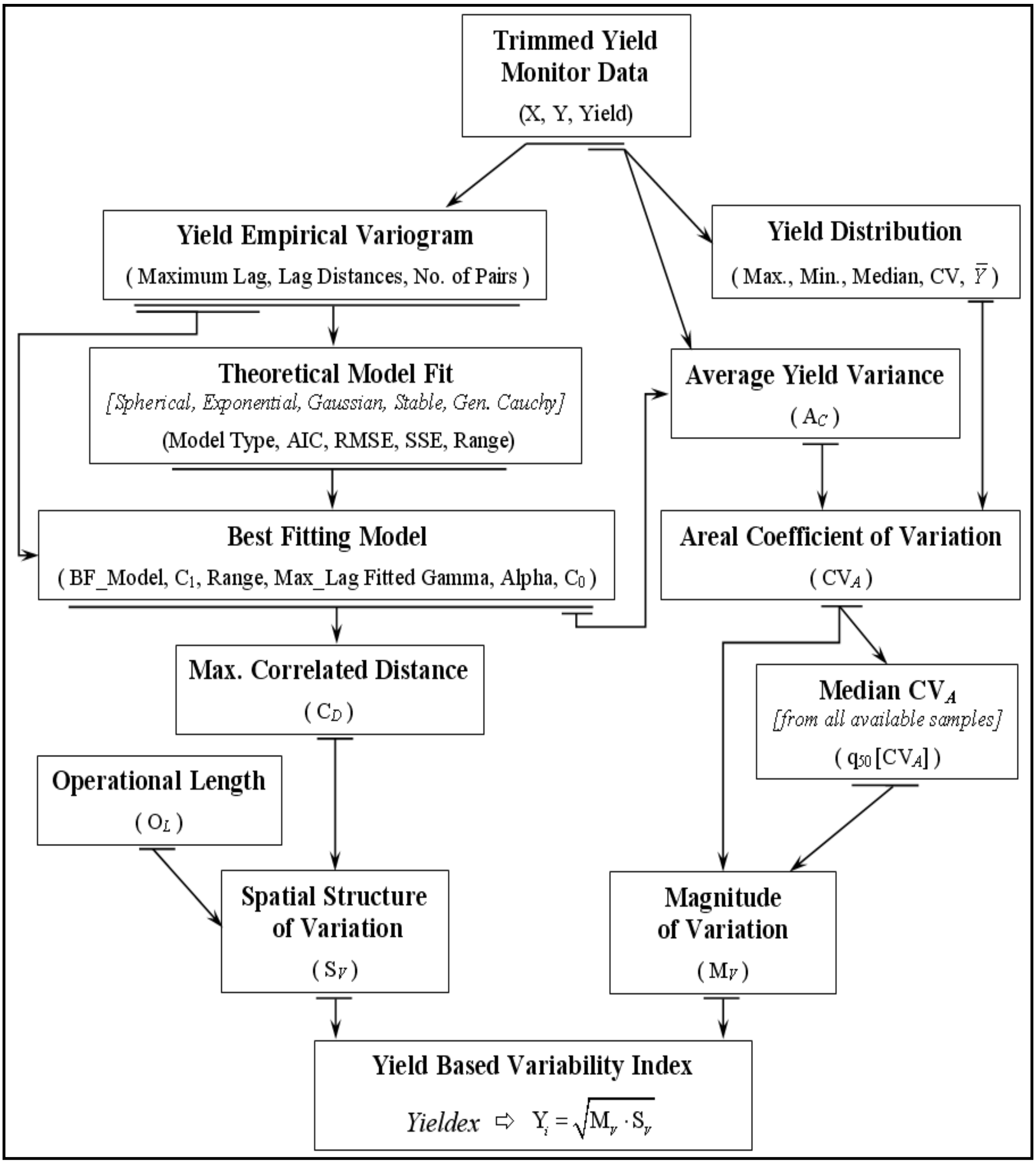


Figure 4.2: Y_i methodology diagram, illustrating the procedural and the parameter flow.

* Calculated parameters in each stage are underlined, and their use in subsequent procedures is indicated by the arrows, describing that some parameters (ML, C_0, CV_A) are used in more than one stage of the method.

4.5.3 - Y_i results and discussion

The overall Y_i distribution for the 218 samples has shown a mean of $\bar{Y}_i = 5.7$ (CV = 41.5%) and a median of $\tilde{Y}_i = 5.2$, with values ranging from 1.6 and 17.3 (**Figure 4.3**). Individual means for the three agronomic regions have shown a fairly stable response even if a very dissimilar number of samples is observed: 51 samples in SPAA ($\bar{Y}_i = 5.2$), 119 samples in CFI ($\bar{Y}_i = 6.0$), and 48 samples in Riverine ($\bar{Y}_i = 5.6$). A good opportunity for site-specific management is suggested when Y_i is greater than 6. Samples having the index above this value have intuitively shown large magnitude variability and well structured distribution of variance when visually interpreting yield maps through expert knowledge. This threshold matches the greater regional mean index, in CFI, and it is just above the overall $\bar{Y}_i$ and $\tilde{Y}_i$ characterized in each individual region (4.8 for SPAA, 5.6 for CFI, and 4.6 for Riverine) as well as median calculated using the majority of crops, excluding canola and chick pea.

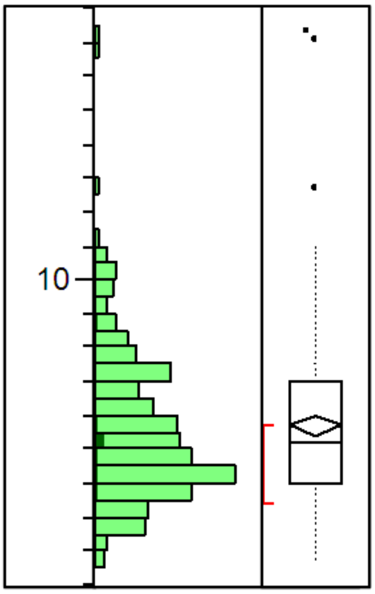


Figure 4.3: Histogram for Y_i results from 218 field-year samples in Australia.

Upper and lower limits of valid Y_i were explored by empirical experimentation. It showed that if the Y_i was found to be less than 1 or greater than 45, then some inconsistencies in the input data were observed. This suggests that the proposed method is sensitive to noise input. Still, results showed the flexibility of the new approach in that it delivered a stable range of index values over a very diverse input data set, including distinct regions (soil, topography and climate), a variety of fields (size and shape), different crops, and possible incomplete data gathering. The idea of offering an index capable to support a quantitative analysis on the opportunity characterized by individual field-seasons is illustrated in **Table 4.3,** for selected fields of non-stationary variability which have previously shown inconsistent results of the preliminary O_i method. The variation of density in the number of observations previously observed in section 4.1 was also present in this enlarged data set. An equivalent increase in processing time is not observed during the variogram analysis in Vesper, since a random sub-sampling procedure is executed prior to the variogram computation, reducing the input data dimension to around 15,000 observations.

Table 4.3: Y_i and its components' results from selected fields with occurrences of non-stationarity in association with O_i values.

Farm	Field	Year	Crop	$\bar{Y}$ *(ton.ha^{-1})*	CV *(%)*	M_V	S_V	Y_i	O_i
Bearbung	**Creek**	2001	canola	2.7	27.8	1.5	14.0	3.4	645
		2002	wheat	0.5	48.4	2.1	30.6	8.1	53
		2003	canola	0.6	68.9	4.0	35.4	12.6	1258
		2004	wheat	4.1	31.7	1.7	40.0	8.3	1279
Tarnee	**Comet B**	1997	wheat	3.7	33.3	1.8	62.4	10.7	58
		1998	sorghum	5.4	17	1.0	14.4	3.7	23
		1999	chick pea	1.3	30.3	1.0	54.8	7.4	516
		2000	wheat	2.6	28.3	2.2	49.1	10.3	573
		2003	wheat	5	23	0.5	77.3	6.3	13
		2004	wheat	4.9	17.8	0.9	52.6	6.8	23
		2005	sorghum	3.5	19.6	1.1	22.9	5.1	25
		2006	chick pea	1.8	23.9	1.2	42.4	7.1	29
Grand View	**44**	2000	canola	1.9	24.2	1.6	39.8	5.8	22
		2001	wheat	2.8	23.4	1.5	17.4	5.1	35
		2002	wheat	0.2	129.2	4.6	62.2	17.0	1069
		2003	canola	2.3	12.4	0.9	66.4	7.7	272
		2004	wheat	1.8	15.9	0.4	54.4	10.0	393
		2005	barley	4.4	18.9	0.7	32.1	3.3	365
Brook Park	**Road**	1999	wheat	1.3	24.3	0.3	68.2	5.0	467
		2000	barley	3.4	14.2	0.6	57.5	5.8	20
		2001	lentil	1.7	34.5	1.1	44.1	6.8	28
		2002	wheat	0.6	110.7	4.8	61.3	17.2	781
		2003	wheat	2.1	16.7	0.6	56.7	5.7	670
		2004	field pea	1	14.8	0.7	25.0	4.2	21
		2005	wheat	3.1	10.1	0.5	67.3	5.9	21
Clifton Farm	**Blackflat**	1998	wheat	4.4	22.6	1.3	34.7	6.8	21
		1999	faba bean	3.5	18.8	0.5	30.1	3.8	33
		2000	wheat	5.2	15.6	0.4	21.3	2.9	7
		2001	barley	4.8	19	0.3	18.9	2.4	299
		2002	canola	1.8	25	1.4	11.0	3.9	22
		2003	wheat	4.4	12.3	0.9	26.0	4.8	10
		2004	faba bean	2	16.2	0.4	39.8	4.0	473
		2005	wheat	5.7	12.4	0.9	23.6	4.6	400
RayvillePark	**Field 27**	1997	wheat	3.9	29.0	0.7	46.5	5.6	600
		1999	canola	1.3	34.6	2.1	13.7	5.4	594
		2000	wheat	4.7	17.8	0.7	36.4	5.2	25
		2001	barley	4.4	12.4	0.3	46.0	3.6	351
		2002	faba bean	1.6	37.1	1.7	46.2	8.9	600
		2003	wheat	3.8	12	0.4	46.1	4.1	378
		2004	barley	1.9	17.2	0.5	46.5	4.7	455
		2005	wheat	3.4	25.4	0.6	46.4	5.2	525

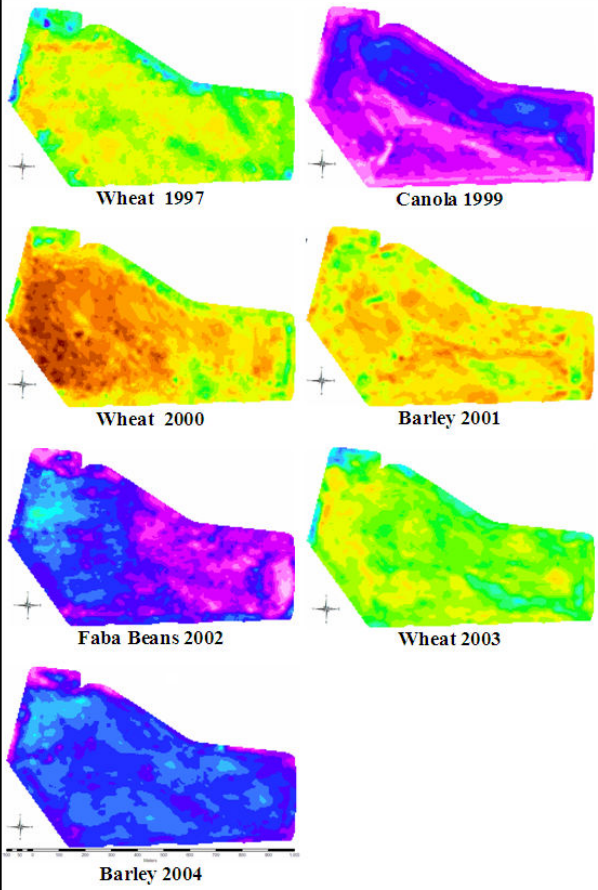
The new method for determining the CV_A has shown results that were strongly correlated (r = 0.93) with previous CV_a values from the O_i methods. However, the mean CV_A of 16.9% (CV = 64.4%) suggests a moderate to low overall areal coefficient of variation for the three agronomic regions (SPAA = 15.3%, CFI = 17.4%, and Riverine = 17.3%), when compared with results in Pringle *et al.* (2003) with CV_a = 26.9. % and Taylor *et al.* (2005) with CV_a = 27.4%, perhaps having a wider spread of values (3.6% to 93%) being related to a greater variety of crops considered. CV_A values have contributed to the final M_V distribution (mean = 1.2; median = 1; min. = 0.3; and max. = 4.9) after normalized by the median CV_A (14.2%) calculated from responses of all crop types. An attempt to normalize M_V by crop, using median CV_A relative to each specific crop, has presented biased results for crops with low occurrences (e.g. canola, lentil, and field pea).

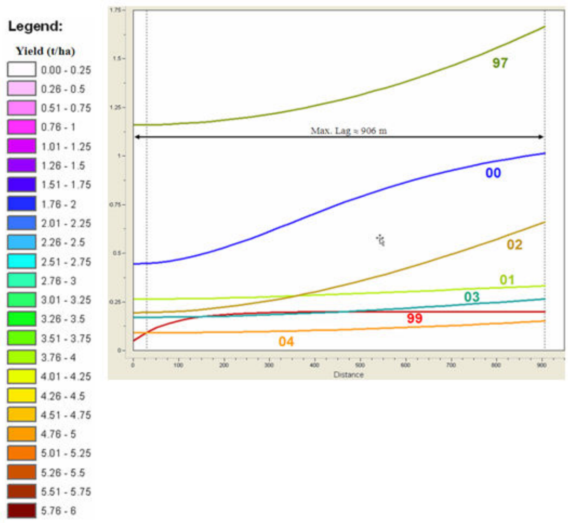
Different from previous O_i responses, the new CV_A computation has given a stable M_V response, even when calculated with yield means either in the lower or in the upper deciles of the yield distribution (less than 1.1 tons/ha or greater than 5.2 tons/ha). Only 2 samples (Field 44 and Road in 2002) from 17 in the lower decile appear to have the final index influenced by high values in the magnitude factor (**Table 4.4**). However, both samples were also the only ones having a combination of very low yield means, very high coefficients of variation, and a strong spatial structure component (respectively; $\overline{Y}$ = 0.2 and 0.6; CV = 129% and 111%; and S_V = 62.2 and 61.3). This may explain their final top two positions in the Y_i rank for all samples (Y_{i_44} = 17.0 and Y_{i_Road} = 17.2). Perhaps not characterizing a systematic influence of low yield means in high Y_i values, since the remaining samples were in the medium Y_i range.

The visual validation of the results from the new methodology used local management knowledge to rank yield maps from numerous years in a single paddock. The Y_i values for individual samples were considered in agreement with the spatial distribution of yield magnitudes. In general, the order of ranked maps by Y_i values was very coherent with the over plot of the associated variograms, in particular when many years in one field were of stationary yield variability (**Figure 4.4**). However, for the few fields with a strong occurrence of non-stationarity present in the majority of the seasons, Y_i ranked values did not consistently correspond to the overlay of variogram curves and expected results from field knowledge. Still, for some of the fields that were difficult to characterize, such as fields Road, 44, and Comet B in **Table 4.3**, the final rank corresponded with the observed variability and appears very consistent with variogram parameters. An example of these cases the field 27 from Rayville Park farm is detailed in **Figure 4.4**, which introduces interpolated yield maps normalized to a single legend, their related variograms plotted to a single scale and the resulting Y_i ranking the opportunity of adoption for SSCM. In this case, only yield data from 1999 and 2000 have shown practical range within the approximate length of the maximum lag in Field 27 (**Figure 4.4**). The strong non-stationarity observed for remaining years accounts for sill values at distances much greater than the field maximum lag (≈906m). For variograms of these years, the best fitted variance at maximum lag is used to calculate the distance (*h*) by which the correlated distance (C_D) is determined using the inverted covariance function of the best fit model (**Table 4.1**). This result shows the robustness of the Y_i, properly ranking the crop variability for cases of critical occurrence of non-stationary variation. It is therefore suggested that the Y_i ranking approach provides a good means for the temporal analysis of the spatial yield response variation.

Table 4.4: Selected fields where low mean yield and variation of components' values didn't affect a stable range of the final Y_i response.

Field	Year	$\bar{Y}$ *(ton.ha^{-1})*	CV *(%)*	CV_A *(%)*	M_V	S_V	Y_i
Creek	2002	0.5	48.4	29.9	2.1	30.6	8.1
Creek	2003	0.6	68.9	56.1	4.0	35.4	12.6
Cris	2004	0.6	32.2	16.1	1.1	27.6	5.6
Doolies	2002	0.7	58.6	36.4	2.6	42.7	10.5
Racecourse	2003	0.6	21.0	12.7	0.9	38.4	5.9
Bridge	2003	0.7	27.3	22.6	1.6	46.0	8.6
Glens	2002	0.7	50.8	35.1	2.5	39.4	9.9
Glens	2003	0.6	22.6	10.5	0.7	34.9	5.1
Woolshed	2006	0.8	52.4	19.1	1.3	36.7	7.0
WA	2003	0.9	26.3	13.4	0.9	43.4	6.4
Field 44	2002	0.2	129.2	65.9	4.6	62.2	17.0
East Ridge	2002	0.7	34.2	23.4	1.6	14.5	3. 6
Freeling	2002	0.6	29.7	25.2	1.8	17.7	5.6
Rhombus	2002	0.8	35.8	30.8	2.2	18.1	4.7
Bills	2002	0.8	50.4	36.5	2.6	22.9	5.7
Road	2002	0.6	110.7	68.8	4.8	61.3	17.2
Field 41	2004	0.9	20.3	15.8	1.1	25.2	4.0





Year	Model	Practical Range (m)	M_V	S_V	Y_i
2002	Stable	38,152	1.7	46.2	8.9
1997	Stable	49,887	0.7	46.5	5.6
1999	Exponential	260	2.1	13.7	5.4
2000	Stable	909	0.7	36.4	5.2
2004	Stable	75,827	0.5	46.5	4.7
2003	Stable	105,410	0.4	46.1	4.1
2001	Stable	108,862	0.3	46.0	3.6

Figure 4.4: Y_i results for Field 27, ranking yield maps by season and related variograms.

From the five (5) theoretical models initially used in the Y_i method, only the Spherical, Exponential, and Stable variograms satisfactorily represent most of the variability present in yield data. The variogram analysis has shown that from 43% of field-year samples of strong non-stationarity, few samples had the Gaussian model as best fitting. Still in those cases, variogram curves were presenting a upward-concave slope at small lag distances. This aspect cannot be correlated with existing knowledge of typical yield variability processes. In fact, yield variation usually accounts for steep increases at small ranges. The same situation was observed for the Generalised Cauchy model fitting, again having the best AIC for only 2 samples. Even if considered for final Y_i computations, the Stable model only responds with the best AIC when small values of the smoothness parameter were observed ($0 \leq \alpha \leq 1.3$), resulting in a variogram shape of downward-concave curve as normally expected for yield variances.

It was observed that differences in Y_i values when shifting parameters between different models where influenced by typical experimental variogram outlines. When patterns were of strong exponential behaviours, no significant differences in Y_i results were observed with Gaussian, Stable, or Generalized Cauchy models. In contrast, variograms showing standard stationary behaviours were mostly best-fitted by the Spherical model, having an AIC just below the Exponential model and much smaller than for the unbounded group. A summary on the total number of best-fit by theoretical model shows 101 samples fitted by the Stable variogram model, 86 by the Spherical model, and 31 by the Exponential model.

Comparable to the technical O_i analysis by Tisseyre *et al.* (2007), the Tukey-Kramer test was conducted in order to compare differences of Y_i means by crop type. This conservative method for different size samples (Hayter, 1984), further illustrates the need for more well distributed samples among crop types (**Figure 4.5**), as no final conclusion could be effectively drawn for Y_i thresholds by crop (**Table 4. 5**). The mean Y_i for wheat **(**$\bar{Y}_i$ = 5.5) is just close below to the overall mean as this crop provides many more samples than all the other crops together (129 against 89 samples). Faba bean samples show a mean just below this value ($\bar{Y}_i$ = 5.7), and barley was the only crop that could be characterized by a lower mean ($\bar{Y}_i$ = 4.4). Canola, chick pea, and sorghum have shown potential for higher mean values. However, lupin, triticale, lentil, corn, and field pea are still requiring more samples.

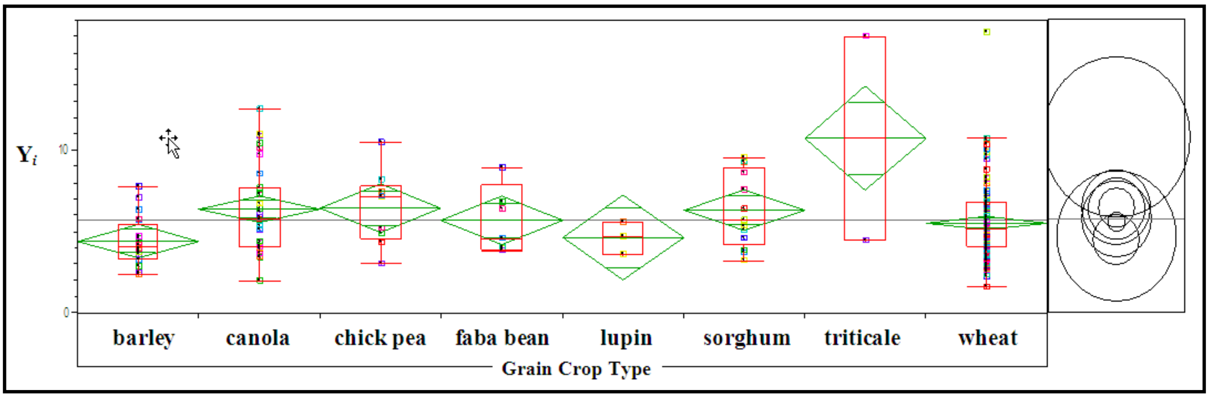


Figure 4.5: Comparisons of Y_i means by crop using the Tukey-Kramer test.

Table 4.5: The response of Y_i values to different grain crops.

Crop	Samples	Y_i Min.	$\tilde{Y}_i$	Y_i Max.	$\bar{Y}_i$	CV *(%)*
wheat	128	1.6	5.2	17.2	5.5	40
canola	31	2.0	5.8	12.6	6.4	42
barley	20	2.4	4.1	7.8	4.4	33
sorghum	13	3.2	5.7	9.6	6.3	36
chick pea	9	3.0	7.1	10.5	6.4	35
faba bean	9	3.8	4.6	9.0	5.7	38
lupin	3	3.6	4.7	5.6	4.6	22
triticale	2	4.5	10.7	17.0	10.7	82
lentil	1	.	6.8	.	.	.
corn	1	.	8.1	.	.	.
field pea	1	.	4.2	.	.	.
All crops	218	1.6	5.2	17.2	5.7	41

An uneven distribution in the number of field-year samples between crops and between regions has restricted the analysis of specific Y_i thresholds values for those variables. When considering median and mean values by crop, no correlations could be observed between mean yield ($\bar{Y}$) and Y_i values, respectively r = - 0.09 and r = 0.01. For the same correlations by region, median values have a significative result (r = 0.62) contrasting with a weak correlation for mean values (r = 0.27), perhaps only illustrating an expected wider spread in regional yield variations. Mean Y_i values by region are shown in **Table 4.6**. In the case of a more even number of samples by crops, it would be possible to calculate the median CV_A relative to crop type when standardizing the M_V component.

A random downsize procedure in the number of observations from the total of 128 wheat crop fields, in steps of 10%, was executed in order to estimate the minimum mumber of observation that would be necessary to have a better confidence of threshold values by crop type. Results have indicated that less than 30 observations would not sufice to characterize a medium Y_i values that could be used to compare indices in terms of crop per field per season (**Figure 4.6**). In which case, all other crops considered, except canola, would be under sampled for this type of analysis (**Table 4.5**). This also points out the number of missing samples per crop that would be required for the normalisation of the magnitude component (M_V) using a median areal coeficient of variation (CV_A) by crop type.

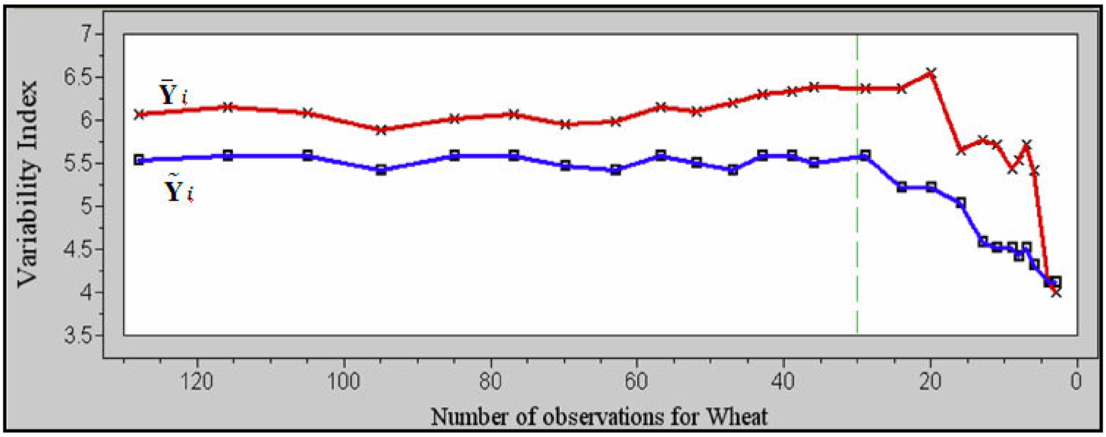


Figure 4.6: Graph showing the influence of the number of field-year samples in the stability of threshhold values.

Table 4.6: Y_i distribution by different agronomic regions.

Region	Samples	Y_i Min.	$\tilde{Y}_i$	Y_i Max.	$\bar{Y}_i$	CV *(%)*
CFI	119	1.6	5.6	12.6	6.0	38
Riverine	48	2.0	4.6	17.0	5.6	48
SPAA	51	2.4	4.8	17.2	5.2	42

Seasonal influences were observed in low index values for samples in years of relatively good rainfall and characterized by high magnitude means and spatially homogeneous distributions of crop yield (**Figure 4.7**). In contrast, a greater percentage of high Y_i values occur in relatively dry years, where low yield means and higher soil attribute contrasts favour an increase opportunity for SSCM technology. In 1996 and 2005, 88% and 73% of samples, respectively, were below the overall median Y_i as potential effect of a relatively favourable weather. This case is especially evident in 1996 for the SPAA region, where all the samples of lower mean were located. As a contrast, in dry years (2002 and 2006) most of the samples were above the overall median (71% and 92% respectively), as 2006 was considered the driest year for the last 100 years. Another example can be seen in the rainfall map (**Figure 4.7**), where the balance between the majority of samples (119) in the CFI region, distributed through an average to above average rain fall area, and remain samples (99), distributed through an average to below average area, is reflected in the index graph for 2004.

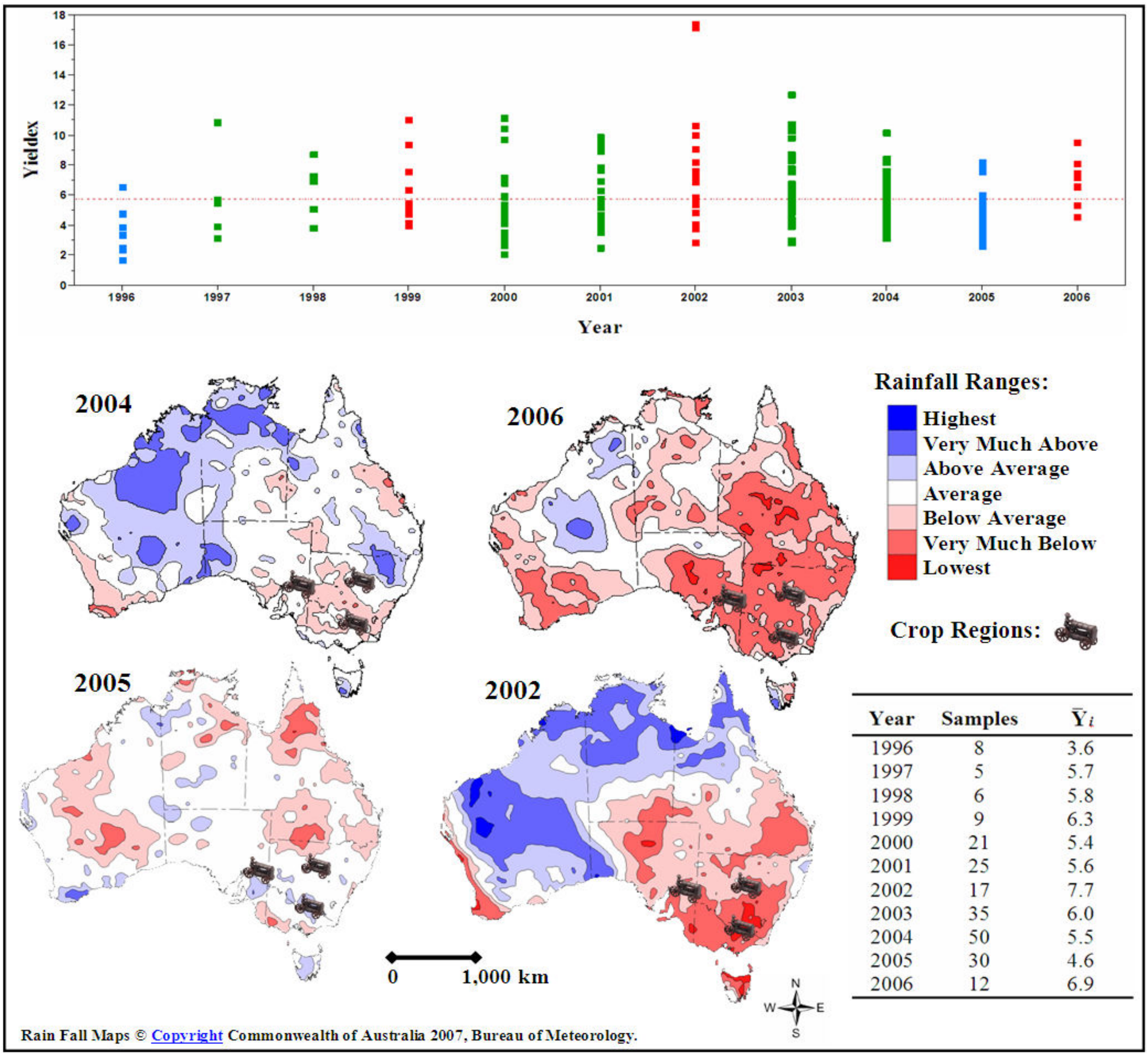


Figure 4.7: Y_i distribution by year showing response to wet and dry seasons.

Correlation analysis between the final Y_i value and its components shows equal weight in contributions from M_V and S_V. Although very high CV_A values for the top two ranked samples (i.e. Field 44 and Road in 2002) have imposed a little more weight to the magnitude component, a slight inversion in contribution occurs in favour of the spatial structure factors when those two samples were excluded (**Table 4.7**).

Table 4.7: Correlations between final Y_i values and its individual components.

	A_c	CV_A (%)	M_V	C_D	S_V
Yi	0.10	0.54	0.54	0.62	0.62
95% Yi	0.16	0.46	0.46	0.68	0.68

In a practical way, the analysis of the average Y_i by field (**Table 4.8**) shows the yield variability index to be suitable as a decision support tool for whole-farm management. It can give insights for future investments in data collection by ranking the stability of the variation in each field within the farm over a certain period of time. The observation of fields having a higher median index value over a bigger number of seasons indicates a greater opportunity for adoption of technology in those areas of the farm. **Figure 4.8** shows a map that illustrates fields from Bearbung farm with their respective values of the median Y_i ($\tilde{Y}_i$) and number of seasons of yield data gathering. For this farm, it would be suggested that the west region has a greater potential for technological adoption with fields of high median index over several years, thus fields "Doolies" with 8.3 during 5 years and "Creek" with 8.3 during 4 years. Fields in the central region of the farm would have secondary priority for investments with fields "Racecourse" ($\tilde{Y}_i$ = 6.2) and "Camerons" ($\tilde{Y}_i$ = 6.3), however with the field "Racecourse" having more potential of return with an average rank over 4 seasons against only one year of data monitoring at "Camerons".

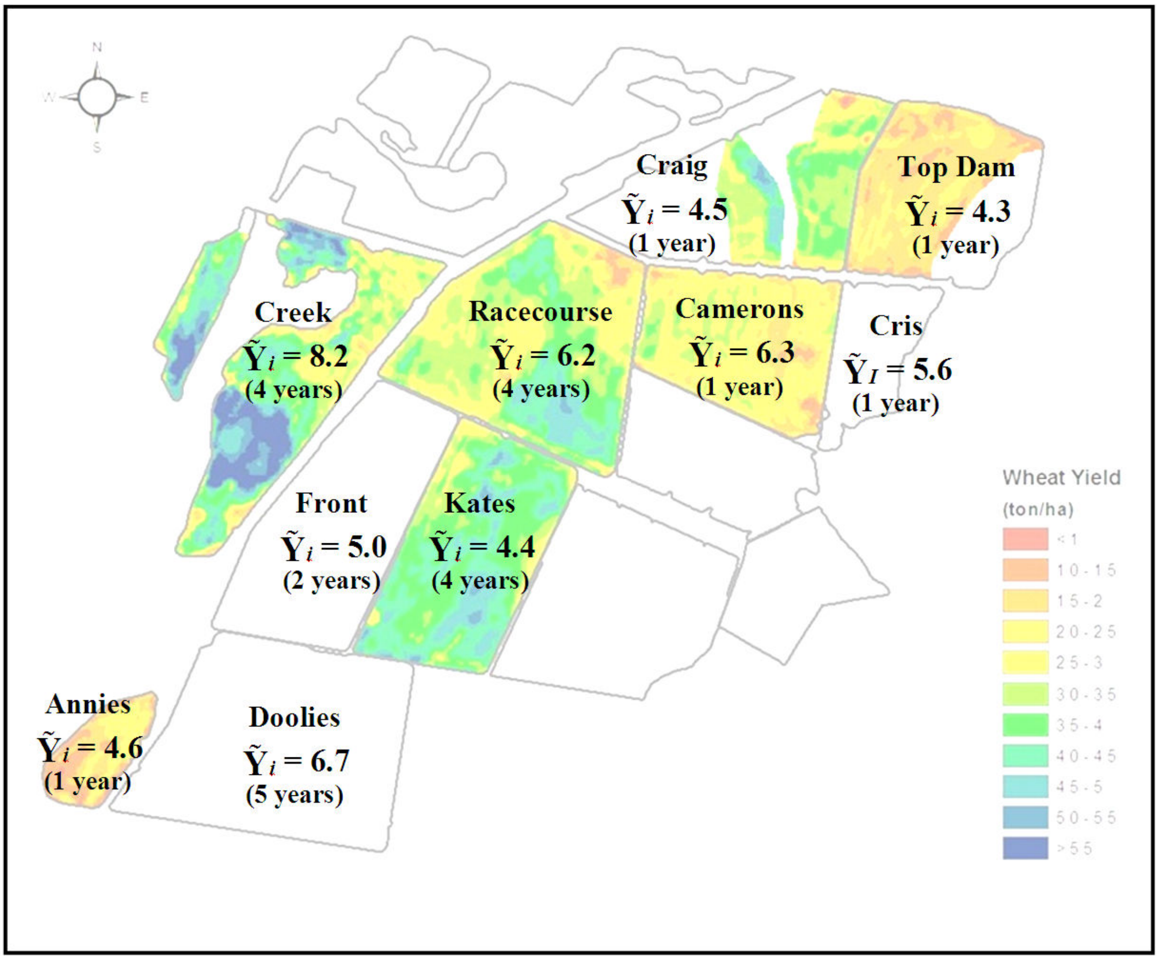


Figure 4.8: $\tilde{Y}_i$ ranking fields by farm in support of whole-farm management.

Table 4.8: $\tilde{Y}_i$ values by field indicating fields of greater yield variation within a farm in support to whole-farm strategic decision making.

Region	Farm	Field	Seasons	Med. M_V	Med. S_V	Med. Y_i	Min. Y_i	Max. Y_i	CV (%)
CFI	**Bearbung**	Creek	4	1.91	33.0	8.2	3.4	12.6	46
		Doolies	5	1.55	44.6	6.7	3.8	10.6	39
		Kates	4	1.08	24.7	4.4	3.0	9.4	53
		Racecourse	4	1.46	25.1	6.2	4.3	7.5	22
	Kiewa	Bottom L	3	1.06	30.0	5.6	4.6	6.4	16
		Diamond	2	2.54	10.9	3.3	2.6	4.1	32
		Mugs	3	1.08	48.9	7.3	2.8	8.8	50
		Swamp	3	1.63	19.3	4.2	2.9	4.9	26
	Romaka	Lease	2	0.89	47.5	6.0	2.4	9.6	85
		Pine	2	0.62	42.1	5.0	4.6	5.4	11
		West Creek	4	0.92	30.1	4.0	3.0	5.0	24
	Tarnee	Bt	5	1.07	64.3	8.6	6.4	9.7	16
		Comet B	8	1.07	50.8	7.0	3.7	10.7	33
		Kerrett	5	1.28	41.3	5.7	4.1	11.0	44
		TC	6	1.02	49.7	6.8	3.8	9.3	29
Riverine	**Glenmore**	WA	6	1.24	40.3	7.0	4.0	8.2	29
		WC	6	1.41	62.9	8.6	4.7	10.9	27
	Grand View	12	5	1.73	24.6	4.5	2.7	7.0	38
		13	3	0.50	40.5	4.1	2.0	4.6	39
		44	6	1.19	47.1	6.7	3.3	17.0	60
SPAA	**Book Park**	Bills	4	1.07	30.8	5.5	4.7	6.3	13
		Road	7	0.58	57.5	5.8	4.2	17.2	62
	Clifton Farm	Barn	2	0.54	36.8	4.4	4.0	4.8	13
		Blackflat	8	0.68	24.8	4.0	2.4	6.8	32
		Top D	4	1.03	27.0	5.2	3.8	5.2	1
	Rayville Park	Field 27	8	0.63	46.2	5.2	3.6	8.9	30
		Field 41	7	1.11	33.7	6.3	4.0	7.2	24

Finally, the $\tilde{Y}_i$ approach has proved to be more flexible and robust in addressing both stationary and non-stationary processes in spatial yield distributions. By excluding the nugget contribution of yield variation on both the magnitude and spatial structure calculations, it more readily reflects yield variability promoted by environmental (physical) properties in a field. The procedure now implemented has made the yield variogram analysis less dependent on expertise and reduced the overall computational complexity, and program source codes are presented in **Appendix Sections A1.1** and A**1.2**.

A final comment on results concerns the computation of complex algorithms, where high dimensional inputs remain a nontrivial problem. Likewise the example of the LM method discussed in **Section 1.5.3**, the A_c computation time (**Figure 4.9**) for data files ranging from 13,000 to 180,000 yield observation points (average of 35,000 after trimming procedures) accounted for an abrupt increase in cost (CPU time). This resulted from the recursive aspect of the field average variance algorithm computed in Java between all pairs of points in the field.

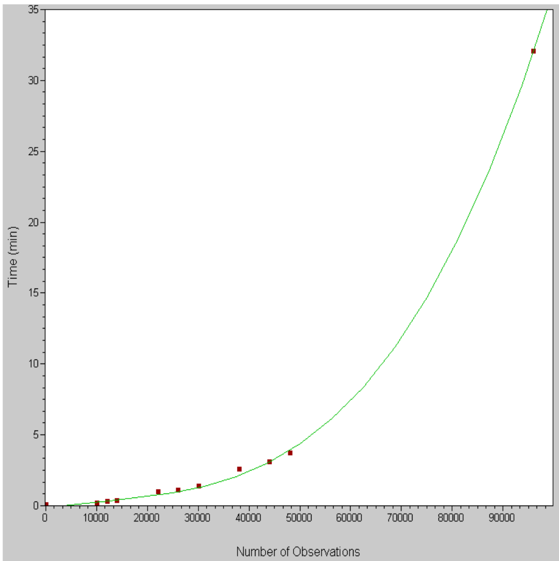


Figure 4.9: Increasing computation time complexity relative to a high-resolution yield monitoring data.

4.6 - General discussion

It is believed that the concepts of magnitude and spatial structure of variation have been proved relevant when assessing the opportunity for differential crop management. A fair bit of work is still required to establish an environmental-economic component to make a complete opportunity assessment. However, a final and pragmatic index could be conceived as a function of Y_i and the associated environmental cost/benefits (E), as shown in **Equation 13**.

$$O_i = f(Y_i, E) \qquad (13)$$

So far, it has not been possible to evaluate the influence of crop type in the final Y_i results due to heterogeneous sample distribution. The lack of a more comprehensive and equally distributed data set has limited the Y_i to be grouped and normalised according to crop type, region, farm, field, or season. Therefore, adjustments in the areal coefficient of variation (CV_A) by crop type are only dependent of equally available samples from all crop types, what would directly improved the characterization of the magnitude of variation by specific crops.

In relation to characterization of the S_v, the use of the Y_i in production systems of different industries with different harvesting strategy or monitoring procedures or treatment machinery would require the adjustment of operational distance parameters (O_L) to cope with their specificities.

In closing, it is suggested that further investigations could also account for a directional or topological property, addressing the Y_i sensitivity observed in relation to input data quality as potentially promoted by harvesting artefacts, monitoring gaps, or irregular field shapes. Sample fields with different formats and management system could include circular, rectangular, and random polygonal shapes. It would be opportune to compare rain-fed quadrilateral shaped fields with central pivot circular fields.

4.7 - Concluding remarks

This chapter explores the quantification of field variability over a significant number of fields in Australia, addressing parametric methods when modelling yield variation as a function of its magnitude and spatial structure. "Raw" yield monitor data collected on broad-acre crop fields from three grain grower groups across distinct agroclimatic zones in Australia is the only input source used. Trimmed yield data is organized by region, farm, field, year, and crop; according to procedures described in Taylor *et al.* (2007) and using 218 field-year samples from South Australia (SA), Victoria (VIC), and New South Wales (NSW) States. Parameters from data exploratory statistics, variance and spatial dependency analysis are used to measure the magnitude and the spatial structure of variance via geostatistical approaches. Initially, a preliminary approach for the Opportunity Index (O_i) was applied (Pringle *et al.*, 2003), but problems were identified when dealing with frequent non-stationarity in yield variability.

As a result, new methods of assessing a yield variability index, denominated Yieldex (Y_i), are proposed, proving more flexible and robust when addressing both stationary and non-stationary spatial yield distributions. Furthermore, the Y_i methods can be put into practice as behavioural procedures of the object classes abstracted in the conceptual framework introduced in **Chapter 3**, thus formulating a simple software solution that embraces underlying geostatistical knowledge for yield variability assessment.

The rationale for an opportunity index is to identify the areas of a farm where the cost of gathering further site-specific data is likely to be best matched by results. It is clear that quantitative threshold information is useful to determine whether the observed variability warrants differential treatment. It can also give some extra insights of factors affecting variability.

Combined with local field management knowledge over multiple seasons, the Yieldex method can be considered a reliable indicator supporting the efficiency in crop management. With automated response for simple to understand formulations, it has proved to be stable over a variety of crop management systems and input data characteristics, providing practical applications as a decision tool at several adoption stages.

With the typical volume of data currently available in family farms and producers associations, the field median Y_i can already be used to rank the opportunity in fields per farm. If a fair distribution of samples is available, the farm median Y_i can also be used to rank the opportunity in farms per region per season via the aggregation of information.

As more data became available, a broader scope of practical applications can be foreseen. With more seasons of information across a crop rotation, the field crop median Y_i would support the ranking of opportunity in crops per field. With even more specialization having many determinations by season, the Yieldex would give an opportunity ranking in crops per season per field. The Y_i could not systematically support the ranking of individual season samples per field as initially expected due the lack of more comprehensive data sets. Therefore, this yield monitor based index directly helps farmers at intermediate phases of technological adoption. On the other hand, the analysis of the average Yieldex per field over multiple seasons has shown suitability to support future whole-farm management investments in technology.

The research in this chapter addresses the lack of cost-effective automated methods to assess the within field variability in crop production. Once implemented as an open Web Service available for farm managers and technical service advisors, it can offer a pragmatic decision support tool.

Apparently, incomplete data gathering procedures in asymmetric field shapes have mostly influenced index outliers. For this reason, the use of protocols for exploratory yield data analysis and specific software applications for yield data management are reinforced.

Present thresholds have been standardized to 3 Australian agroclimatic zones, requiring data from different contexts (biophysical and managerial) in order to standardize a general index for pragmatic decision support.

The Y_i simplifies the parameterisation of the magnitude and spatial structure yield variability components, as in relation to the preliminary opportunity index formulation. However, it does not address any aspect of the opportunity associated with the economic-environmental cost/benefit of SSCM adoption.

Chapter 5

Applying the variability index to remote and proximal sensor data

Summary

The investigation in this chapter aims to help the development and validation of methods that could effectively quantify and rank the degree of inherent, manageable production variability within a field. The applicability of the methods used in the quantitative crop yield variability index, the Yieldex (**Section 4.5.2**) is tested using alternative input datasets generated by remote and proximal monitoring devices commonly used in SSCM. The potential for assessments using indices obtained from less invasive surveys is evaluated, showing the methods to be robust and providing quantitative and ranked correlations between all datasets. Using these different indices could be very useful in supporting more efficient within-field variability management via in-crop growth monitoring data or soil parameters that are independent of management practices. The main evaluation uses datasets of crop reflectance imagery and soil EC_a gathered on 14 broad-acre fields from the 80 considered for yield data in **Chapter 4**. The best correlated vegetation index between imagery and interpolated yield data was chosen for each field for the process of determining the opportunity index from the imagery. Final indices from imagery (I_i) and soil EC_a (S_i) are correlated with yield index absolute values (Y_i) for field-year analysis, and with mean yield index values from all seasons per field for farm-field analysis. Importantly, both new applications of the index have shown an ability to incorporate both the magnitude and spatial nature of the encountered production variability in a manner that matches the physical understanding of the data produced by the respective sensing systems. The I_i calculations appear to be most useful in single season assessment between paddocks and farms. S_i results suggested it to be a better indicator of the 'opportunity' realised in the final crop yield expected across seasons. Finally, the S_i and I_i show potential for use in situations where no yield monitor data is available.

5.1 - Introduction

Conceptual decision-tree diagrams related to the "null hypothesis" concept (Whelan & McBratney, 2000) have recently been described to the level of individual field-operations (Fountas *et al.*, 2006). Still, limited attention has been given to quantitative methods evaluating the spatial production variability, once restricted to statistical analysis (Gangloff *et al.*, 2004; Reyniers *et al.*, 2006) or visual interpretation of interpolated maps (Taylor *et al.*, 2003), and usually over-parameterised (Cox *et al.*, 2006). Still, the extraction of management information from SSCM monitoring activities is a crucial issue for Australian growers, in order to increase efficiency in crop management as a means for profitable and sustainable farming.

Following on from the work on Chapter 4, the application of the opportunity index developed for use with yield monitoring systems, the Yieldex (Y_i), could be the restricted by an adoption of harvester-mounted yield monitors which remains relatively low. In addition, available monitoring devices mapping other crop production influencing factors could offer the ability to assess the scale of within-field variability using less invasive sensing technologies that may prove useful on many farms.

This chapter addresses the potential use of alternative input data sources for the Y_i methods, given that results using yield monitor data have readily reflected the scale of yield variability. The investigation aims to help in the process of developing a decision support system for differential crop management by examining index input options other than yield data, which could cost-effectively quantify and rank the degree of inherent, manageable production variability within a field. The basic idea is that it would be ideal if such assessment could be undertaken using non-invasive remote or proximally sensed data gathered either external to farm operations or apart from harvesting procedures. There are three main hypotheses on the application of the variability index in this research. Firstly, the proposed methods should be robust and stable enough to quantify field variability responses from different data monitoring sources. Secondly, there is a potential for using less invasive monitoring methods that would be suitable for more pragmatic variability assessments and could support both initial PA adoption and mid-season evaluations. Finally, variability responses which are based on soil properties could help to explain within-field variations in yield that are independent of optimal management practices and the more random seasonal impacts such as hail, pest and frost damage.

5.2 - Remote information: what can we see from far above?

From classic passive reflectance scanners, through multispectral and higher resolution satellite and active radar or laser sensors, to more recent aircraft-based hyperspectral imagers, the potential for remote sensing has been keenly explored in agricultural crop management. Over 35 years of technological development have been required to reach the present standards of commercial products and analytical capabilities that may serve as pragmatic tools in operational management. Well documented literature supports the stepwise evolution of sensor platforms and the improved capability of information extraction for regional production systems (Kalluri *et al.*, 2001; Kalluri *et al.*, 2003; Ferencz *et al.*, 2004), for small-scale crop inventories and yield estimations (De Wit & Clevers, 2004; Chuan *et al.*, 2007; Prasad *et al.*, 2007), and for precision agriculture (Reyniers *et al.*, 2001; Seelan *et al.*, 2003; Reyniers *et al.*, 2006)

Up to now, applied research has been mostly focused on crop yield forecasting (Kalluri *et al.*, 2003; Hayes & Decker, 1996; Cox *et al.*, 2001; Ferencz *et al.*, 2004; Prasad *et al.*, 2007), generally using the support of crop canopy growth and vigour index assessments as a source of parameters for crop grow models. Typical vegetation indexes are derived from relationships between spectral signatures mostly related to canopy biophysical predictors (e.g., vegetation density and vigour, chlorophyll and light absorption, soil water availability). The most widely used applications make use of the Normalised Difference Vegetation Index (NDVI), as detailed in Section 1.3.1.2, where indices are obtained from coarse spectral resolution imagery for yield averages in large areas within a province, a county or an agronomic region (Hayes & Decker, 1996; Ferencz *et al.*, 2004; Qingyuan *et al.*, 2007; Prasad *et al.*, 2007).

Although improvements have been made on direct imagery distribution to farmers (Kalluri *et al.*, 2001), imagery data for quantitative crop modeling at local scales is still facing requirements of higher accuracy, reliability and timeliness in delivery for broader use in SSCM applications (Moran *et al.*, 1997; Lamb & Brown, 2001; Ferencz *et al.*, 2004; Lee *et al.*, 2007). However, a new generation of remote sensing imagery based on inexpensive digital narrow-band cameras deployed on platforms such as a mobile high-lift crane or remotely-controlled helicopters may provide additional options for PA applications for yield predictions (Lee *et al.*, 2007) or weed management (Lamb & Brown, 2001).

Investigations applied to site-specific management have also evaluated new variations of spectral imagery derived indexes, commonly described in relation to spectral responses of specific crop biophysical parameters (Daughtry *et al.*, 2000; Haboudane *et al.*, 2007; Chuan *et al.*, 2007). Some of the vegetation indices which are further untroduced in **Appendix 5** (e.g., NDVI, TRVI, PCD, PPR, GNDVI, OSAVI, MSAVI, TVDI) have been further applied as potential sources for spatial assessment of crop variability and delineation of management zones (e.g., Shanahan *et al.*, 2001; Boydell & McBratney, 2002; Zarco-Tejada *et al.*, 2004; Adams & Maling, 2004; Reyniers *et al.*, 2006). The capability of aircraft-based crop reflectance information supporting field-level nitrogen recommendations has been explored by Flowers *et al.* (2000) in wheat and corn rotation and in corn and legume rotation by Mulla *et al.* (2000). Multi-spectral scanners (MSS), similar to satellite instruments, have also been used on integrated aircraft and GPS platforms to obtain agricultural field imagery for the evaluation of crop health (*e.g.* TRWIS III in MacDonald *et al.* (1996) and GERDIAS 3715 in Broge *et al.* (1997)) and weed management (CASI in Johnson *et al.*, 1996). The CASI system was also used by Protz *et al.* (1998) to study early season imagery to detect variations in agricultural landscapes at a spatial resolution of 1 m. Recently, additional technologies also include new multi-sensor platform and either tractor mounted or handheld sensors for soil, canopy, and nitrogen; like: the Greenseeker® mapping systems (NTech Industries©, www.ntechindustries.com/greenseeker-home.html), Cropcircle® (Holland Scientific Inc.©, www.hollandscientific.com/products.html), and N-sensors (e.g. ALS Yara International©, www.yara.com/products_services/fertilizers/ support_services/ support_tools/index.aspx).

For site-specific weed and disease management, imagery can also serve for detecting the proportional coverage as an indication of weed or infestation patch size and distribution based on the contributing percentages in each pixel ("weed" or "non-weed" and "infested" or "non-infested"). Johnson *et al.*, 1996 used 1.8 m pixel resolution imagery from the Compact Airborne Spectrographic Imager (CASI) scanner taken from an elevation of 1200 m to evaluate vineyard health relative to phylloxera infestation. Lamb & Brown (2001) present a comprehensive review on the application of remote sensors for mapping weeds in crops and highlight the potential of new hyper-spectral airborne imagery for precision weed management, as offering higher spectral and spatial resolution, timeliness of delivery, and flexibility for re-visit frequency or specific sub-field monitoring. However, the cost of using these sophisticated systems for the detection of weed patch proportion and distribution may still be restrictive to surveys over broad-acre paddocks. Lamb & Brown (2001) also suggest that weed management research must concentrate on quantifying the sensitivity of remote-sensing systems for detecting weed density and patch distribution, at point at which the use of the Yieldex methods my be useful. Based on the description of sensor properties and previous results, the evaluation of several vegetation indices to characterize the within-field variability using available datasets of airborne multispectral imagery, with sensors for visual (RGB) and near-infrared (NI) reflectance, appears suitable in this study. Therefore, the specific equations for the determination of the indices used in this work are listed in **Appendix 5 (Table A5.1**).

5.3 - Proximal information: what can we grasp from near the surface?

A geophysical approach for penetrative environmental investigations using electromagnetic proximal sensors, which respond to apparent soil electrical conductivity (EC_a), is now being frequently applied in precision agriculture. This technique has over the last 15 years proved useful to soil mapping, offering some advantages over sparse and costly soil horizon core sampling and traditional lab analysis. This more efficient and timely monitoring approach generates higher spatial resolution datasets that can support more accurate spatial interpolations (Sudduth *et al.*, 1995), better characterize the degree of within-field variations in several soil properties (Corwin *et al.*, 2003), and delineation of management zones (Cockx *et al.*, 2004).

Electromagnetic fields are well suited as a source for determining soil properties to different profile depths which are useful for agricultural practices (McNeill, 1992). This “on-the-go” technology has also been used to direct soil sampling schemes that have proven useful for yield prediction (Brenning *et al.*, 2006). Commercially available instruments can be of two types (Sudduth *et al.*, 2003), an electrode-coulter-based contact sensor (e.g., Veris 3100) or induction-based non-contact sensors (e.g., Geonics EM31 and EM38). These tools have been evaluated and their typical responses to agricultural soil properties at distinct depths compared for use as input into operational-level decision making. They have been applied to a wide range of agricultural operations such as prediction of soil-water regime in Canada (McBride & Bober, 1993); salinity management in Western Australia (Bennett *et al.*, 2000); and characterization of production systems across the north-central USA (Sudduth *et al.*, 2005). Sudduth *et al.* (2003) concludes that each type of commercial EC_a sensor has its own operational advantages and disadvantages.

Electromagnetic Induction (EMI) instruments can provide an indirect indicator of important soil physical and chemical properties through correlations with factors that influence soil conductivity such as soil moisture availability; soil salinity; soil texture; and the presence and type of clays (Brune & Doolittle, 1990). In addition to the characterization of relatively constant factors affecting soil EC_a, Eigenberg *et al.* (2002) have related temporal changes in available soil nitrogen with a time sequence of EC_a maps suggesting that this measurement could be useful to identify temporal variations in soluble nitrogen. The potential of EC_a information to match the pattern of spatial variation in grain yield has also been investigated due to its correlations with soil properties (texture and moisture availability) that vary considerably across the landscape (Jaynes *et al.*, 1993; Sudduth *et al.*, 1995; Corwin *et al.*, 2003; Taylor *et al.*, 2003).

A comprehensive evaluation of depth-weighted responses between different EC_a measurements (i.e. Veris 3100 and EM38) and soil clay content and CEC is given in Sudduth *et al.* (2005), where highly contrasting correlation results were associated with differences in soil parent material, levels of organic matter, drainage classes, profile layering and variations in crop management. A great variability is also observed in correlation coefficients between EC_a and grain yield data (Sudduth *et al.*, 1995), which were related to annual climatic differences. A similar analysis for corn and soybeans in Jaynes *et al.* (1993) shows negative correlations in dry years, having no significance found in a year with more optimum precipitation patterns. Studies have shown that relationships between EC_a and crop yield may vary both spatially due to soil differences, and temporally due to climatic and managerial differences (Sudduth *et al.*, 2005).

EMI readings under different management and soil physical properties are not directly comparable (Sudduth *et al.*, 2001). Results from Corwin *et al.* (2003) show strong correlation coefficients between EM38 surveys at different depths and profile distribution of soil salinity, with a higher coefficient ($r = 0.81$) for vertical dipole orientation (EM38V). Corwin *et al.* (2003) suggest EM38 surveys as a pragmatic means of characterizing three-dimensional distributions of soil salinity and conclude that EC_a analysis should not be conducted in a one to one comparison of absolute readings, as measurement discrepancies only permit ranks on a relative basis. To overcome this measurement discontinuity limitation Brening *et al.* (2006) have proposed a geostatistical approach to rescaling single field measurements to a common scale for adjacent fields by minimizing the root-mean-squared discontinuity error between fields using local kriging. This linear scaling approach has relatively reduced the discontinuity error of kriging across field boundaries (17%) within a single year; however it was limited to very similar conditions of crop management.

Finally, access to proximal sensor data is becoming more widely available and their use in a quantitative index on production variability seems an obvious choice. The EC_a variation based index can potentially overcome problems of ranking distributions of absolute EC_a values relative to individual field measurements.

5.4 - Methods

The Y_i methodology is used with datasets of crop reflectance imagery and soil EC_a gathered on broad-acre fields where Y_i results have also been calculated from historical production data. The use of historical production data reflects the 'opportunity' captured in past seasons based on the associated crop type and management interactions. For the process of determining the opportunity index from imagery (I_i), the best correlated vegetation index between imagery and interpolated yield data was chosen for each field as defined from previous work (Boudal & Whelan, 2007). The opportunity indices computed from the imagery (I_i) and soil EC_a (S_i) were then compared with the Y_i results calculated from the corresponding yield monitor data. Finally, an overall analysis of results reinforces the Yieldex response sensitivity to environmental properties and the intrinsic characteristics of the data source, potentially responding to distinct crop growth influencing factors.

5.4.1 - Data preparation

Within the time frame for the yield monitoring datasets (1997-2006) previously used in Chapter 4, it was possible to match one year of EC_a monitoring data and a couple of seasons of imagery datasets for at least two fields in 7 of the farms. The farms are distributed within three agronomic regions, i.e. South Australia (SPAA – Rayville Park, Clifton Farm, and Brook Park); Riverine (Grandview and Glenmore); and Northern NSW (CFI - Bearbung-Kiewa and Tarnee). In each of the 14 fields, one survey for each of three different EC_a measurements was available. Two proximal sensors, EM31 and EM38, were used on the same day during the pre-season (either in 2004 or 2006) for measurements of EM31 in vertical position (31V) and EM38 in both vertical and horizontal dipole orientations (i.e. 38V & 38H). Related imagery data for the 14 fields was gathered with airborne Advanced Visible and Near-Infrared Radiometer (AVNIR) sensors (Specterra ®) at Zadocks' Stage 30 in the crop development. For details on the decimal code for the growth stages of cereals refer to Zadoks *et al.* (1974). The temporal crop reflectance imagery data set included 33 field-year samples, from 2003 to 2006; with at least two years of derived vegetation indexes for each field. A list of grain crops with their respective number of field-year occurrences includes: wheat (20), canola (4), barley (3), faba bean (3), chick pea (1), triticale (1), and field pea (1).

Soil EC_a and crop reflectance imagery data files have been organized and processed for variability assessment in the same fashion as described in **Sections 4.4.1** and **4.5.1**, for file folder structures, outlier data clean up, and analytical software procedures. Data pre-processing procedures have followed data clean up steps described by Taylor *et al.* (2007) in a protocol for a cost-effective approach in SSCM adoption.

Imagery pre-processing procedures for spectral and geometrical adjustments were conducted in ERDAS Imagine software (© ERDAS Inc.). In order to provide proper correlation analysis and fast processing of individual field variability averages, original imagery datasets were cropped to actual field boundaries and randomly sub-sampled to a maximum of 35,000 observations per field-season using shapefiles of field boundaries.

After pre-processing EC_a datasets, the number of measurement points per hectare varied minimally across fields with a maximum difference of 10% in total number of observations pre hectare between all individual fields. There was an average density of 100 observations per hectare across the data set. This characterizes the EC_a data as a more density-stable, yet coarser resolution, input set compared with yield monitor datasets. Yield data densities were up to 8 times larger (i.e. field “Black Flat” with 33,713 yield observations against only 4,270 EC_a measurements), with sampling differences between seasons up to 82% for individual fields (i.e. field “WC” ranging from 8,320 yield observations in 2002 to 46,932 in 2004). These differences arise due to changes in observation cycle time and/or harvest speed. The variation present in the EC_a input set could not be related to field dimensions and appears to be much less influenced by gathering artefacts or monitoring gaps. The size of the individual field EC_a datasets varied from 2,590 to 18,700 observations respectively in fields “Top D” and “Field 44”. This range of data set size did not compromise computation performances for the soil EC_a based index ($\mathbf{S}_i$).

5.4.2 - Additional imagery dataset

For a wider examination of the most relevant vegetation index as a source of field variability assessments, an extra imagery data set is used including fields not matching the EC_a data availability. Crop reflectance monitoring from 2003 to 2006 was available for 32 additional fields. This expanded data set for 46 fields, including 87 field-seasons, served as data input for better comparison between different vegetation indices, composing a more diverse and balanced input with more crop types per farm, more field-seasons per region, and more vegetation indices per season.

This data was used in a systematic evaluation of four vegetation indices per field-season of available airborne AVNIR, for which a summary of the equations are introduced in **Appendix 5**. Imagery data was processed according to algorithms previously defined in JMP© by Boudal & Whelan (2007), and full references for the vegetation indices considered may be found on several comprehensive reviews (e.g. Baret *et al.*, 1994; Bannari *et al.*, 1995; and Haboudane *et al.*, 2007).

The I_i determinations, a total of 348 in all, used input data from the three commonly used vegetation indices (NDVI, PCD, and PPR) and a fourth vegetation index chosen from the best vegetation index as suggested in previous work (Boudal & Whelan, 2007) that evaluates the correlations between imagery and yield monitor kriged maps, from the same datasets, using 9 different vegetation indices (NDVI, GNDVI, PCD, PPR, PVR, VI, OSAVI, MSAVI, and TRVI) as summarized in **Table A5.1**. Imagery data tables were organized by field-seasons using JMP statistical software in order to formulate the best vegetation index from original spectral numbers from the Red, Green, Blue, and Near-Infrared bands. For 24 samples, where the suggested best vegetation index matched one of the three commonly used (i.e. NDVI, PCD, and PPR), the OSAVI index was used instead.

5.4.3 - Correlation between indices from different monitoring sources.

This investigation applies methods developed using variogram parameters for quantitative analysis of the crop yield variability index, Yieldex (Y_i), proposed in **Section 4.5.2**. The concept is to quantify the degree of within-field variability in within-season crop or soil as a function of the magnitude of variation (M_v) and the cohesion of spatial variability patterns relative to the present ability of variable-rate machinery to react (S_v). Multivariate correlations between variability indices computed from yield data (Y_i) and from the alternative input datasets, EC_a (S_i) and vegetation index (I_i), are evaluated. Value ranges and means for the variability indices constructed from different inputs (S_i and I_i) were expected to validate the stable response and index distribution thresholds previously observed for index values (Y_i) calculated from 10 years of yield monitoring data.

Correlation coefficients will also provide a means of evaluating the suitability of remote (crop reflectance) and proximal (soil EC_a) sensors as optional sources of quantitative information for ranking the degree of production variability across fields and farms. It would be very opportune if ranked field variations from less invasive surveys could indicate variations reflected in harvesting data.

For the imagery index (I_i) correlations, the best correlated vegetation index between imagery from each field and the corresponding interpolated yield data was chosen for the I_i calculation. The indication of the best vegetation index by field-season is given by previous work (Boudal & Whelan, 2007) that used the same monitoring data and vegetation indices here considered, comparing each field-year yield map with associated maps from the 10 individual vegetation indexes kriged to a common grid. Variogram parameters from the best vegetation indices were obtained from the best-fit theoretical variogram model for the process of determining I_i.

Opportunity index values from the imagery (I_i) and soil EC_a (S_i) are compared with yield index results (Y_i) by individual absolute values and individual index ranked-position. Correlation coefficients are obtained by field-season between absolute I_i values and absolute Y_i values in order to analyse imagery responses by region, field, season, and crop. Because EC_a related properties are relatively stable over time, EMI surveys are usually done once per field, forcing correlations with absolute S_i values to be considered with mean yield index values by field ($\bar{Y}_i$) only for region and field relationships. To support analysis of S_i coefficients by crop type, correlations with absolute Y_i values considered a constant absolute S_i value by field over all seasons of available yield data.

The analysis of ranked-positions by field-season used the Spearman method for correlations between absolute index values (I_i, S_i, and Y_i). This method calculates the "Spearman's ρ" correlation coefficient using the principle for the Pearson product-moment correlation coefficient for the absolute ranked position values between variables.

Datasets were further imported to GIS (ArcMap®) for visual interpretation of new index values (S_i and I_i). The rank of field-season maps based on each index is observed by field and compared with Y_i ranked map overlays.

Analyses are expected to support questions related to the new methods, such as:

i) Can the Y_i approach be applied to data from other continuous survey technologies?
ii) Can an imagery based index (I_i) support in-crop growth variability assessments? and
iii) Can an EC_a based index (S_i) support between field assessments that are less dependent on best agronomic practices?

Assessment of the significance level (α) in this work uses critical values from the evaluation table for Pearson's correlation coefficients for maximum alpha value of 0.05. Correlation coefficients that do not match the minimum critical value associated with the number of observations for α = 0.05 are considered no-significant. Correlation coefficients in tables of results will be highlighted by additional symbology indicating the significance level ($\alpha = 0.05$; $\alpha = 0.02$; or $\alpha = 0.01$).

5.5 - Results

5.5.1 - Yieldex responses from different monitoring data

The observed stable range of index values calculated from the imagery and soil EC_a datasets as compared to that obtained from the crop yield data confirms the robustness of the process across data sources (**Table 5.1**). **Table 5.2** shows a higher contribution from the magnitude component (M_v) in I_i, which is considered consistent with the finer resolution and response characteristics of the imagery data which provides more information on small scale variability. A higher observed contribution from the spatial structure component (S_v) in the S_i is consistent with the lower sampling resolution and the more continuous nature of soil properties being detected by soil sensors. This more continuous, less variable nature of the soil EC_a data at the field scale contributes to the relative lower maximum in M_v seen in **Table 5.1**.

Table 5.1: Y_i distributions from different data sources.

Index	Minimum	Median	Maximum
Yield (Y_i)	1.6	5.2	17.3
Imagery (I_i)	2.6	7.7	18.1
EC_a (S_i)	2.0	3.7	9.0

Table 5.2: Partial correlations between magnitude (M_v) and spatial structure (S_v) components and final index from different data sources.

Index	r (M_v)	r (S_v)
Yield (Y_i)	0.82	0.85
Imagery (I_i)	0.82	0.71
EC_a (S_i)	0.83	0.94

5.5.2 - The variability index from crop reflectance imagery data (I_i)

Correlation of imagery index (I_i) with Y_i for all fields-years in all regions shows no overall significance, having a weak positive result (**Table 5.3**, r = 0.19). The correlation improved when individual years were examined over all regions ($0.27 \leq r \leq 0.35$), with the smallest coefficient for a dryer season in 2004, in particular at lower latitudes, as compared with higher correlation in seasons with average to above average rainfall deciles in 2003 and 2005. Analysis of I_i correlations of all 33 field-years by each region only shows a higher positive coefficient in the Riverine region (r = 0.61), where the number of field-years was the least (6). More detailed correlations by year and region show I_i results strongly varying in relation to seasonal and regional production variability (**Table 5.3**). These results range from negative correlations (2004 in CFI, r = -0.77) to significant positive correlations (2005 in CFI, r = 0.99). Large differences in responses also appear to be related to seasonal moisture conditions with higher coefficients by region for 2005, when relatively higher average rainfall was recorded across all regions. Obviously the Y_i and I_i discrepancies are seasonally dependent and potentially related to the mid-crop development stage timing of the imagery observation. Adverse impacts on crop performance closer to the end of the season would be picked up in the Y_i determination but not reflected by the I_i, potentially justifying negative correlations between them. This spread is also observed when determining the best vegetation index, ranging from r = - 0.39 for I_{i_MSAVI} to r = 0.97 for I_{i_VI} (data not shown).

Coefficient results of the ranked correlation (Spearman's ρ) for the same type of analysis described above are shown in **Table 5.4**. Ranked correlations by field-season may improve the coherence between the imagery index (I_i) and the production based index (Y_i). However, overall and detailed ranked analysis coefficients (ρ) have not greatly improved individual results.

Table 5.3: Correlation coefficients by agronomic regions between Y_i values computed from yield and I_i values from the best vegetation index by field-season.

Year	All Regions		CFI		Riverine		SPAA	
	Field-Years	*r*	Field-Years	*r*	Field-Years	*r*	Field-Years	*r*
2003	11	0.35	3	0	2	-	6	-0.44
2004	13	0.27	3	-0.77	4	0.49	6	-0.16
2005	7	0.34	3	0.99†	-	-	4	0.49
2006	2	-	2	-	-	-	-	-
All years	33	0.19	11	-0.08	6	0.61	16	-0.13

† Significant correlation for $\alpha = 0.02$.

Table 5.4: Spearman correlation coefficients by agronomic regions between ranked Y_i positions and ranked I_i positions from the best vegetation index by field-season.

Year	All Regions		CFI		Riverine		SPAA	
	Field-Years	ρ	Field-Years	ρ	Field-Years	ρ	Field-Years	ρ
2003	11	-0.06	3	0.50	2	-	6	-0.26
2004	13	0.37	3	-0.50	4	0.80	6	-0.14
2005	7	0.39	3	0.50	-	-	4	0.40
2006	2	-	2	-	-	-	-	-
All years	33	0.21	11	-0.06	6	0.71	16	-0.11

Additional analysis of field-year samples was conducted by crop type (**Table 5.5**) to evaluate correlations between Y_i and I_i to explore the potential of I_i thresholds for different production systems. Correlations were strong for Barley and Canola. The Barley data is only from the southern region (3 field-years in 2 seasons), but the significant results from Canola data spans 2 seasons over the 3 regions. No significance was found for wheat, even though it was the most sampled crop across all regions (r = 0.03 for 20 field in all regions and r = 0.60 for 3 field-years in Riverine). Ranked correlation results by crop are presented in **Table 5.6**. A significant correlation is found for Canola (ρ = 1) across two seasons (2003 and 2004). A rank correlation equals to 1 show that indices are ordering the degree of variability between field-years in identical fashion. The individual field ranking for wheat in 2004 was also preserved (ρ = 1) for the Riverine plains (fields "WC", "44", and "WA").

Table 5.5: Correlation coefficients by crop type between Y_i values computed from yield data and I_i values from the best vegetation index by field-season.

Crop	Seasons	All Regions Field-Years	r	CFI Field-Years	r	Riverine Field-Years	r	SPAA Field-Years	r
barley	**2**	3	0.85	-	-	-	-	3	0.85
canola	**2**	4	0.96*	1	-	2	-	1	-
chick pea	**1**	1	-	1	-	-	-	-	-
faba bean	**2**	3	-0.16	-	-	-	-	3	-0.16
field pea	**1**	1	-	-	-	-	-	1	-
triticale	**1**	1	-	-	-	1	-	-	-
wheat	**4**	20	0.03	9	-0.06	3	0.60	8	-0.19

§ Significant correlation for $\alpha = 0.01$.

Table 5.6: Spearman correlation coefficients by crop type between Y_i ranked positions and I_i ranked positions from the best vegetation index by field-season.

Crop	Seasons	All Regions Field-Years	ρ	CFI Field-Years	ρ	Riverine Field-Years	ρ	SPAA Field-Years	ρ
barley	**2**	3	0.50	-	-	-	-	3	0.50
canola	**2**	4	1.00§	1	-	2	-	1	-
chick pea	**1**	1	-	1	-	-	-	-	-
faba bean	**2**	3	-0.50	-	-	-	-	3	-0.50
field pea	**1**	1	-	-	-	-	-	1	-
triticale	**1**	1	-	-	-	1	-	-	-
wheat	**4**	20	0.09	9	0.02	3	1.00§	8	-0.21

* Significant correlation for $\alpha = 0.05$.

5.5.3 - The variability index from soil apparent electrical conductivity (S_i)

Correlations between the soil EC_a indices from all sensors (S_i) and the $\bar{Y}_i$ by field from all years of available yield data did not show strong relationships, with a low overall coefficient ($r = 0.16$) when all three sensors were considered together (**Table 5.7**). Ranked correlation results could not significantly improve the overall correlation ($r = 0.17$) for all sensors and all regions. At the regional level, using data from all 3 seasons provided significant correlations only in the Riverine area. From the overall correlations by individual instrument measurements, the EM38H shows up as the best individual instrument ($r = 0.45$), with weak positive results for vertically oriented readings of EM31 and EM38. The correlations with the S_i from EM38H data have also provided the best coefficients by region with always positive ρ for ranked position correlations (**Table 5.7**). The EM38H appears to be the soil EC_a based variability measure with the greatest potential to match the final index from the actual production data

Comparisons between S_i and $\bar{Y}_i$ have been useful in identifying which sensor orientation and depth is most suitable, with the proviso that measurements were only taken at one time. For a detailed S_i seasonal examination of sensor by year, sensor by year and region, and sensor by crop (respectively **Tables 5.8**, **5.9**, and **5.10**), individual Y_i for all seasons per field were compared with a constant S_i value for each of the three sensors per field. Results in **Table 5.8** report the correlation of EC_a based index (S_i) as presenting a clear, strong seasonality. Coefficients were mostly positive but ranged from significantly negative in 2006 (r = -0.95) to significantly positive in 1998 (r = 0.62), and better correlated with the S_{i_38H} index. Higher correlations are observed for all sensors in years of average to very much above average rainfall (i.e. very wet for 1998 and average for 1999 and 2001). While not statically significant due to the sample number, the EM38H orientation provides consistently stronger correlations. In general, the higher correlation values are observed in the wetter seasons (i.e. 1998, 1999, 2001, and 2005). The Spearman ranked correlation has once more added very little. It mostly improved the correlations for the vertically oriented measurement with seasons of below to very much below rainfall deciles. Examples are the ranked coefficients for 2002 and 2004 (**Table 5.8**).

Additional to the observed seasonality, analysis by region and year has indicated that coefficient contrasts are also regional. The S_{i_38H} provided the strongest correlations for the majority of years across all regions (**Table 5.9**), only showing negative correlation for 2004 (dry year) in the CFI. EC_a surveys in vertical orientation (S_{i_31V} and S_{i_38V}) only showed comparable correlation with the S_{i_38H} for the dry seasons of 2002 and 2004 (**Table 5.9**).

Table 5.7: Correlation coefficients, by sensor and region, between average Y_i (**$\bar{Y}_i$**), by field, and S_i values from EM31V, EM38H, and EM38V monitoring data.

Region	Fields	$S_{i\_All\ EM}$		Fields	S_{i_31V}		S_{i_38H}		S_{i_38V}	
		r	ρ		r	ρ	r	ρ	r	ρ
CFI	**12**	-0.35	0.04	4	-0.52	-0.20	-0.13	0.40	-0.50	-0.40
Riverine	**12**	$0.93^{\S}$	$0.71^{\S}$	4	0.93^{*}	0.80	$0.95^{\dagger}$	0.80	0.94^{*}	0.80
SPAA	**18**	-0.22	-0.22	6	-0.36	-0.37	0.33	0.14	-0.52	-0.54
All Regions	**42**	0.16	0.17	14	0.03	0.06	0.45	0.42	0.09	0.06

* Significant correlation for α = 0.05; † Significant correlation for α = 0.02; and § Significant correlation for α = 0.01.

Table 5.8: Correlation and ranked correlation coefficients (r and ρ), by year, between Y_i and S_i values from EM31V, EM38H, and EM38V monitoring data.

Year	Fields	$S_{i\_All\ EM}$		Fields	S_{i_31V}		S_{i_38H}		S_{i_38V}	
		r	ρ		r	ρ	r	ρ	r	ρ
1998	**12**	0.62*	0.63*	4	0.68	0.80	0.71	0.80	0.49	0.20
1999	**21**	0.49*	0.22	7	0.46	0.21	0.57	0.39	0.43	0.25
2000	**30**	0.01	-0.07	10	-0.02	-0.24	-0.06	0.02	0.10	0.20
2001	**27**	0.19	0.20	9	0.10	0.07	0.58	0.52	-0.01	0.02
2002	**33**	0.14	0.24	11	-0.02	0.20	0.44	0.46	0.02	0.11
2003	**42**	0.27	0.33*	14	0.33	0.33	0.27	0.34	0.23	0.35
2004	**39**	0.27	0.41§	13	0.20	0.50	0.35	0.37	0.30	0.40
2005	**30**	0.13	0.12	10	-0.06	-0.12	0.46	0.47	0.10	-0.01
2006	**6**	-0.95§	-0.88†	2	-	-	-	-	-	-
All years	**243**	0.15§	0.21§	81	0.09	0.17§	0.30§	0.36§	0.09	0.15§

* Significant correlation for $\alpha = 0.05$; † Significant correlation for $\alpha = 0.02$; and § Significant correlation for $\alpha = 0.01$.

A comparison of S_i values between years for the same region shows a smaller median standard deviation (median *sd* = 0.31) than the spread of S_i values between regions in the same year (median *sd* = 0.55 for 2003 and median *sd* = 0.83 for 2004). The SPAA data includes a larger number of samples in all years, accounting for the majority of negative correlations for vertical orientation readings (EM31V and EM38V) in contrast with positive correlations for the EM38H. While for the Riverine data, only positive correlations are presented from correlations with all EM measures (**Table 5.9**). The CFI region accounts for a limited number of samples that don't show any significant correlation, presenting the highest variation in correlation results between different EM sensors (median *sd* = 0.60) when compared with average standard deviations for SPAA (median *sd* = 0.33) and Riverine (median *sd* = 0.26) data. The S_{i_38H} correlations have a much greater contrast in results from all regions and years (median *sd* = 0.44) than indices of vertical oriented measures (S_{i_31V} median *sd* = 0.10 and S_{i_38V} median *sd* = 0.07), but the least variation in results between all regions with S_{i_38H} median *sd* = 0.29, against S_{i_31V} median *sd* = 0.31 and S_{i_38V} median *sd* = 0.34.

Results of S_i coefficients by crop were obtained using a constant EC_a index by sensor per field. The S_{i_38H} correlations were stronger for all crops over the other EC_a sensor orientations (**Table 5.10**). Individual S_i sensor coefficients, in particular for S_{i_38H}, were always greater than overall $S_{i\_All\ EM}$ with individual field-year Y_i. This more specific analysis shows that variation in EC_a indices has become less random, beginning to show some coherent patterns relating crop to seasonal weather variations in specific years or regional rainfall conditions. Faba Beans and Canola have shown strong positive relationships with all sensors, with the best individual response from S_{i_38H}.

The EM38H was also the highest correlated sensor for the other crops. The strong positive correlations were also related to years of relatively dryer conditions in all regions. Most of the Canola and Faba Beans samples were either from 2001 surveys in the Riverine plains, with below average rainfall deciles, or from dry 2002 surveys in the CFI region, with very much below average rainfall deciles. Only Chickpeas have provided non significant negative correlations with all sensors (**Table 5.10**), however showing much stronger ranked correlation coefficients (ρ). Once more, low S_i coefficients for wheat could be observed, with maximum coefficient (r = 0.23) for S_{i_38H} with well supported analysis (42 field-year samples in 10 seasons). Sorghum coefficients were of strong significance, with very high positive values for all sensors (**Table 5.10**), which matches the agronomic conditions of this summer crop being strongly influenced by soil moisture characteristics. All Sorghum samples are from the CFI region in the farm “Tarnee", fields “BT” and “Comet B”, and only three seasons under variable rainfall distribution ranging from average to above average rain fall deciles, in 2001 and 2005, to very above average rain fall deciles in 1998.

Table 5.9: Correlation coefficients, by year and region, between Y_i and S_i values from EM31V, EM38H, and EM38V monitoring data.

Year	Fields	S_i in SPAA (31V)	S_i in SPAA (38H)	S_i in SPAA (38V)	Fields	S_i in Riverine (31V)	S_i in Riverine (38H)	S_i in Riverine (38V)	Fields	S_i in CFI (31V)	S_i in CFI (38H)	S_i in CFI (38V)
		r	*r*	*r*		*r*	*r*	*r*		*r*	*r*	*r*
1999	**4**	-0.13	0.44	-0.40	2	-	-	-	1	-	-	-
2000	**4**	0.02	0.38	-0.27	4	0.25	0.19	0.53	2	-	-	-
2001	**4**	-0.32	0.37	-0.49	4	0.76	0.81	0.55	1	-	-	-
2002	**6**	-0.40	0.42	-0.51	4	0.60	0.62	0.78	1	-	-	-
2003	**6**	-0.06	-0.04	-0.20	4	0.93*	0.91*	0.79	4	0.04	0.08	-0.25
2004	**6**	0.60	0.15	0.49	4	0.82	0.87	0.78	3	-0.55	-0.79	-0.89
2005	**5**	0.03	0.74	-0.17	1	-	-	-	4	-0.07	0.58	0.31

* Significant correlation for α = 0.05.

Table 5.10: Correlation and ranked correlation coefficients (*r* and *ρ*), by crop, between Y_i and S_i values from EM31V, EM38H, and EM38V monitoring data.

Crop	Years	Field-Years	$S_{i\_All\ EM}$ *r*	$S_{i\_All\ EM}$ *ρ*	Field-Years	S_{i_31V} *r*	S_{i_31V} *ρ*	S_{i_38H} *r*	S_{i_38H} *ρ*	S_{i_38V} *r*	S_{i_38V} *ρ*
barley	**5**	21	0.03	0.06	7	-0.09	-0.07	0.43	0.36	-0.23	-0.14
canola	**6**	45	0.51	0.48	15	0.52^{*}	0.51^{*}	0.58^{*}	0.59^{*}	0.43	0.36
chick pea	**5**	15	-0.18	-0.39	5	-0.06	-0.15	-0.39	-0.56	-0.36	-0.87^{*}
faba bean	**4**	15	$0.62^{\dagger}$	$0.60^{\dagger}$	5	0.59	0.67	0.81	0.87^{*}	0.55	0.15
sorghum	**3**	12	$0.93^{\S}$	$0.79^{\S}$	4	0.97^{*}	0.89	0.97^{*}	0.89	0.97^{*}	0.89
wheat	**10**	126	0.05	0.06	42	-0.06	-0.05	0.23	0.23	0.01	0.02

* Significant correlation for α = 0.05; † Significant correlation for α = 0.02; and § Significant correlation for α = 0.01.

5.5.4 - The I_i compared among commonly used vegetation indexes

For the larger imagery dataset (87 field-seasons) used in the systematic evaluation of the I_i determinations, results have shown significant correlations for two of the common indices (I_{i_NDVI} and I_{i_PCD}) (**Table 5.11**). The I_{i_PPR} was the least correlated across regions except for SPAA, where it presented the only positive ranked correlation among generally weak negative correlations across the indices. The I_{i_NDVI} and I_{i_PCD} have shown to be very suitable alternatives for variability monitoring in CFI and Riverine regions, with I_{i_PCD} having a better ranked correlation in both. Regionalism is again clear in this analysis, with strong positive correlations for all available I_i in Riverine, moderate relationships for most of the indices in CFI, and no significant relationships at all in SPAA. In contrast with previous ranked correlation analysis, **Table 5.11** shows improved correlations for all vegetation indices. High positive correlations have shown a good potential for indices obtained from less common crop reflectance indices, such as I_{i_TrVI} and I_{i_PVR} (respectively r = 0.81 and r = 0.76). Of the indices trialled, only the I_{i_MSAVI} index gave for a negative correlation (r = -0.32).

Other suitable applications of the I_{i_NDVI} values may include the prediction of final crop variation or the timely support for short-term variability assessment. Alternatively, the potential in the I_i use may be further computed with alternative vegetation indices such as the I_{i_TrVI} and the I_{i_PVR}, which have proved highly correlated matching the final production variation even if with limited number of observations.

Table 5.11: Correlation and ranked correlation coefficients (r and ρ), by region, between Y_i and I_i (NDVI, PCD, PPR and the best vegetation index) from all available imagery data (field-season samples).

Vegetation Index	Samples	All Regions		Samples	CFI		Samples	Riverine		Samples	SPAA	
		r	ρ		r	ρ		r	ρ		r	ρ
NDVI	**87**	0.36§	0.39§	56	0.27*	0.32†	13	0.68§	0.44	18	-0.14	-0.13
PCD	**87**	0.33§	0.38§	56	0.25*	0.37§	13	0.67†	0.52	18	-0.07	-0.02
PPR	**87**	0.08	0.12	56	0.11	0.14	13	0.36	0.24	18	-0.13	0.08
OSAVI	**24**	0.35	0.30	13	0.12	0.16	2	-	-	9	-0.09	-0.08
MSAVI	**9**	-0.32	-0.28	7	-0.16	-0.11	1	-	-	1	-	-
GNDVI	**6**	0.30	0.75	5	0.49	0.82	1	-	-	0	-	-
VI	**6**	0.19	0.37	3	-1.00§	-1.00§	1	-	-	2	-	-
TrVI	**5**	0.81	0.90*	4	0.86	0.80	0	-	-	1	-	-
PVR	**3**	0.76	0.50	1	-	-	2	-	-	0	-	-

* Significant correlation for $\alpha = 0.05$; † Significant correlation for $\alpha = 0.02$; and § Significant correlation for $\alpha = 0.01$.

5.6 - General discussion

Y_i results are calculated from historical production data and so reflect the 'opportunity' captured in past seasons based on the associated crop type and management interactions. The methods developed have responded with stable ranges of absolute index values (**Table 5.1**) from input data with completely different characteristics (e.g., distribution histograms, density of observation, spatial resolution, survey frequency, stationarity, crop growth stage, and physical process response). In addition to the robustness and flexibility of the final index response, both new applications of the index (I_i and S_i) have shown an ability to incorporate both aspects (M_v and S_v) of the encountered production variability in a manner that matches our understanding of the agronomic process involved and the nature of the data gathered by the respective sensing systems (**Table 5.2**). For example the EMI data is expected to show lower M_v than the imagery data due to physical differences in the attributes being observed. The EMI data should show a higher $\mathbf{S_v}$ due to the differences in sampling resolution.

The S_i appears to be a more relevant indicator of the potential 'opportunity' realized in the final yield than the I_i. While the S_i result for the overall correlation (all years and regions) was marginally lower than that of the overall imagery correlation (**Table 5.3**), it was always positive and more strongly correlated in all regions (**Table 5.7**) when individual EC_a instruments were analysed. Further analyses of coefficients by region, year, sensor and crop have suggested seasonal relationship patterns for specific crop-region-rainfall combinations. They have also shown a high correlation for the S_{i_38H} with Y_i, including strong positive coefficients over the majority of region, season, and crop comparisons (**Tables 5.8**, **5.9**, and **5.10**). These results are interesting in light of the penetrative depth of EC_a surveys using the EM38H, which indicates higher correlations between soil variation in the root zone and final production variability.

The relevance of I_i calculations to final yield harvested in a paddock appear to be very specific to paddock and season. Overall correlations of the imagery index (I_i) in the 3 regions only showed weak and not always positive correlations (**Table 5.3**). Specific correlations for the most used vegetation indexes (i.e. I_{i_NDVI}, I_{i_PCD}, and I_{i_PPR}) were systematically lower than S_{i_38H} coefficients. Still, the I_i has shown potential for more specific analysis with greater data availability. The correlation analysis of common vegetation indices over the full available imagery dataset (87 field-seasons in **Table 5.11**) has indicated this imagery based variability assessment as a valid optional approach for middle-season management decisions. The value of this imagery index increases as a pragmatic decision support if imagery gathering becomes cheaper, spectral resolution advances, and novel crop reflectance indices can be validated.

With the evolution of remote sensing technologies, a higher spectral and spatial resolution combined with a lower cost and flight mission flexibility will play in favor of routine mapping and decision support. Therefore, the I_i can be foreseen as a tool to improve the assessment for variation in plant, or weed, development and spatial distribution. Temporal differences of variability index values from imagery data (I_i) in-crop could be assessed by determining the I_i from images taken weeks apart. This variation in indices combined with knowledge from common growth rates of crop and weed, time of emergence, differences in vigor and differential stages of inflorescence would give farm managers the ability to monitor the effectiveness of past or current management strategies and dynamically adjust chemical and fertilizer spraying requirements. Attending research requirements from the weed management literature, the I_i could deliver effective means of quantitative assessment of weed patch distributions, which can improve weed identification and the understanding of weed's emergence and growth behavior. Also in the light of new multi-sensor platform technologies like the Greenseeker® mapping systems, temporal series of variability indices, which would be determined for pre-, early-, mid- and post- season, could offer a pragmatic tool for adaptive operational management, supporting the analysis of in-season progress in spatial patterns and crop growth limiting factors.

The S_i may be more useful in a general long-term assessment, for which multitemporal assessment of soil variation indices would only be relevant when considering sensors of more dynamic soil properties (e.g. soil pH or water and nitrogen availability). In contrast, the I_i would be useful in a single season comparison and particularly under conditions of good growing conditions. Such assessments would provide valuable information in ranking fields for further investment in site-specific management technologies or in-season variation monitoring.

The use of these indices in crops other than broad acre would also be appropriate. The S_i may be particularly useful in perennial cropping enterprises such as vineyards and orchards where the seasonal conditions and imagery capture requirements would cause less discrepancy with Y_i.

Finally, an overall analysis of results reinforces the sensitivity of the Yieldex methods to environmental properties and the intrinsic characteristics of the input data source. The S_i and I_i indices show potential for use in situations where an assessment of the production variability between fields and farms is required, but where no yield data is available.

5.7 - Concluding remarks

The extraction of management information from remote and proximal fine-scale data monitoring activities is fundamental to the adoption of PA. The accurate measurement of within-field variability and the ranking of the opportunity given by the quantity and patterns of variation would be useful to farmers when contemplating further investment in site-specific crop management. Opportunity indices calculated from soil EC_a and crop reflectance imagery have shown promise to support farmer's decisions in instances where spatially dense data on crop yield are unavailable. These results suggest a new aspect in the original concept for the "opportunity index" O_i**.** Besides incorporating ecological and economic aspects for the final "opportunity" assessments, the within-field variability aspect could be determined using the same parametric methods with different monitoring sources, in accordance to specific production system context and/or technological adoption levels (i.e. Y_i, S_{i_38H}, I_{i_NDVI}, S_{i_31V}, I_{i_TrVI}, $S_{i\_Veris3100}$). Comprehensive evaluation of the variability index using data from new vegetation indices is further suggested for research, in particular considering the I_i for GNDVI, TRVI, and PVR over the available Australian dataset.

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Chapter 6

A decision tree for the opportunity in adopting SSCM technology

Summary

The investigation in this chapter targets the requirements for simple tools supporting site-specific management decisions in analysing the pathways and risks in PA adoption. It aims to address basic questions about the adoption of differential management technology from initial to advanced users by means of crop variation indices ranking the opportunity given by crop and soil related spatial production variability. A simple decision analysis tool is suggested for systematic support of farm investments in continuous differential actions, by defining pathways for opportunity in the use of alternative field monitoring devices. A decision tree model is defined according to the knowledge acquired with the use of the quantitative method of measuring production variation based on geostatistical parameters, as introduced in **Chapters 4** & **5**.

It considers a pathway for the potential use of alternative field monitoring devices, electromagnetic induction and imagery, through their respective indices of production related factors; soil EC_a (S_i) and crop vigour (I_i), to support long term strategic decisions at initial phases of adoption for differential management of grain crop fields. Support for the use of individual yield monitoring and historical datasets is given with threshold values for single field-season yield variability index (Y_i) and field median variation index ($\tilde{Y}_i$). This yield monitor based decision pathway directly helps intermediate adopters and further suggests the use of combined index analysis for advanced users considering in-season sort-term management decisions.

The proposed decision tree model is evaluated against actual production monitoring datasets from historical grain industry yield monitors, crop vigour imagery, and crop related soil parameters in three different agroclimatic Australian regions. Results show that thresholds from scientific experimentation can provide indicators to guide users through a decision pathway.

6.1 - Introduction

This chapter focuses on how to incorporate new knowledge, acquired from empirical observations with different field variability indices, into main stream farm decision making. Crop production variability indices have been obtained by parametric methods from variogram analysis of the magnitude and the spatial structure of within-field variations as determined by alternative intensive monitoring devices.

By using some knowledge gathered in the quantitative assessments of crop production variability, questions on the opportunity for the adoption of SSCM technology are systematized within practical processes of farm management. The availability of several spatial-related crop variation indices offers the opportunity to define optimal pathways for the adoption of SSCM technology. Pathways can be defined according to different stages of technological adoption, from initial adopters to advanced users, and supported by simple numerical indices normalized across different agronomic production systems. Initial adopters are likely to question the permanent investments in yield monitoring devices by assessing crop variation indices from monitoring services readily available, while advanced users would be searching for simple analytical tools optimizing variable-rate interventions. In addition, the systematic use of indices ranking the opportunity in crop variation expressed in terms of spatial measures can help management knowledge to be built over time, increasingly supporting different decision-making levels (e.g. crops per field, fields per farm, and farms per region).

In this generalized adoption decision context, fundamental constraints in the decision model for the adoption of SSCM technology introduced by Whelan & McBratney (2000) are considered. In their model, the opportunity to change from uniform field management to the adoption of SSCM is limited by the amount of crop yield variation. In this work, the use of the Yieldex method (**Section 4.5.2**) appears suitable for determining threshold values of adoption pathways when comparing the opportunity in using alternative field monitoring devices such as: for yield monitors (Y_i), soil electromagnetic induction (S_i), and crop vigour imagery (I_i). In the decision model suggested here, the flow of decisions branch into pathways supporting long-term strategic decisions at initial phases of adoption and later on in-season operational management decisions. Decisions are supported using: a single field-season variability index (Y_i, S_i, or I_i) for farmers at initial phases of adoption; median yield variation index ($\tilde{Y}_i$) for farmers with some experience, or a combined analysis for farmers with historical investments in fine-tuning site specific actions.

Classic decision analysis graphs (Howard, 1964) are used in modelling meaningful patterns of individual farm actions and agribusiness knowledge in the form of a SSCM adoption decision tree. Further attention to information and knowledge representation aspects in agricultural DSS (**Section 1.4.3**) are related to system design issues, which are now a well recognized concern in knowledge intensive farm management activities (Rosskopf & Wagner, 2005; De & Bezuglov, 2006; Llewellyn, 2007; Lisec *et al.*, 2008). For this, the conceptual decision tree model has been also mapped into an Activity Diagram according to contemporary recommendations addressing unified model driven approaches and open system developments (Booch *et al.*, 1999; OMG, 2001).

The proposed decision tree represents processes assessing the opportunity for adoption of SSCM based on threshold values from field variability indices. It considers their correlations with the actual production variation associated with different crop-seasons, fields, farm, and regions. Thresholds have been established across historical datasets and production knowledge for three PA farmer groups (SPAA, Riverine, and CFI) from distinct production systems. According to Llewellyn (2007), this type of information can support decisions reducing the waiting time and/or the risk of making a premature decision about adopting new management strategies. A simple and straight forward decision technique guiding individual decisions through numerical indices is expected to contribute to improvements in information quality that can reduce uncertainty related to spatial crop yield variation.

Experimental correlations between indices and actual production variation have had limited analysis by crop type and region due to the uneven distribution of available samples (e.g. field-seasons by crop). At this stage of site specific DSS developments, it seems that the determination of a minimum number of samples within specific characteristics to underpin an effective supporting tool for the optimal approach for farm management at different levels (e.g. strategic, tactical, and operational) is still missing. Addressing this knowledge gap, a tentative table defining the type of decisions, which are suitable according to a minimum sample population, is introduced. This knowledge management is expected to be built up over time, increasing the number of simpler decision steps that could be supported by individual farmers. The idea is that these decision processes wouldn’t necessarily require from farmers a comprehensive understanding of the analytical interpretation of their paddock’s variation.

Examples of fields showing high and low adoption opportunity indices have been selected where different adoption pathways from the conceptual decision tree have been matched by actual production historical monitoring. Results from this preliminary decision approach have shown promising application of the variability index method as a spatial related utility function for SSCM adoption decision analysis.

6.2 - Knowledge support & decision analysis

6.2.1 - Knowledge support in agricultural decision making

The impact of improved knowledge management systems supporting effective farm decision-making is well accepted by the system approach community (Wagner, 1993; McCown, 2002; Rosskopf & Wagner, 2005; Llewellyn, 2007). Knowledge exchange via semantic service networks have also been defined for the strategic framework of FAO (Food & Agriculture Organization), in which knowledge is defined as a function of the coverage, quantity, timeliness and accessibility of the information being collected, stored, and disseminated (Fisseha *et al.*, 2001).

In fact, these new system development approaches just represent practical development solutions for classic concepts of “strategic control” (Mintzberg & Waters, 1985). From decision making theory, Mintzberg & Waters (1985) suggest the importance of learning how managers track the realized strategies of their own organizations in order to infer researcher’s knowledge into streams of organizational actions. In this context, pattern discovery in management processes are likely to provide farmers with facilitated learning and self-awareness of potential pathways of their own actions and related consequences over time. This would be well suited for intensive crop monitoring as suggested by Wong & Wang (2003) as a framework towards knowledge support by analysing large amounts of data with a mixture of continuous and categorical values.

Wagner (1993) has explored knowledge-based systems as composed either by several production rules or production functions, where only hybrid solutions could support some improved farm performance. Garcia *et al.* (2001) suggested two reinforcement learning methods considering a sequence of crop management decision problems modelled as a Markov Decision Problem (Kennedy, 1988), from which only very simple decision rules were considered appropriate. These were also lacking hierarchical representations that may distinguish overall planning and operational activities. Cortés *et al.* (2000) present an overview of Environmental Decision Support System (EDSS) development that have been impacted by AI techniques (e.g. neural networks, decision trees, knowledge engineering, genetic algorithms, machine learning). They conclude with a selection of successful applications of the AI technology that have reached the implementation phase but never effectively getting to the market of routine farm management processes.

A recent review of tools for farm management decision support is presented in Matthews *et al.* (2008), who were searching for explanations for the lack of success in aDSS. They identify suitable aDSS functionalities and suggest best methods for a tool to be deployed, and undertook market research on the nature of requirements and commercialization potential. Matthews *et al.* (2008) reinforce that even facing practical limitations, end-users are still recognizing the functionality that a proper aDSS may offer to farm management.

6.2.2 - Decision analysis tools

Decision analysis is a decision theory approach that promotes choosing the decision of which the consequences have the maximum expected utility (Howard, 1964), and it has been used to represent business knowledge in a variety of applied fields (Howard, 1977). Decision trees are a commonly used graphical model for decision analysis problems, and they are here understood as a pathway that maximizes the probability of achieving an aspiration level, i.e. the opportunity for adoption of differential management technology. Although there are concerns that these tools may not improve decision making (Klien, 2003), decision trees have for a long time been accepted as a simple and practical decision tool in decision theory (Fischhoff *et al.*, 1982) and in applied fields of agriculture (Breman & van Reuler, 2002).

There are basically three levels of decision-making as defined in the science of management decisions (Simon, 1960). They can be characterized in the time and/or space dimensions usually describing: i) short-term operational control decisions, mostly involving predictable task operations; ii) periodic tactical control decision, involving monitoring activities to rectify problems; and iii) long-term strategic decision, often requiring analysis for new methods and investment in technology. Similar farm management information flow has been suggested in the PA context for different levels of SSCM decision making (Fountas *et al.*, 2006). Information flow diagrams introduced in Fountas *et al.* (2006) represent a hierarchical decision framework for several generic farm management functions.

In particular for complex multistage decisions, decision trees are systematic tools widely used for direct contact with farmers knowledge and simplified agronomic decision-making (Struif Bontkes & Wopereis, 2003). Decision trees have been suggested among technologies helping to increase the efficiency of use of fertilizer nitrogen (Giller *et al.*, 2004). Also at field level, they have been used for simple field assessment analysis, allowing the translation of production indices as a form of discussion between farmers and technology development teams (Giller, 2000); and for associations between averages of corn yield, management and soil information (Lapen *et al.*, 2001). At the whole farm management level, conceptual models have been introduced by Fountas *et al.* (2006) for a multilevel farm management information flow and by Perini & Susi (2004) for development of a DSS for integrated production agriculture, however no key evaluation is suggested that maximises a probability function for the best decision action. At landscape level De & Bezuglov (2006) suggest an UML Activity Diagram representing the tree of actions related to decision processes for efficient nutrient management, as modelled for a Web knowledge base service. Similar standards in system design have been introduced in Lisec *et al.* (2008), addressing modelling diagrams for the activities related with procedures in rural land transactions in a system that provides land market analysis for basic spatial planing. Other agricultural applications using UML diagrams to represent crop management activities have been introduced by Blackmore *et al.* (2002) concerning a better control of autonomous tractor behavioural transitions in a State Diagram; and by Nash *et al.* (2006) representing an Activity Diagram for soil testing activities in a Web field control service for PA that uses the AgroXML schemes optimizing vector data exchange.

The term “decision tree” is also related to the applied data mining field of predictive models, in particular to cluster classification techniques. Extensively used for natural resource assessments (e.g. forestry, soil, and irrigation systems), this data mining technique has been also applied for site-specific management related research, although is not the subject of this research. Often using NDVI or another index from imagery data, some examples of this approach for the mapping of field level variations include: different crop and weed populations (Yang *et al.*, 2004); weed and nitrogen stress detection in corn (Karimi *et al.*, 2005); soil texture (Zhai *et al.*, 2006); categories of water stress, presence of weeds and nitrogen application rates in corn plots (Waheed *et al.*, 2006); economic benefits of site-specific decision rules for nitrogen fertilization (Wagner & Schneider, 2007); sunflower yield affected by infestation (Gutiérrez *et al.*, 2008); in-season N management (Shanahan *et al.*, 2008).

6.3 - A decision tree for the adoption of SSCM technology

6.3.1 - Factors influencing the decision of technological adoption

Basic constraints for the adoption of SSCM

Conditional factors influencing the opportunity for the adoption of PA technology have been investigated in Whelan & McBratney (2000), and related to the assessment of both economic and environmental components that affect the risk perception associated with the management of complex cropping system. In their premises, the null hypothesis of PA implies that the variation of soil and crop requirements within a field has been properly characterized across space and time dimensions. Whelan & McBratney (2000) provide an example of the PA decision process employing a study of field variability, where a simple model based on crop yield and the economic imperative is represented in a management decision-tree for the adoption of SSCM (**Figure 6.1**). In this model, differential treatment strategies are examined as an option based on: i) the degree of variation; ii) the cause's of variation; and iii) the suitability for management intervention.

Addressing the proper characterization of spatial and temporal crop production variation, this study is focused on basic adoption questions from farmers concerning investments in new SSCM technology. Basic questions like: "Should I stay in uniform field management or should I go for within-field differential management?" are here directly associated with the assessment of the spatial and temporal variation in crop production and influencing factors. The opportunities for continuously variable treatment or the delineation of management sub-units will be determined as a function of the spatial dependency observed in intensive monitoring datasets.

As observed in Whelan & McBratney (2000), the type of answers required by present adoption questions associated with differential crop management are mostly complex, variable from field to field, and as yet unclear or limited by technological and agronomic knowledge gaps. In which case, simple decision tree models are likely to support and suggest decisions under high risk perceptions, and provide potential pathways for the optimal technology adoption.

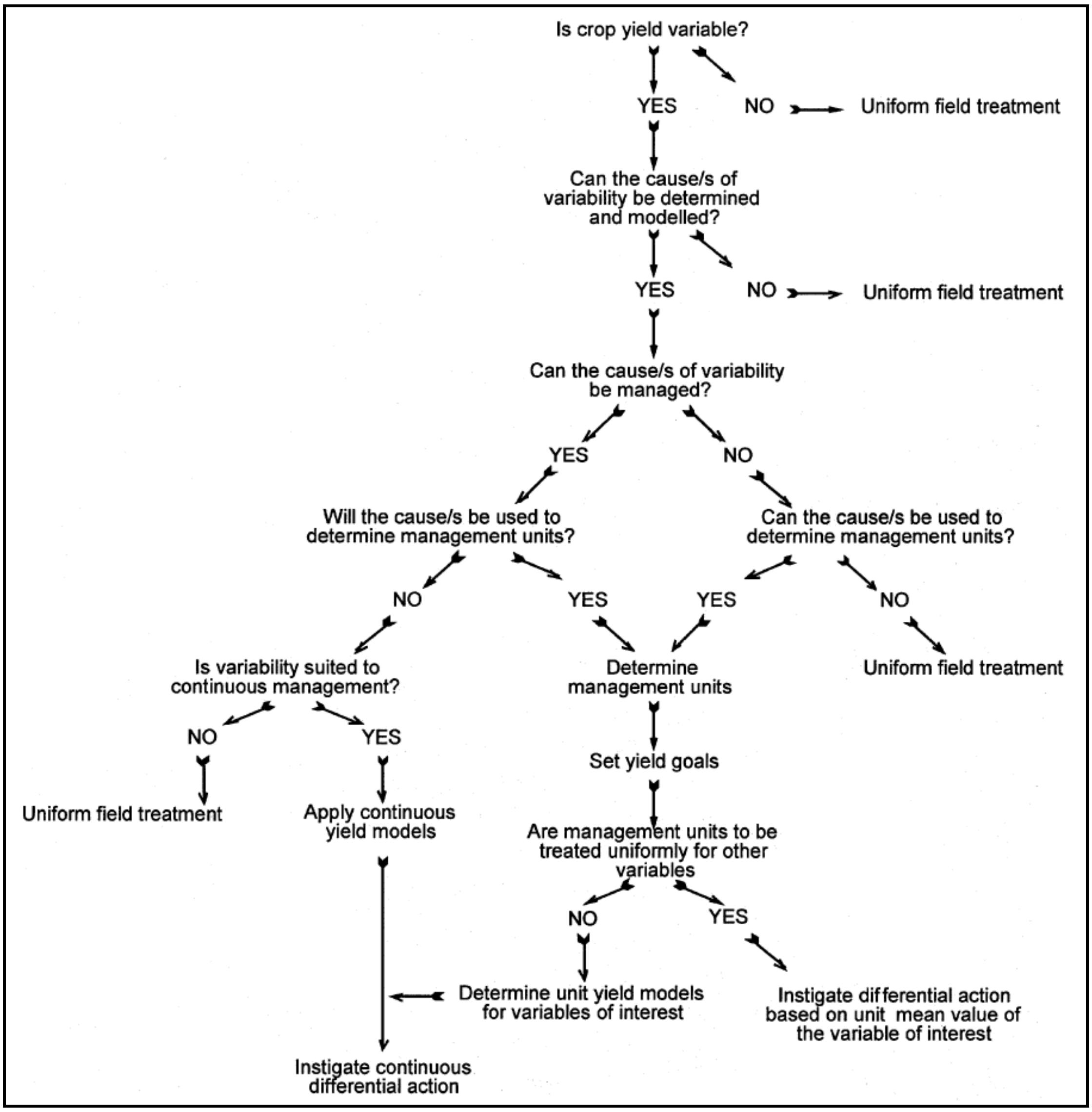

Figure 6.1: A management decision tree for SSCM in Whelan & McBratney (2000).

Different adoption phases

As previously detailed in **Section 1.3.1**, agricultural decision making processes may be categorized in different ways. They are generally abstracted either in terms of a spatial scale (e.g. Bouma, 2000; Hayman, 2004; Blackmore *et al.*, 2007); a managerial scale (e.g. McCown, 2002; Fountas *et al.*, 2006); or a time frame (e.g. Struif Bontkes & Wopereis, 2003; Sadler *et al.*, 2007). Struif Bontkes & Wopereis (2003) for instance, suggest a simple categorization defining farm decisions through time frames that are also related to three levels of managerial decisions, typifying them as of: i) short-term (e.g. when and where to apply fertilizer); ii) medium-term (e.g. choice of crop variety); or iii) long-term (decision to start new management).

In contrast, an overview of a number of DSS given by Struif Bontkes & Wopereis (2003) provides a guide to overcome constraints of a variety of tools, showing a common agreement by several authors when distinguishing five phases of a decision making process. These decision phases can be understood as reassembling the continuum of five main process for adoption of different components in SSCM as illustrated in Whelan (1998), and they are defined within a research development continuum including:

- The strategic site selection phase, in which suitable zones are identified for a particular technology satisfying a number of criteria;
- The diagnosis/analysis phase, in which problems are identified and analysed;
- The options identification phase, in which options for improvement are identified and evaluated (e.g. financial consequences and risk analysis);
- The evaluation phase, in which results obtained in the field are evaluated and interpreted, also supporting the improvement of tools; and
- The technology diffusion phase, in which the likelihood of success of a technology is evaluated for different sets of environmental and management conditions.

In this study, a simplified categorization of three SSCM adoption phases is used covering the relevant decision phases defined above, as a cyclical process. Farmers in the process of adoption of SSCM are then identified as initial, mid-term, or advanced adopters. Initial adopters of PA technology are likely to assess the risk of long term returns, the need for historical yield monitoring interventions, and the evaluation of alternative monitoring devices. Another aspect in initial phases of adoption is related to spatial referencing for field level operational processes, in which attention is mostly given to machinery related efficiencies which are not considered in the decision context investigated here (e.g. GPS accuracy, auto steering, robotic harvesting). Mid-term adopters are involved in tactical management decisions, observing the opportunity in the spatial and temporal variation of crop production at specific fields. Advanced adopters have historical investments in the technology, being able to consider in-season tactical management decisions, based on temporal indices, and strategic decisions prioritizing fields for future investments.

A contribution to the establishment of the necessary amount of observations that may be required to minimize risk in site-specific at different decision processes is suggested in **Table 6.1.** This table tries to quantity the minimum number of specific field monitoring observations that are required to support different adoption phases, according to decision scale and type. It is observed that for several farm management levels, the knowledge about the required information to support specific decisions is not available (na), while other datasets have been empirically or preliminary suggested.

Considering the response of the different indices, it is suggested that new multi-sensor platforms and simple sensors are to be considered in early phases of adoption. From results discussed in the next section, it is possible to observe that the combined use of different monitoring devices can support an improved analysis of the spatial related crop variation even when field yield index averages only reflect average suitability for the opportunity in the adoption of differential crop management (e.g. fields Road and 44). Therefore the minimum of 7 observations including different measures of production variation is suggested for intermediate phases of adoption, such as for supporting field to farm management levels of tactical decisions. As an example of the potential of developing normalized variability indices by crop, the minimum of 30 field-seasons is suggested (as computed in **Section 4.5.3**) for the determination of wheat crop threshold values supporting specific crop decisions.

Table 6.1: Tentative table of data requirements at different SSCM adoption phases.

Minimum Data Set	*Observation Type*	*Adoption Phase*	*Decision Scale*	*Decision Type*
1	EMI or imagery per field	Investigation	field	Strategic
3*	yield maps per field	Initial	field	Operational
7**	multi-platform interventions per field	Intermediate	field to farm	Tactic
na	crops per field	Intermediate	field to farm	Tactic
na	crop rotations per field	Intermediate	field to farm	Strategic
2	imagery per season	Advanced	within-field	Operational
30***	field-season per crop	Advanced	field to region	Tactic
na	farms per region	Advanced	farm to region	Strategic

* Minimum of 3 data sets is suggested in the literature.
** Minimum of 3 EMI measurements (pre-season), 1imagery (in-season), and 3 yield maps (post-harvesting).
*** Minimum number of samples to determine an index threshold value supporting crop decisions (Wheat = 30).

The importance of temporal assessments

For advanced adopters, the use of combined measures of field and crop variation can be considered by using several alternative monitoring devices. A multi-platform monitoring system can support high dimensional information analysis, by observing several influencing factors at different spatial and temporal scales of correlation. This complete overview analysis is then suitable for precise in-season action, considering spatial and temporal variation in crop growth, pre-season soil variation, and post-season crop yield variation.

Preliminary research in Shanahan *et al.* (2008) supports this concept when addressing the spatial variability within the growing season in order to synchronize nitrogen inputs to timely match crop nitrogen uptake and minimize levels of inorganic soil nitrogen formation before crop uptake. In a dynamic field intervention context, Shanahan *et al.* (2008) also suggest a promising response from ground-based active-light reflectance measurements converted to several crop vigour indices. The analysis of in-season variability factors in wheat is suggested in Vrindts *et al.* (2003) by the integration of crop and soil properties correlations with continuous monitoring of nitrogen inputs, temporal NDVI, and pre-season EC_a information layers. Pena-Yewtukhiw (2008) gives another example using airborne imagery for determining an appropriated observation scale, when analysing patterns of NDVI spatial structure for early predictions of wheat canopy variation. Another temporal aspect is investigated in Massey *et al.* (2008) using long-term multiple-crop yield-map for the generation of profitability maps, considering the potential for different investment returns.

6.3.2 – A preliminary decision-tree for the opportunity in adopting SSCM

The opportunity for the adoption of differential crop management is addressed in a simple and generic decision support model that follows a tree-structure of sequential questions providing optimal pathways for technological adoption. The gradual and cyclic adoption of different monitoring technologies follows threshold values from variability index obtained in **Chapters 4** and **5**, providing the basis for pathways regarding the spatial-temporal production variation.

Spatial-related crop variation indices can support questions in the process of SSCM adoption (Whelan & McBratney, 2000), in which the opportunity to change from uniform management to SSCM is limited by the amount of crop yield variation. Therefore, a quantitative analysis of the magnitude and the spatial structure of within-field variations are used to determine optimal pathways for the opportunity of adoption of site-specific management technology.

Pathways are abstracted according to different stages of technological adoption, considering the availability of alternative monitoring devices.

A basic assumption in the suggested decision model is that crop variation is a key signal that differential management might be warranted, which considers the economic imperative of optimizing crop production as a major management decision. The opportunity for differential treatment is then examined as an option based on: i) different technological adoption phases (initial adopters and advanced users); ii) the degree of field variation in relation to average thresholds from historical field monitoring datasets; and iii) the suitability for management interventions using alternative data source devices (yield monitors, EMI, or imagery).

The use of the Yieldex method (**Section 4.5.2**) seams suitable when determining specific threshold values of adoption pathways that may consider alternative field monitoring devices. Indices are calculated using parameters from crop production variogram analysis from: yield monitors (Y_i); soil electromagnetic induction sensors (S_i); and crop vigour imagery (I_i). **Figure 6.2** introduces the logic for the decision process employed towards a strategic evaluation of field variability. The flow of decisions branches into pathways guiding long-term strategic decisions at initial phases of adoption and in-season operational management. Decisions are supported according to the data availability and accessibility as: i) single field-season variability index (Y_i, S_i, or I_i) for farmers at initial phases of adoption; ii) median yield variation index ($\tilde{Y}_i$) for farmers with some PA experience; or iii) a combined analysis for farmers with historical investments in fine-tuning site specific actions. The decision tree uses threshold values from field variability indices, having considering their correlations with the actual production variation associated with many different crop-seasons, fields, farms, and regions. Thresholds have been established across 10 years of historical datasets from broad-acre grain crop fields from three Australian farmer's associations in different regions.

From initial adopters to advanced users, a simple numerical decision tree underpinned by relevant crop variation indices should be understood as a systematic tool that can be directly used by farmers, promoting improved management knowledge, learning on crop variation analysis and simplified agronomic decision-making. Initial adopters are likely to question permanent investments in yield monitoring by assessing crop variation indices from monitoring services readily available. Based on normalized index thresholds and correlations across different agronomic production systems, first time adopters may first invest in alternative monitoring devices and the associated indices to help decide about future investments in yield monitoring equipment.

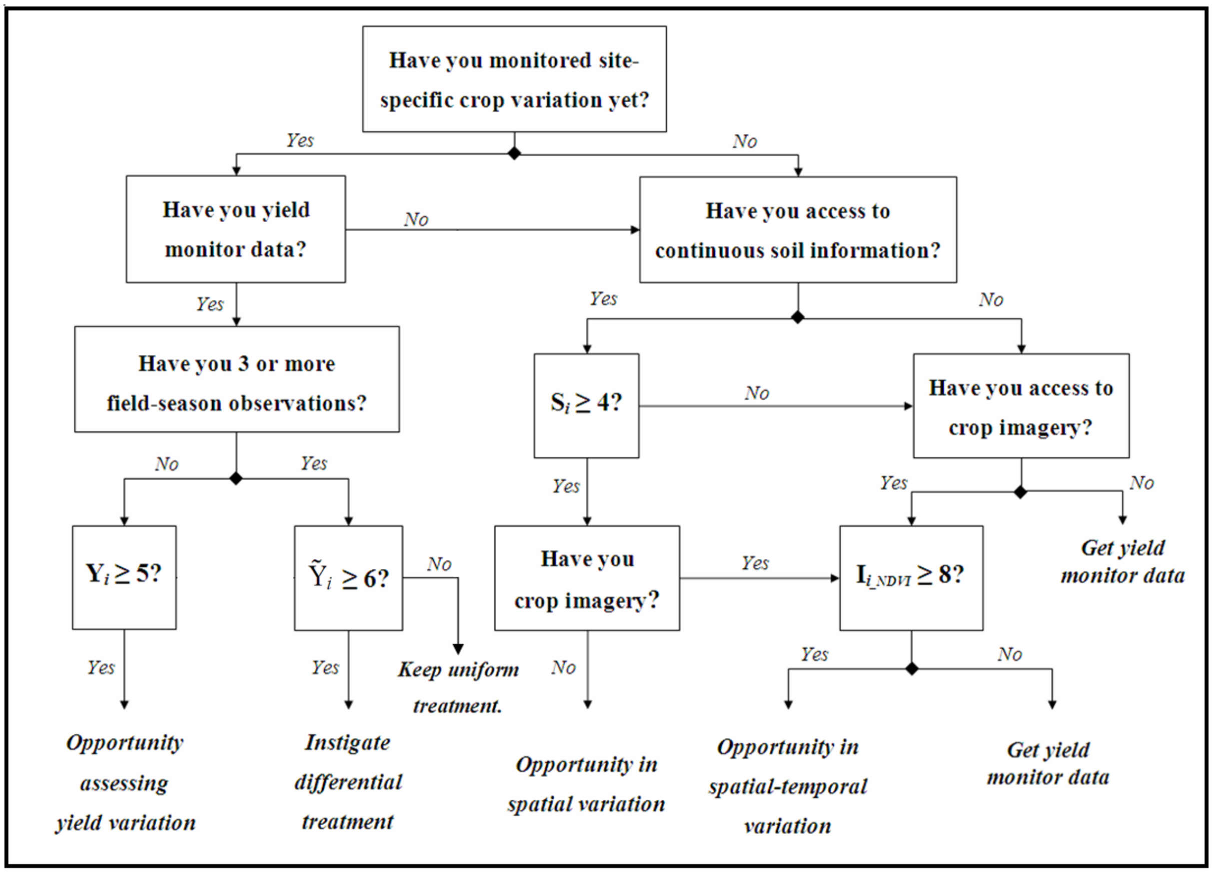

Figure 6.2: An opportunity decision-tree for the adoption of SSCM technology.

* Different index thresholds (Y_i, S_i, and I_i) obtained from average values from datasets introduced in **Chapters 4 and 5.**

It is considered that a minimum of three years of yield monitor data by itself is usually required to show whether or not there are specific field areas with consistently better or poorer yields. This consideration addresses advanced users that would be searching for simple analytical tools optimizing farm level variable-rate interventions, ranking priority fields for differential management. Finally, the systematic use of indices ranking the opportunity in crop variation can help management knowledge to be built over time, increasingly supporting different decision-making levels (e.g. crops per field, fields per farm, and farms per region).

6.3.3 - Testing the decision-tree

Although the ultimate assessment and treatment of crop variation is expected to be undertaken in real time at the scale of minimum equipment restrictions, current agronomic and technological developments are mostly limited to the identification of relevant layers of information to assess distinct management areas within a paddock. The present knowledge gap has in one direction inhibited adoption by farmers, and for the research side restricted the number of available observations that could support models characterizing crop production variation.

It is clear that the levels of feasible decisions are directly related to the availability of well distributed observations across different fields, crops, seasons and regions. Such a database is presently unavailable. Limited adoption of PA and the potential data waste due to non-expert equipment operation have also restricted a wider scope of analysis.

Still, the empirical experimentation conducted in this research has shown a great variation of index correlation outcomes, from which some particular conclusions can be drawn. Specific opportunities from results in the Australian production areas considered can be further mapped in the decision model, extending a particular case of the general decision-tree to different production systems as suggested in **Figure 6.3**. Although based on a limited number of samples, highly significant correlations where observed with imagery responses to all regions using the vegetation index for Photosynthetic Vigour Ratio (PVR) and with all EMI measures (31V, 38V, and 38H) in sorghum crops. Other crops like barley, canola, chick pea, and faba bean were detailed as extending decision pathways related to the opportune use of NDVI and/or EMI information as good predictors for the management opportunity given by the final production variation for specific crops and regions (**Figure 6.3**).

For the specific cases of agronomic regions in Australia, thresholds were considered according to particular cases of high significant correlations between alternative indices and the actual production index. As for the example, the EM38H data that was a significant predictor for faba bean (87%), in particular in the Riverine region (93%), while EM38V and EM31V appear to respond better to chick pea (87%) and canola (60%) respectively across all regions. For the NDVI index, particular cases were observed by region for barley (85%) in SPAA, canola (96%) and wheat (80%) in Riverine. The capability for decision making using these quantitative indices for crop production variation will increase when more homogeneously distributed datasets became available.

Feasible SSCM decisions are likely to require a significant number of field monitoring interventions to match practical management processes and reduce the risk perception in equipment investments from optimising tactical and operational actions. Knowledge is still being built in incorporating tailored on-field trials research developments within routine procedures for efficient farm economic, ecologic, logistic, and spatial management.

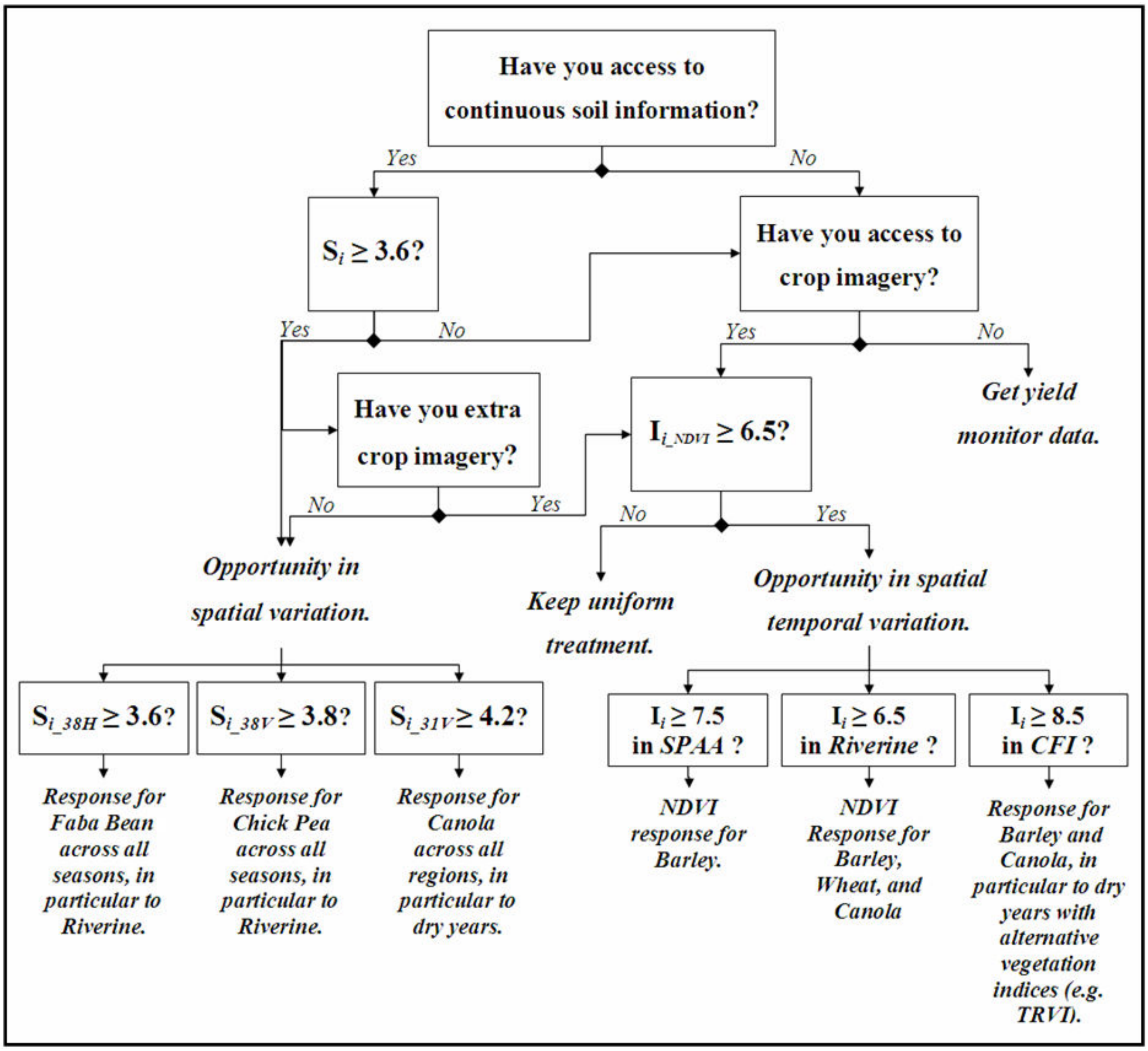

Figure 6.3: Extending the opportunity decision-tree for specific areas in Australia.

* Different index thresholds (S_i and I_i) obtained from average values from datasets introduced in **Chapter 5.**

6.3.4 – A system design of actions and decisions in SSCM

This last methodological section introduces the use of standard recommendations for generic system development technics in the software industry, which has been applied in the design of knowledge management systems (Breuker & van de Velde, 1994; Schreiber *et al.*, 2001). The Activity Diagram is part of the UML methodology (Booch *et al.*, 1999; OMG, 2007) as previously introduced in **Section 3.4** and presents a logical system overview of activities and decisions. In this sense, the diagram describes actions concerning pathways of decision processes for the adoption of SSCM technology and complements the conceptual framework for knowledge support, introduced in **Section 3.5**, with a business view of the specific farm management decision-making.

Figure 6.4 suggests a new method of application of the Activity describing the basic flows of activities and core decisions when supporting the analysis of the opportunity for differential crop treatment. The idea is to add a knowledge system representation perspective that could enrich the understanding of the practical flow of the possible adoption pathways described in the decision tree suggested in **Figure 6.2**. It is also understood that the diagram representation in **Figure 6.4** offers a simple way of communication with farmers for participative actions either validating or extending the decision pathways proposed.

The Activity Diagram is a visual representation of any system activity basically used to describe either flows of data or decisions between activities. It is based on standard UML notations, as described by the Java IDE (Interactive Development Environment) used for open development in this research (NetBeans IDE 6.1, www.netbeans.org). This approach favours both the cooperative exchange of the conceptual design API's (Application Public Interfaces) for model reuse or change, and the automatic object class generation of software source codes. However, this system design approach has received limited attention within the agronomic sector, in particular to PA developments, being relatively behind the commercial and industrial sector (Papajorgji, 2007).

Few examples address the representation of practical decision-making models in agribusiness, in particular as related to field level abstractions (De & Bezuglov, 2006; Nash *et al.*, 2007; Lisec *et al.*, 2008). These authors have mostly described system architectures related to new agronomic proposes in WEB service developments. De & Bezuglov (2006) introduce a data model supporting a Web module for a knowledge base in nutrient management. This model description also includes an Activity Diagram that supports decisions of nutrient allocation that account for spatio-temporal actions at a field level. Relative to data flows for intensive field soil testing, Nash *et al.* (2007) illustrates an Activity Diagram for optimization of open geospatial Web services in PA. Nash *et al.* (2007) show the potential of this design technique when dealing with parallel treads when exchanging field level maps across three decentralized Web map services: a geological survey agency; a topographic mapping agency; and a soil-testing consultant. An example of Activity Diagrams representing comprehensive decision flows is given by Lisec *et al.* (2008) for rural land transaction procedures. Although less related with site-specific management questions, Lisec *et al.* (2008) shows how several Use Case designs composing many simultaneous parcel related transactions could be summarized into two easy to read diagrams.

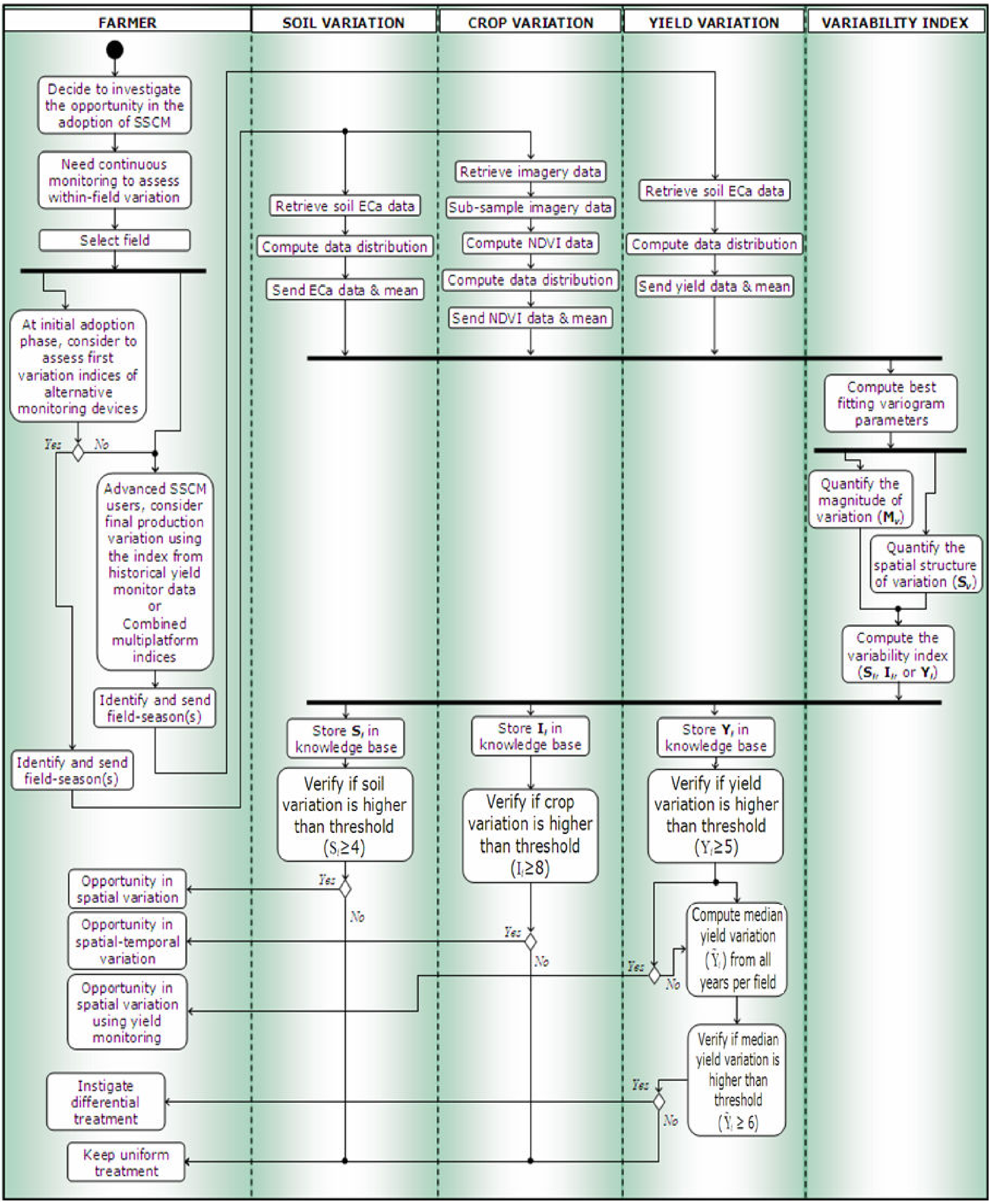

Figure 6.4: Activity diagram representing synchronized or concurrent actions of different actors involved in decision-making for the opportunity of SSCM adoption.

The Activity Diagram shown in **Figure 6.4** describes the farmer interaction with assessment actors (software modules) of a knowledge support system, thus: soil related field variation, crop vigour related imagery variation, and final production related crop yield variation. The system interaction is abstracted through two main phases of technological adoption as also considered in the decision model pathways described in **Section 6.3.2**. The conceptual system interaction is designed to automate field intensive data management procedures and the computation of variability indices. In conjunction with the Sequence Diagram introduced in the preliminary framework design previously introduced (**Section 3.5.2**), the Activity Diagram in **Figure 6.4** provides a clear picture of the synchronism and concurrence of actions and decisions in processes for the adoption of differential management

6.4 - Applying the decision model

From the overall dataset, fields monitored by several different sensors were selected from all different agronomic regions, when showing high and low Yieldex means over three (3) or more cropping seasons (including occurrences of non-stationary crop variation) are used as critical cases to describe variation in production. Selected fields of high mean yield variation include: the Road field, at Brook Park farm (SPAA); the BT field, at Tarnee farm (CFI); and fields 44 and WC, respectively at Grandview and Glenmore farms (Riverine). Low mean yield variation fields include: the Blackflat field, at Clifton farm (SPAA), and the Swamp field, at Kiewa farm (CFI).

Figures 6.5 to **6.10** present kriged yield maps interpolated from historical monitoring datasets of the selected fields, showing the response of indices related with the actual production variation. Using the ArcGIS® environment for georeferencing and information overlay, colour palettes were standardized across all available crop yield ranges for individual field-season observations, EC_a, and vegetation index maps. This standardization facilitates the visual interpretation of the spatial variation in crop yield magnitude. Mean index values by field are displayed against yield mean value maps, which were obtained from raster calculations over all seasons by field.

Through the observation of maps, quantitative indices, and related follow up of branches in the decision-tree, three types of analysis are possible as will be presented in the following sub-sections. General responses of alternative sensors (i.e. EMI & Air-borne Imagery) can be observed in relation to crop and region. A whole-farm analysis that includes selected fields in the SPAA region is feasible due to recent reports on economic returns (SPAA, 2008) advanced PA adoption farms (i.e. Brook Park and Clifton Farms). Finally, a detailed observation of the information extraction obtained by the use of the indices delineates the decision flow of each individual field.

6.4.1 - Response from alternative sensors

The overall response for EMI indices (S_i) was positively correlated (**Table 5.8**) with the final crop production variation index (Y_i), in general with better responses for the EMI 38H index (S_{i_38H}) as observed for fields WC (**Figure 6.7**) and 44 (**Figure 6.8**) in the Riverine region. The field Road (**Figure 6.5**) is one example of low correlations between S_{i_38H} and Y_i values mostly particular to wheat crops (r = 0.23; **Table 5.10**). Yield maps for wheat seasons in **Figure 6.5** (i.e. 1999, 2002, 2003, and 2005) poorly match patterns of EC_a variation either in spatial structure or in the magnitude of variations, even if the EM38H index (S_{i_38H} = 4.7) conforms to the decision function for EC_a variation measures ($S_i \geq 4$) and is significantly higher than other EMI observations for the same year in Road (S_{i_38V} = 2.2 and S_{i_31V} = 2.5). These findings could support a threshold to decisions on the use of EM38H as a predictor of final wheat production variation, which could also support similar decision pathways if observing dissimilar variation patterns between EMI and wheat yield maps for field 44 (**Figure 6.8**). Another good S_i correlation, but now considering low figures for Y_i and S_i (**Figure 6.10**, Faba Beans 2004, average yield, and EMI 2004), is shown in field Blackflat where no clear pattern association can be observed. In Swamp (**Figure 6.9**) the higher temporal variation appears once more to indicate lower opportunity for the isolated use of $\mathbf{S_i}$, whereby the incorporation of imagery indices in analysis is mostly opportune.

In relation to overall imagery indices, low variability correlations of NDVI to wheat yield (i.e. 2003 and 2005) in crop production from the Road paddock in the SPAA region (14%) can be observed in poorly correlated variability patterns shown in imagery samples from field Road (**Figure 6.5**). This contrasts with the significant similarity between patterns in the Field Peas yield map and the 2004 NDVI imagery, also reflected on index values in both cases (Y_i = 4.2 and I_i = 8.6). These observations would lead to decision pathways where EMI measures would be assessed in combination with the in-season temporal aspect given by the NDVI monitoring in order to evaluate the opportunity assessing spatial-temporal production variation. This indicates a higher opportunity in temporal yield variations for this field, which matches the bigger multi-year average yield index than most of the individual crop-seasons (**Figure 6.5**). A similar temporal analysis is also suitable to field 44, which presents a strong temporal variation in production in a region (Riverine) that correlates better with NDVI predictions (**Figure 6.8**, i.e. canola 2003, wheat 2004, barley 2005, average yield and NDVI 2004) and requires a lower threshold for the opportune use of imagery (**Figure 6.3**, $\mathbf{I_i}$ = 6.5).

Another example of short-term management capability offered by imagery variability indices is given in the field BT (**Figure 6.6**), showing imagery indices for 2005 (I_i = 9.4) and two in-season flights in August (I_i = 9.8) and September (I_i = 16.1) of 2006. These properly indicate the opportunity for adoption also shown in high Yieldex values for both the final wheat production variation in the same year (Y_i = 6.4), and the median Y_i ($\tilde{Y}_i$ = 8.3) over 5 years (1998, 2001, 2003, 2005, 2006). Although showing relative spatial pattern stability in production (**Figure 6.6**) that is also characterized with high measures of Soil EC_a variation (S_{i_38H} = 5.7, S_{i_38V} = 5.9, and S_{i_31V} = 6.8), questions remain in this field when considering the scattered nature in patterns of variation and a temporal stability in large yield magnitude variations (from 2 to 6 ton/ha per year). Applications of the I_i may include timely predictions of final crop variation or short-term variability assessment, which should consider the computation of alternative vegetation indices as previously discussed in **Section 5.5.4**.

6.4.2 - Response from whole-farm economic returns

The more detailed decision model suggested in **Figure 6.3** can be better analysed for whole-farm management decision pathways using field observations for the South Australian region (SPAA), where reports on the economic returns of investments in site-specific management for broad-acre farms include overall figures for Brook Park and Clifton Farms (SPAA, 2008). These figures could be used to evaluate decision-tree outcomes for fields in advanced stage of SSCM adoption. Returns for the Brook Park Farm (1,600 ha) are estimated in AU$12.60/ha per year across the whole farm, that include fields Road (112 ha) and Bills (52 ha) under intensive field monitoring. The field Road ($\tilde{Y}_i$ = 7.0) accounts for 13 multiplatform observations (7 yield monitor, 3 EMI's, and 3 Imageries) from 1999 to 2005, and the field Bills ($\tilde{Y}_i$ = 5.5) accounts for 9 multiplatform observations (4 yield monitor, 3 EMI's, and 2 Imageries) from 2002 to 2005. Investments in differential crop management for these fields can be considered as opportune, showing yield variation means around the condition of manageable spatial variation ($\tilde{Y}_i \geq 6$). Accounting for long run returns (around 5 years) the benefits could reach the AU$62.00/ha investment break even point (SPAA, 2008). The strong temporal yield variation that can be observed in Road (**Figure 6.5**) may question the relative SSCM opportunity given by the spatial variation in crop yield, which is mostly characterized around the average Y_i value, with the exception of the outstanding measure for wheat season in 2002 (Y_i = 17.3). The strong temporal aspect in Road could suggest two farm management alternatives regarding the relative opportunity of spatial yield variations: an advanced operational decision (**Table 6.1**) considering in-season imagery monitoring for Road; and a shift to strategic decisions towards intermediate monitoring investments in Bills, increasing the number of observations that can improve future decision pathways.

The same type of whole farm analysis prioritizing fields for site-specific investments would support a single pathway outcome for the adoption decisions drawn out of the Clifton Farm (960 ha) dataset. According to SPAA (2008), PA investments of AU$64.00/ha from 1997 to 2006 have now estimated returns of AU$37.00/ha per year (around two years to break even investments) that include fields Blackflat (42 ha, $\tilde{Y}_i$ = 4.2 over 8 crop-seasons), Barn (40 ha, $\tilde{Y}_i$ = 4.4 over 2 crop-seasons), and Top D (22 ha, $\tilde{Y}_i$ = 5.2 over 4 crop-seasons). In this farm, a clear pathway is determined by highly temporal and spatially unstructured variations in Blackflat (**Figure 6.10**), diminishing adoption opportunities as shown by its lower mean variation index. The observed indices would prioritize monitoring investments in Top D, being the only field satisfying the utility function for differential management in 2 out of 4 yield monitoring observations.

6.4.3 - Response from multi-temporal field data

For field Road (112 ha), an investigation phase for the adoption of SSCM (**Table 6.1**) that considers the EMI (S_{i_38H} = 4.7) or imagery (I_i = 8.6) monitoring in 2004 would positively lead decisions along the pathway through thresholds ($S_i \geq 4$ or $I_i \geq 8$ respectively) towards the "opportunity assessing the spatial-temporal variation" (**Figure 6.3**). This suggested management pathway of investments for intermediate levels of technological adoption, in 2004, actually matches the opportunity given by the final production variability observed for wheat in 2005 (Y_i = 5.9). A simulation for an intermediate decision phase would consider an average yield variation index across all seasons (Road $\tilde{Y}_i$ = 7.0) above the conditional value ($\tilde{Y}_i \geq 6$), leading pathways towards advanced levels of adoption to "instigate differential management". These decision pathways for Road simulations at different management levels match the actual opportunity for the adoption of SSCM as shown by estimated returns around AU$12.00/ha recently reported (SPAA, 2008).

Although showing significant yield magnitude variations (up to 3 ton/ha in one season) and some consistent patterns of variation, a closer observation of the Road dataset shows that a high Yieldex mean ($\tilde{Y}_i$ = 7.0) is mostly influenced by an outstanding Yieldex value (Y_i = 17.3) for wheat production in 2002, which is associated with a large range in magnitude and a spatially well structured variation (**Figure 6.5**). This analysis may to some extent put in question the suggested opportunity for SSCM adoption in Road, perhaps accounting for knowledge gaps on the proper assessment of temporal variations across several crop seasons that could overtake the opportunity given by the stable and manageable spatial variation.

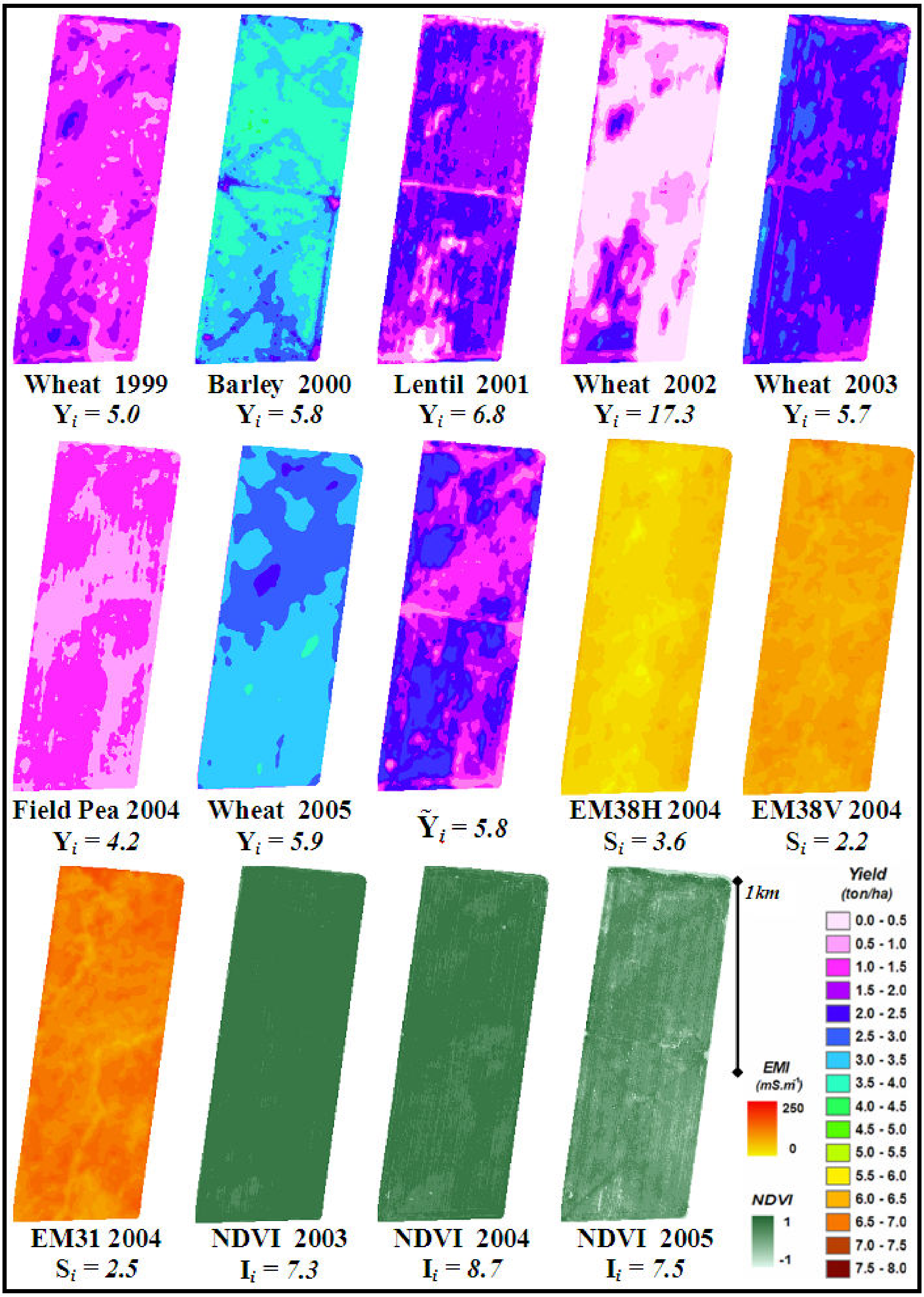

Figure 6.5: Maps of the field Road dataset showing relative opportunity.

For the field BT (135 ha) dataset, observations from 1998 to 2006 show a relative temporal variation of spatial patterns contrasting with a manageable production variation, accounting for large ranges of yield magnitude and some stable spatial features (**Figure 6.6**). The overall assessment of the production variation has mostly shown high indices, with a mean index over 5 crop-seasons ($\tilde{Y}_i = 8.3$) clearly driving final decision pathways towards differential crop management. In addition, all observations have shown indices (**Figure 6.6**) satisfying all conditional pathways (i.e. $S_i \geq 4$; $I_i \geq 8$; $Y_i \geq 5$; and $\tilde{Y}_i \geq 6$) of the SSCM adoption decision model (**Figure 6.2**). Therefore, opportunities to consider other specific multiplatform investments can be also observed, for examples EM38H variation patterns indicating persistent areas of lower and higher yield across different crops (sorghum, lentil, and wheat) or in-season temporal NDVI indices readily reflecting for the opportunity in wheat crop variation in a very dry season (2006).

Located in the Riverine region, the field WC (100 ha) is another example of an overall suitability for differential management adoption ($\tilde{Y}_i = 8.6$), which presents a less intense temporal variation, a consistent match of EC_a variation patterns with the final production variation, and strong correlations between high NDVI and yield variation indices. In part, these characteristics present a similar analysis to the one for field BT in the CFI region, showing conformity of the proposed decision model for production systems under different agronomic conditions. The kriged yield maps for field WC (1999 to 2004) in **Figure 6.7** show in the 2000 an average yield variation ($Y_i = 5.5$) of wheat, that can be observed with a large range in the magnitude of variation (up to 5 ton/ha) contrasting with a poor spatial structure due to scattered patterns in yield variation. The particular decision pathway for the use of EMI ($S_{i\_3IV} \geq 4.2$) would be satisfied with EMI measures in 2004 ($S_{i\_3IV} = 4.6$), from which visual matching between spatial patterns of EC_a (2004) and canola yield variations (i.e. 1999, 2001, and 2003) can be observed (**Figure 6.7**).

For field 44 (130 ha) in the Riverine region, the available dataset from 2000 to 2005 may have shown a less precise match between quantitative variation measures and visual interpretations (**Figure 6.8**). The overall analysis shows a strong within-field temporal variation across six years of diverse crop variety (canola, wheat, triticale, and barley), which mostly accounts for average index values.

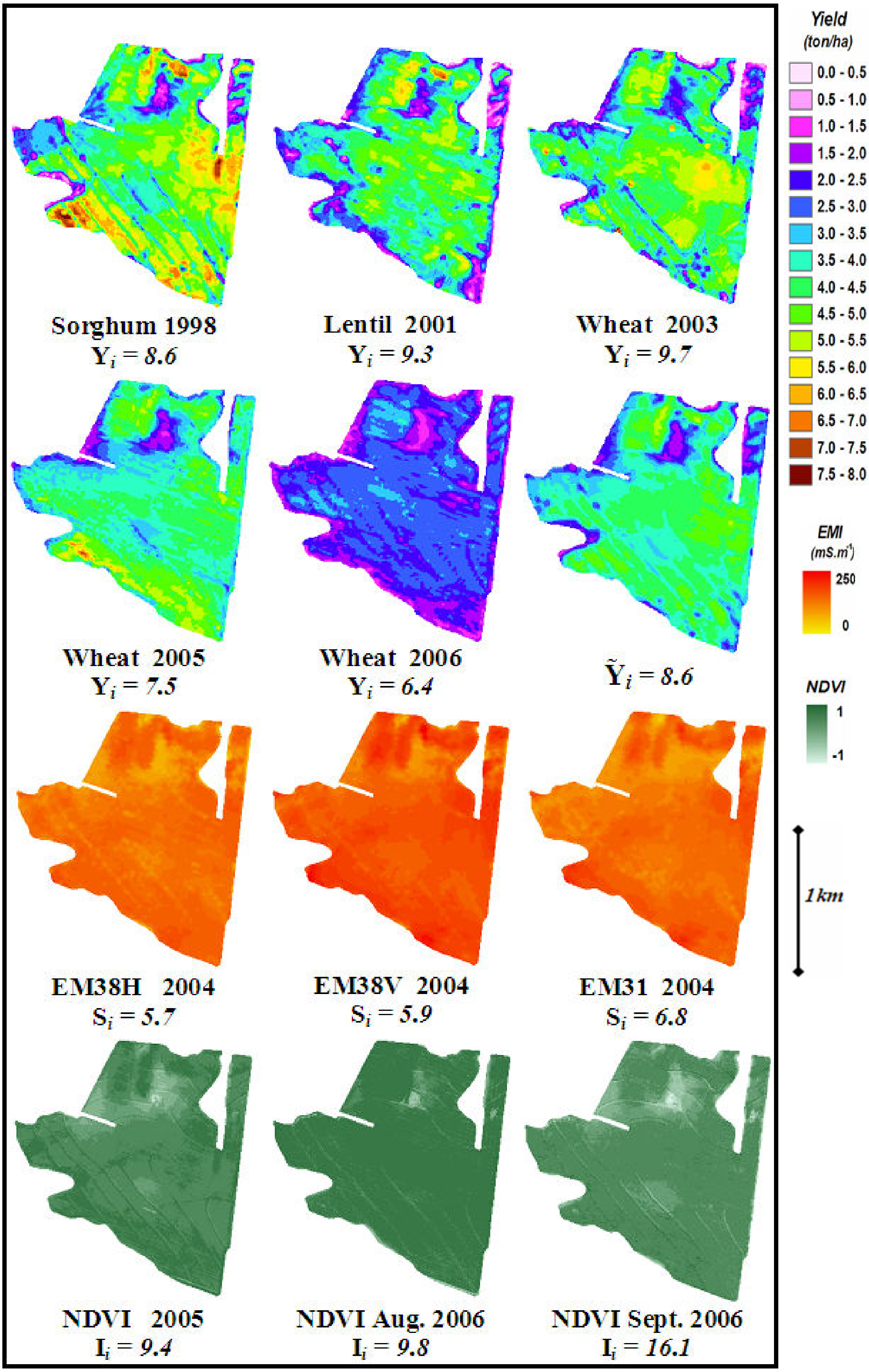

Figure 6.6: Maps of the field BT dataset showing high opportunity for spatial-temporal monitoring.

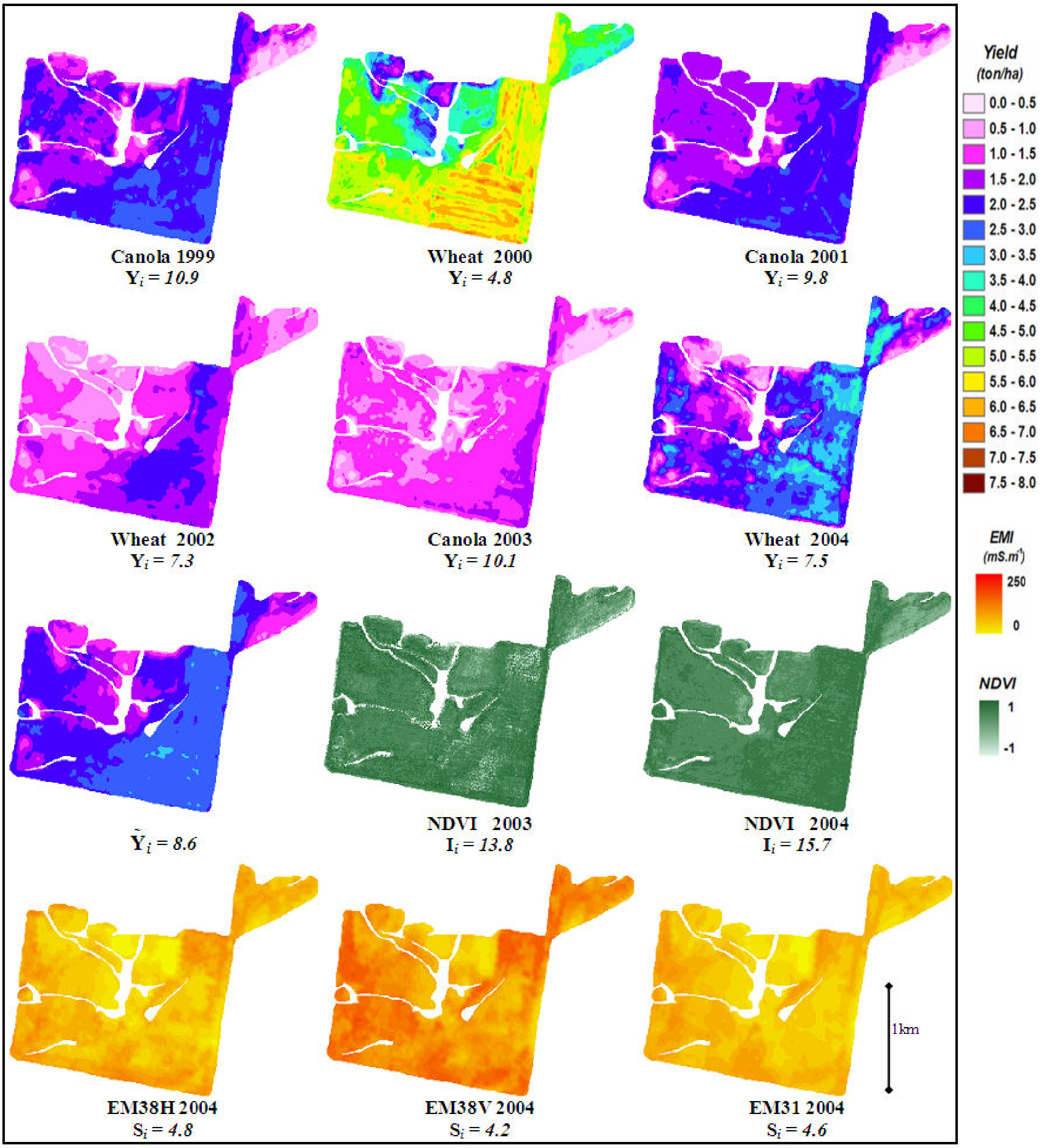

Figure 6.7: Maps of the field WC dataset (1999-2004) showing higher opportunity.

Following the analysis of adoption pathways proposed in the decision model (**Figure 6.2**) for yield monitoring investments, the field 44 (**Figure 6.8**) would have 5 years of initial adoption, from 2000 to 2004, fully satisfying annual thresholds for adoption ($Y_i \geq 5$) and strongly suggesting differential crop management over 6 years ($\tilde{Y}_i = 6.7$).

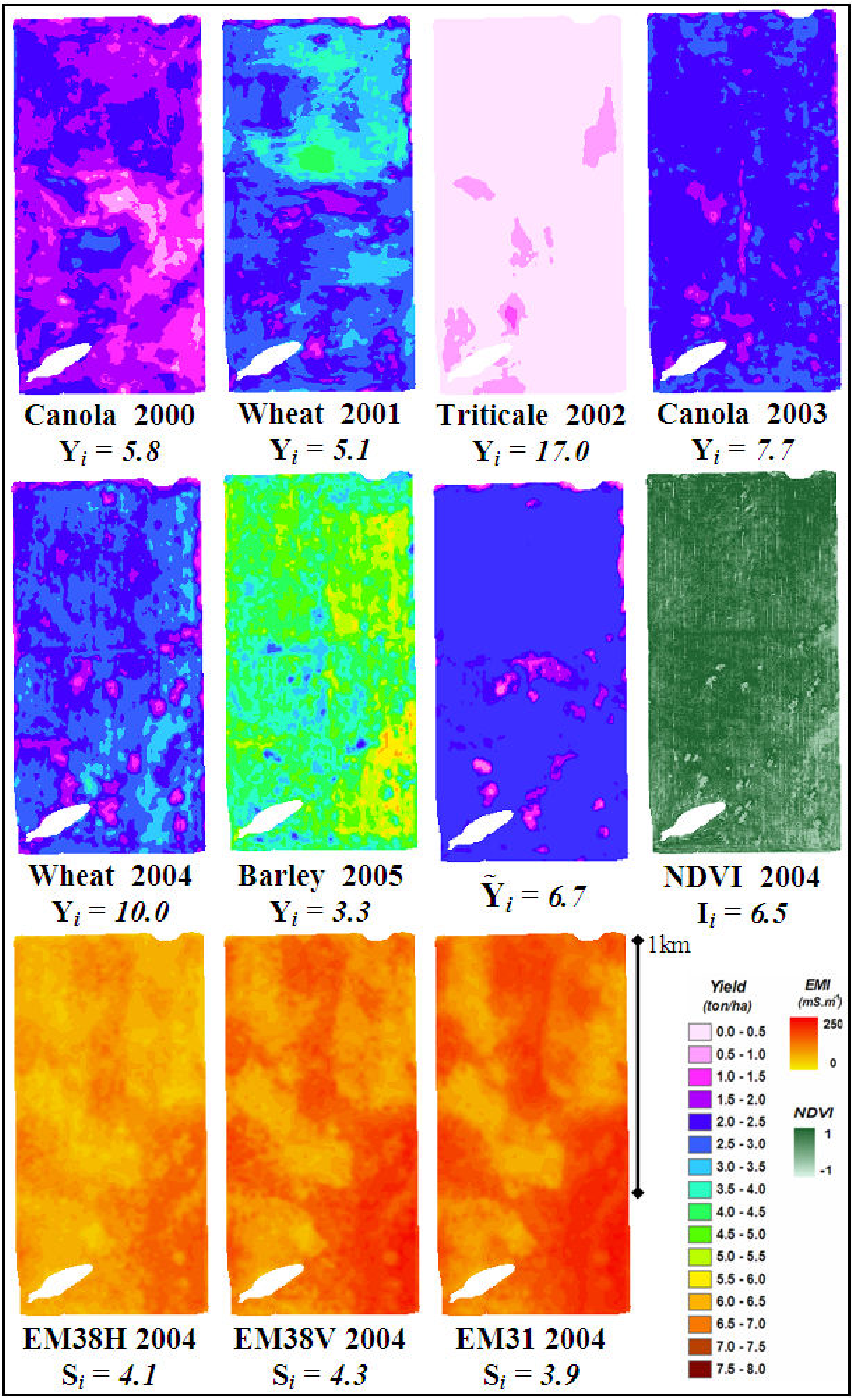

Figure 6.8: Maps from the field 44 dataset (200-2005) showing higher temporal variation.

Additional monitoring investments in 2004 would have shown average opportunity given by soil EC_a variations (i.e. S_{i_38H} = 4.3, S_{i_38V} = 4.1, and S_{i_31V} = 3.9), just about to support differential management ($S_i \geq 4$), and a NDVI index (I_i = 6.5) matching the minimum I_i giving opportunity in crop imagery variation ($I_i \geq 8$) which is latterly confirmed by a final wheat production variation of lower index (Y_i = 4.8) (**Figure 6.8**). The NDVI index has strongly matched the average opportunity in wheat production variation, visually and numerically, just supporting specific decision pathways as predicted for the Riverine region (**Figure 6.3**). A $\tilde{Y}_i$ = 7.0 over 6 years is influenced by an outstanding index value for Triticale in 2002 (Y_i = 17.0), otherwise mostly showing average opportunities (**Figure 6.8**). In face of a strong temporal variation in the field 44, this relative spatial opportunity could question its priority for new SSCM investments, once considering other potential fields of the Grandview Farm at initial phases of adoption, as field 19 with one year of yield monitoring (Y_i = 5.6).

Another way to analyse the applicability of the proposed decision model is to evaluate, over the available dataset for the Swamp field (113 ha), how the opportunity for adoption would have been better optimized by step wise pathways of adoption. The overall observation of maps in **Figure 6.9** suggests very strong predictions from EMI and NDVI variation indices; however it has opportunity measures that just match thresholds towards new investments in spatial-temporal monitoring of crop variation (i.e. $S_i \geq 4$ and $I_i \geq 8$). This suggests that an optimal adoption pathway would start with EMI and imagery monitoring in 2003 given support on manageable variability of canola and wheat crops in 2003 and 2004 respectively. Average soil and imagery variation indices in 2003 (i.e. $S_{i\_38H} \geq 3.6$ and I_i= 8.9) would have in principle predicted a marginal opportunity in the final production spatial variation of chick pea (Y_{i_2003} = 4.9) and wheat (Y_{i_2004} = 4.2). Finally, a third year of yield monitoring characterizing a high magnitude of wheat variation of very random spatial occurrence (Y_{i_2005} = 2.9) would discourage further spatial assessments ($\tilde{Y}_i$ = 4.0) in face of predominantly temporal variations. Therefore, the opportunity for investments of in-season imagery monitoring for temporal assessments of crop variation would be mostly advised for this field.

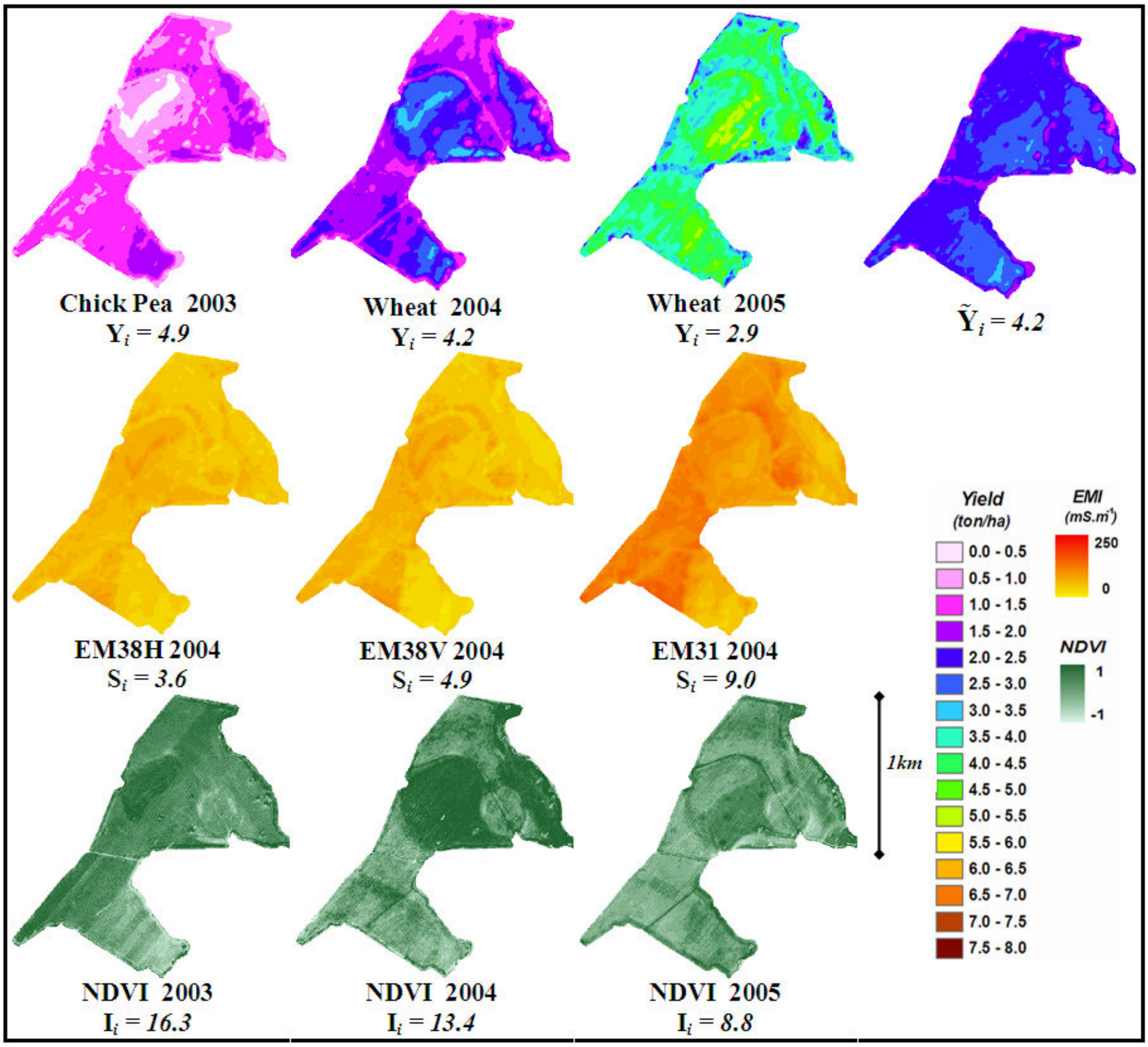

Figure 6.9: Maps for field Swamp (2003-2005) showing higher temporal variation.

Another example where the strong temporal variation has mostly promoted low opportunity for single year and average yield variations is given in field Blackflat (42 ha). The monitoring dataset (1998 to 2006) for this field with respective variability indices are shown in **Figure 6.10**. This field is characterized by strong temporal variations for large ranges of yield magnitude variation, which have not shown any structured spatial variability across 8 years of yield monitoring ($\tilde{Y}_i = 4.0$). In addition, very low EMI and imagery indices further support a spatial variation mismatch observed between crop yield, EC_a and NDVI maps (**Figure 6.10**). The lack of SSCM opportunity as related to spatial variations is observed in this field having most of the variation indices well bellow averages (i.e. $Y_i \leq 5$, $S_i \leq 4$, & $I_i \leq 8$), but wheat yield in 1998 ($Y_i = 6.8$). This case would suggest other field's priority for investments as previously discussed in this section.

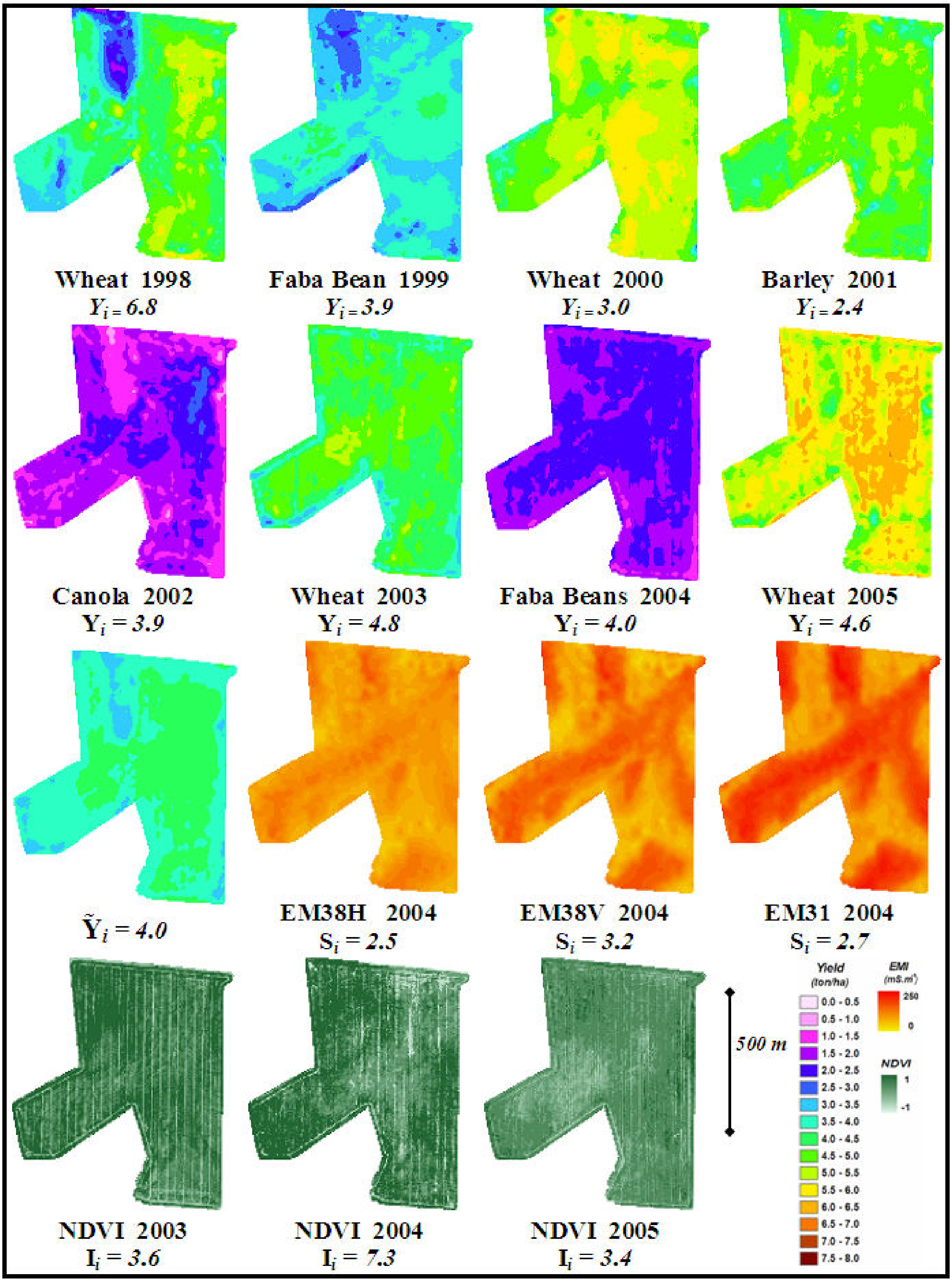

Figure 6.10: Maps for field Blackflat (1998-2005) showing higher temporal variation.

An overview of the historical adoption of SSCM technology is given in **Table 6.2** for the selected fields, where the historical adoption of SSCM technology of several fields support with real numbers the threshold analysis patterns introduced in **Figure 6.2**. The opportunity of using alternative indices can be observed with the matching of decision thresholds provided by the decision model. Following the whole-farm analysis ranking fields by farm as summarized in the analysis of crop yield variation (**Table 4.8**) and the application of the decision model in **Section 6.4.2**, the use of the EMI and imagery datasets would characterize better decisions for some of the historical pathways of adoption. As an example, investments in the field Black Flat of Clifton Farm could be redirected to Top D paddock where the previous use of EMI indices would have shown a better opportunity of investments. A better adoption strategy would also be possible for Tarnee, where both EMI and imagery indices would show better opportunity for field BT rather than for Comet B or Karret, now clear after 8 years of yield monitor investments. Other positive pathways of decision for the better opportunity of fields by farm using alternative sensors are given for the Brook Park and Grandview farms with better averages for fields that received more investments.

6.5 - Concluding remarks

This chapter has introduced a decision model that aims to incorporate simple quantitative methods within the main stream of farm decision processes to assess the opportunity for the adoption of PA technology. Strategic adoption pathways are associated with the opportune use of several field monitoring technologies that may support optimal investments in differential crop management.

A decision model supporting SSCM adoption is suggested using the simple decision analysis technique of dendograms. The model diagram identifies particular adoption phase branches and describes the associated decision strategy alternatives that minimize investment risks, by accounting for the spatial and temporal variation in crop production. Opportune pathways for the adoption of site-specific management are evaluated through decision nodes where expected thresholds are to be satisfied by minimum indices obtained from crop variation assessments. From the decision nodes, outcomes branch through further decision pathways that determine an optimized adoption strategy as based on averaged index values obtained from the historical Australian datasets previously discussed in **Chapters 4** & **5**.

Table 6.2: Step-wise PA adoption using the opportunity given by different indices.

Farm	Field	Yield Monitor									EMI			NDVI		
		1st	2nd	3rd	4th	5th	6th	7th	8th	$\tilde{Y}_i$	38H	38V	31V	1st	2nd	3rd
Brook Park	Road	5.0	5.8	6.8	17.3	5.7	4.2	5.9		**5.8**	3.6	2.2	2.5	7.3	8.7	7.5
	Bills	5.7	6.3	4.7	5.2	-	-	-	-	**5.5**	3.3	2.9	4.9	3.1	9.3	
Tarnee	BT	8.6	9.3	9.7	7.5	6.4	-	-	-	**8.6**	5.7	5.9	6.8	9.4	9.8	16.1
	Comet B	10.8	3.7	7.4	10.3	6.3	6.8	5.1	7.1	**7.0**	2.5	3.7	3.0	9.0	12.8	
	Karret	11.0	6.2	4.1	4.4	5.7	-	-	-	**5.7**	-	-	-	18.1	-	-
	TC	6.4	3.8	9.3	5.4	7.8	7.2	-	-	**6.8**	-	-	-	10.1	-	-
Glenmore	WC	10.9	4.8	9.8	7.3	10.1	7.5	-	-	**8.6**	4.8	4.2	4.6	13.8	15.7	-
	WA	4.1	4.0	7.7	7.5	6.4	8.3	-	-	**7.0**	4.1	3.2	3.5	7.6	-	-
Grandview	44	5.8	5.1	17.0	7.7	10.0	3.3	-	-	**6.7**	4.1	4.3	3.9	6.5	-	-
	12	7.0	3.7	2.7	6.6	4.5	-	-	-	**4.5**	3.5	3.4	3.3	5.5	-	-
Bearbung* & Kiewa	Swamp	4.9	4.2	2.9	-	-	-	-	-	**4.2**	3.6	4.9	9.0	16.3	13.4	8.8
	Doolies	6.7	10.5	10.6	6.2	3.8	-	-	-	**6.7**	2.0	3.3	5.4	6.5	11.4	7.6
Clifton Farm	Black Flat	6.8	3.9	3.0	2.4	3.9	4.8	4.0	4.6	**4.0**	2.5	3.2	2.7	3.6	7.3	3.4
	Top D	5.2	5.2	3.8	5.2	-	-	-	-	**5.2**	3.7	4.7	5.3	8.6	7.3	-
	Barn	4.8	4.1	-	-	-	-	-	-	**4.4**	-	-	-	-	-	-

* Same owner farms.

The Yieldex method is used as a utility function when determining the expected value at specific decision nodes when addressing crop variability questions in different phases of PA adoption. Although the utility function is based on the analysis of several variogram model fitting parameters, the decision model has proved to be easy and flexible to follow through all its branches. This robust mathematical method that also responds to strong non-stationary data, once automated, can provide simple simulation numbers that may facilitate the individual decision process and the inference of practical management knowledge.

A series of decision analysis using actual production variability information from selected broad-acre fields are discussed in **Section 6.4**, showing an effective decision process flow through all suggested pathways. Results have mostly matched the actual potential for SSCM adoption as observed in spatial-temporal variations and estimated economic returns. Kriged production maps are displayed in single standardized legends for crop yield, soil EC_a, and NDVI. They provided visual interpretations matching adoption pathways based on the opportunity indices computed from the final production data across different crops, farms, and regions (**Figures 6.5 to 6.10**).

The ability to determine alternative decision strategies relies on a significant number of correlated observations. The limited datasets available with homogeneous distribution across crops, farms, and regions have imposed on this preliminary decision model a few branches that are directly related with the access to continuous monitoring technology. Aiming to support future efforts defining new decision tree branches for the adoption of SSCM, a tentative table is suggested quantifying the minimum requirements for different types of SSCM monitoring observations, which can support effective decision making at different decision scales. The availability and the improvement of this type of basic information may be of great support when increasing efficiency in SSCM adoption processes.

The Activity Diagram introduced in **Section 6.3.4** translates the simple decision model diagram into standardized notations for system modelling and design, which can facilitate composition and reuse of the proposed decision model. This system design diagram describes sequences of functional activities of the decision-making process, also illustrating the importance of different system functional perspectives representing the conceptual model abstraction.

Finally, a simple and straight forward decision technique is presented; guiding individual decision-making through numerical indices obtained from actual production systems. Decision pathways for SSCM adoption are expected to contribute to a better quality of information that can reduce uncertainty related to spatial-temporal crop yield variation.

Chapter 7

Evaluating the opportunity of differential interventions for Nitrogen application using zone management

Summary

It is now widely accepted that a proper delineation of within-field areas that are subject to a unique combination of crop production influencing factors would allow more accurate management of inputs. Furthermore, the consideration of multi-temporal crop production responses in combination with other production factors is expected to determine zones for crop management that may better conform to strong temporal yield variations and minimize investment risk for the adoption of SSCM technology.

This chapter addresses the evaluation of zone management methods based on *k*-means clustering and morphology-based segmentation. In particular, an integration of the watershed transformation, multiresolution, and grow region algorithms are applied with multiple-year yield maps. It is suggested that object-oriented image segmentation algorithms may support an optimized delineations of MZs, in particular in crop fields of strong spatial yield variation.

An economic evaluation is conducted as a simple way of comparing zone delineation methods applied to field interventions for variable-rate fertilizer applications. Advantages and penalties to zone management of Nitrogen are suggested for procedures that consider 2, 3, and 4 management classes. Financial advantages are based on different values per zone area and the occurrence or not of class area predominance. Penalties are estimated using the cost of Variable Rate Treatment (VRT) services as per meter of required change in application rate, accounting for the number of machinery crosses over the total length of borders between zones. Prices refer to previous work in site-specific Nitrogen intervention in wheat crops. Results show potential for the use of segmentation methods for optimized delineation of MZs. Multiresolution segmentation with a watershed algorithm has systematically resulted in greater net worth for differential zone management.

Finally it is concluded that composite segmentation methods also based on object-oriented concepts have potential application for zone management delineations that can better support functional descriptions of spatial variation patterns. It is suggested that object-oriented segmentation could better support zone management delineations for fields of strong spatial-temporal yield variation.

7.1 - Introduction

Strategies for crop management unit delineation have long been investigated at the field level with the aim of improving fertilizer applications according to local differences in crop yield potentials. Several technological tools and agronomic management approaches have been considered to address this goal (Fridgen *et al.* 2004), mainly involving soil grid sampling (Sawyer, 1994; Fleming *et al.*, 2000), image processing (Mulla *et al.*, 2000), topographic and landform segmentation (Franzen *et al.*, 1998; Martin & Timmer, 2006), crop growth models (Miao *et al.*, 2006), different attribute based clustering and fuzzy classification methods (Fridgen *et al.*, 2000; Van Alpen & Stoorvogel, 2000; Shatar & McBratney, 2001; Li *et al.*, 2007). Still, only a few studies have been undertaken to compare or evaluate this diverse range of solutions (Whelan, 2005).

Early PA approaches for Variable-Rate Application (VRA) of fertilizers based on intensive discrete soil sampling grids have considered that all areas in a field have the same yield potential (Franzen *et al.*, 1994), which could be reached by applying at each sampled point the optimum amount of agrochemicals or fertilizes such as Nitrogen (Ferguson *et al.*, 1996) or Phosphorus and Potassium (Mallarino & Wittry, 2004). However, this approach has proven to be economically and operationally flawed, and it has been overcome by the idea of identifying within-field areas of similar yield potentials (McBratney & Whelan, 2001).

The increasing use of proximal sensing and other new SSCM technologies has brought greater opportunity to delineate smaller areas within a field, which may characterize zones of distinct soil, slope and microclimate types (Luchiari *et al.*, 2000). These zones are usually called MZs and differ from the term management classes, whereby one zone is a spatially contiguous area containing only one management class (Taylor *et al.*, 2007). Approaches aiming for the optimal delineation of management zones have considered production influencing factors such as soil colour, soil EC_a, crop yield, crop reflectance, and topography. Input for these processes have traditionally used data generated by high resolution sensors for digital elevation models, multiple-year yield mapping, crop canopy reflectance and soil properties from remote and proximal sensing.

Statistical classification procedures that use *k*-means (Shatar & McBratney, 2001) or fuzzy *k*-means (Van Alpen & Stoorvogel, 2000) clustering methods are commonly applied as a tool for delineating potential management zones. Usually applied for single field-season, this decision support approach often uses yield averages (Jaynes *et al.*, 2005) with some advantage in combining other crop production factors, such as soil electrical conductivity and elevation (Whelan & McBratney; 2003) when using PCA.

In contrast to comprehensive single field-season studies, limited solutions have been suggested for the use of multiple-year yield maps. The need to consider several years of yield mapping is now well accepted, as its use in the characterization of MZs can minimize the risk associated with strong temporal yield variations (Schepers *et al.*, 2005; Jaynes *et al.*, 2005). However, methods for using multiple-year inputs are still maturing (Whelan, 2005).

Whether to search for the optimal number of cluster classes (Vrindts *et al.* 2005) or for the number of contiguously manageable polygons (Khosla *et al.*, 2002) is still a great matter of investigation. According to Fraisse *et al.* (1999), the optimal number of zones sub-dividing a field may vary from year to year as a function of weather and the crop planted. Recent results in Schelde *et al.* (2007) reinforce the lack of benefits from increasing the number of classes beyond four. Still, Shatar & McBratney (2001) have argued that clustering methods often produce non contiguous subdivisions, increasing the number of small, random zones in contrast to the optimal use of VRT over a few, larger areas.

7.2 - Opportunity in zone management

In PA, the use of delineation techniques for management zones has mostly focused on thresholding-based methods (Kitchen *et al.*, 1998), mostly considered hard- and fuzzy-clustering. Thresholding algorithms used include: isodata segmentation (Fraisse *et al.*, 1999), fuzzy dynamic thresholding (García-Pérez *et al.*, 2001, García-Alegre *et al.*, 2001), and several unsupervised clustering into a predefined number of classes (Vrindts *et al.* 2005).

Simply stating, these are suggested as the pixel-based process whereby a set of entities (e.g. crop yield, median crop yield, soil EC_a, and PCA) is divided into several clusters of similar class membership to each other and different from the members of the other clusters. According to Hartigan (1975) clustering methods very often yield different results, making their classification and evaluation a difficult task. Although analysed in terms of their computational performance (Zaït & Messatfa, 1997), a few studies have been conducted to compare or evaluate the diverse range of results (Whelan, 2005). Processes using the current clustering have been documented in Taylor *et al.* (2007) in a step wise protocol for the delineation of site-specific management zones.

Although a variable number of zones can be expected in a field from year to year (Fraisse *et al.*, 1999), Schelde *et al.* (2007) uses a management zone analyst software to combine several attribute maps and generate 500 zone delineations through fuzzy *k*-means clustering analysis. Results in Schelde *et al.* (2007) considered zones based on 2 to 8 management classes and suggest no benefit from increasing the number of classes beyond four (4). Their findings agree with earlier results in Fridgen *et al.* (2000), whereby no advantage of dividing a field into more than four management zones was obtained.

Alternatively, hybrid segmentation approaches have been suggested (Rushing *et al.*, 2002; Frucci & di Baja, 2007; Frucci *et al.*, 2007; Wang, 2008) for generic image segmentation and pattern recognition studies and data mining applications in computerised food technology (Zheng & Sun, 2008). Many have considered the classic watershed transformation algorithm (Beucher & Lantuejoul, 1979; Vincent & Soille, 1991; Meyer & Beucher, 1993) in conjunction with associative and behavioural functions of spatial objects. Also, hybrid solutions usually combine standard segmentation algorithms either to conform to specific feature extraction requirements (Li *et al.*, 2005) for hierarchical- (Fuh *et al.*, 2000) and region- (Pitas & Cotsaces, 2000) based segmentations.

PA experiments that use segmentation approaches are not new for operational robotic vision in SSCM (García-Alegre *et al.*, 2001), but just recently has been given attention for strategic decisions in the delineation of management zones (Roudier *et al.*, 2008). The watershed algorithm (Beucher & Lantuejoul, 1979) has been introduced to morphological image processing based on immersion simulation concepts originally from topography (Vincent & Soille, 1991; Meyer & Beucher, 1993). In morphological processing images are represented as topographical surfaces on which the elevation of each point is assigned as the intensity value of the corresponding pixel attribute (Soille, 2000). A clear explanation of the watershed transformation is given in Roudier *et al.* (2008), when modifying the original algorithm, as based on the gradient, with constraints of site-specific zone management. Roudier *et al.* (2008) conclude that the objected-oriented approach has proved relevant to zone delineation, but they highlight that the use of standard morphological-based segmentation algorithms in PA have to be specifically adapted to cope with over-segmentation effects

7.3 – Evaluating an object-oriented approach to delineate management zones.

This section describes a simple net worth assessment proposal for a single field intervention for variable-rate fertilizer application. This preliminary economic evaluation uses a simple way of looking at comparing zone delineation methods. Economic advantages and penalties to zone management of site-specific Nitrogen interventions with reference to grain crops are suggested for comparing classic image classification and object-oriented segmentation procedures that consider 2, 3, and 4 zone classes. Zone management delineation methods are based on *k*-means clustering; *k*-means clustering with grow region; and morphology-based segmentation algorithms. In particular, a new composite procedure combining multiresolution, watershed transformation and grow region segmentations is evaluated when applied for multiple-year yield maps.

Multiple-year maps are here considered as better characterizing more stable spatial and temporal crop production variations. Inputs for zone delineation procedures are median yield and first PCA component (PC1) maps that were computed over all seasons of available yield data from selected broad-acre grain crop fields. Methods for basic yield data organization, analysis, and interpolation used in this work have mostly followed preliminary procedures suggested by Taylor *et al.* (2007) in a protocol for a cost-effective approach to management zone delineations. However, the use and evaluation of object-oriented segmentation algorithms, as proposed here, have required new procedures to be prototyped in a proprietary environment. Although contradicting the freeware approach in Taylor *et al.* (2007), a trial version of the Developer 7® software was downloaded from the Definiens AG Homepage (http://earth.definiens.com), being fully operational for the procedures used in this work.

For the evaluation of zone management delineation methods, three (3) fields have been selected from the historical dataset used in this thesis. Selection considered one field by different agronomic region (i.e. SPAA, CFI, and Riverine) and the opportunity for the adoption of SSCM in non-stationary spatial and temporal crop variation, as measured by the indices proposed in **Chapters 4** and **5** (i.e. Y_i, S_i, and I_i). The determination for the opportunity to zone management follows the net worth of variable Nitrogen applications for broad-acre grain crop fields as suggested in **Section 7.3.3**.

7.3.1 – Establishing input data for zone management delineation

Inputs for the three segmentation processes were multi-year yield maps (**Figure 7.1**), as it has been previously suggested for yield map averages by pixel to segment a field into similar temporal yield patterns (Jaynes *et al.*, 2005). This use of PCA is suggested as a technique showing the significance of the temporal variation altering yield spatial variations. Although suggested as yielding better results when combining other crop production factors (Whelan & McBratney, 2003) and landscape attributes (Schepers *et al.*, 2005), PCA components are calculated here only for yield data as a means of facilitating comparison between results using inputs of median yield and PCA maps. Results for inputs of median yield maps were analysed in relation to results for inputs of the first and second principal components (PC1 and PC2, respectively) over all years of available yield data (**Figure 7.1**).

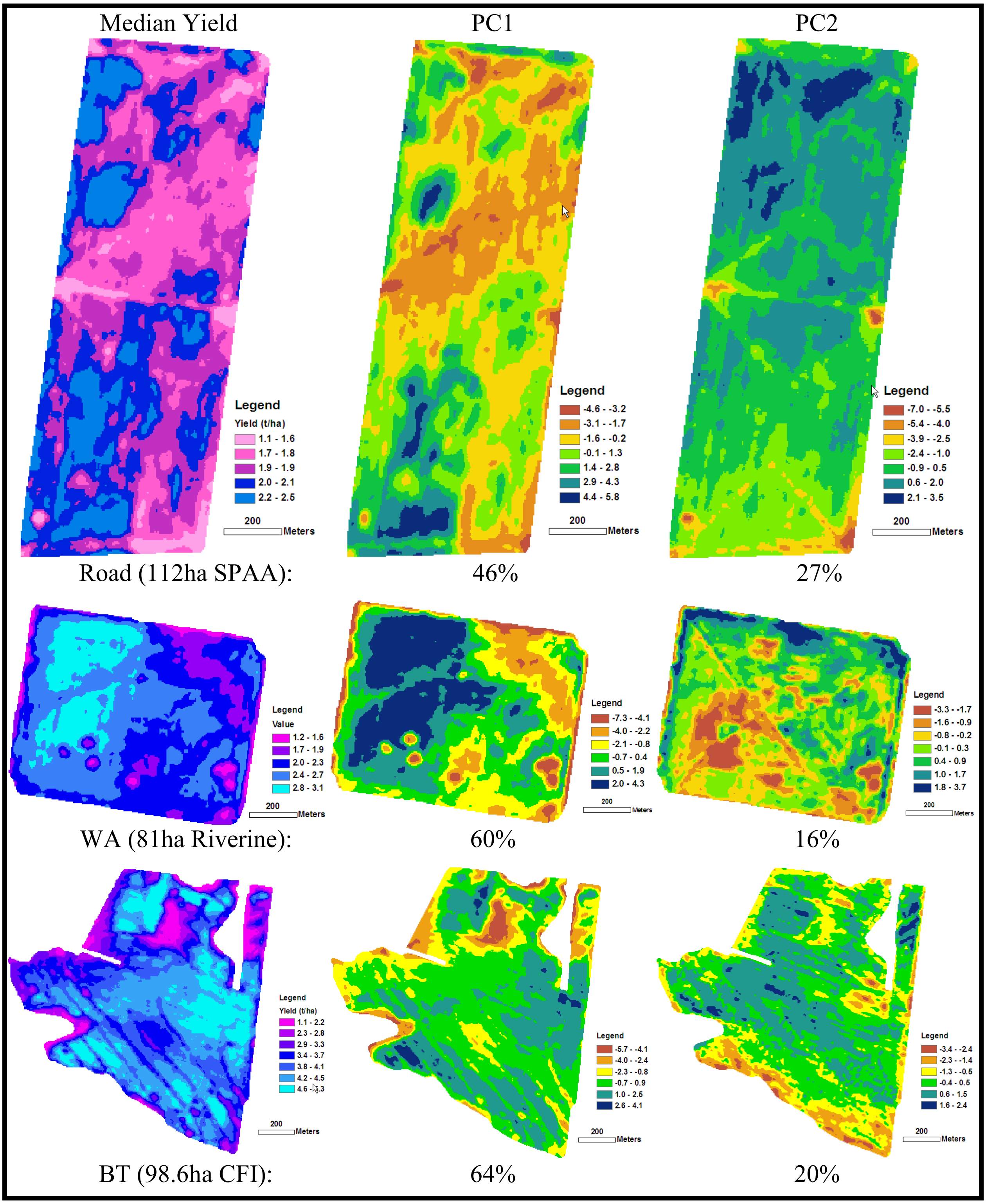

Figure 7.1: Multi-year yield maps of selected fields for median yield and two principal components considered in zone management delineation.

The preliminary evaluation has shown however, that PC2 appears to respond more to machinery footprints or historical changes in management (e.g. field boundaries and/or land use), adding little information that can be associated to actual crop production factors. Therefore, no further economic evaluation considering the PC2 as input was carried in this investigation.

The PCA was conducted using JMP 6.0 statistical software (SAS©, 2005), with results for first and second components exported as a text file. Principal components summarize the variation in the multivariate input for all years of yield monitoring. They are derived from an eigenvalue decomposition of the correlation matrix of the variables, where a component can be seen to represent a linear model of the multidimensional data (Esbensen, 2000).

Percents reported for first (PC1) and second (PC2) principal components measure the amount of variation in the input data that has been accounted by the component. The PCs are calculated using least square fit, meaning that PC1 will describe the largest part of the total variation in the input data. PCA outcomes are imported in ArcGIS (ESRI©, 2003), whereby raster maps are generated and exported in compatible format (.img) for inputs in Developer 7.0. The PC1 raster map is generated by feature to raster conversion and the median yield map is computed by raster calculation of yield averages by pixel. PCA components for the three selected fields (**Figure 7.1**) have accounted for PC1 and PC2 respectively as follows: 41% and 19% in field Road, 60% and 16% in field WA, and 64% and 20% in field BT.

7.3.2 – Classification and segmentation using multiple-years yield maps

This section summarizes the workflow of analysis for the evaluation of a new method of application that uses object-oriented image segmentation procedures in a commercially available IDE for image processing, Definiens Developer 7© (Definiens®, 2007), with detailed process tree code shown in **Appendix Section A1.3**. This solution has provided a powerful means for image object analysis and rule set development. By means of an interactive process design interface, rule sets could be easily prototyped and re-used to develop fast ruleware (image processing scripts) solutions for the three segmentation approaches considered for the economic net worth assessment.

The commonly used *k*-means clustering was the first segmentation procedure conducted, for comparison with the two other hybrid solutions also evaluated on their economic response. Initially, *k*-means clustering over the histogram of inputs is executed in a statistical software (JMP 6.0; SAS© 2005), for the standardization of results with previous work (Whelan *et al.*, 2007). Then the pixel-based class thresholding over image objects using object-based segmentation and classification algorithms in the IDE is performed. The chess board segmentation is defined with object size equal to 1, to simulate the same resolution of the input image as for standard pixel-based segmentations. Classification and region merging processes further generates *k*-means clustering outputs for 2, 3, and 4 cluster classes.

Simple hybrid segmentation has been considered for the second zone segmentation process, which combines thresholding- and region- based segmentation algorithms. It is a simple extension of the previous histogram clustering process, used for *k*-means segmentations, with an additional reshaping technique for grow region that executes splitting and merging operations into sub-objects in the image object domain and allows growing image objects into a larger space (Definiens®, 2007). This process is to evaluate the potential of using object reshaping techniques to address issues of non contiguous zones usually produced by clustering methods (Shatar & McBratney, 2001; Wang, 2008).

The third segmentation process has focused on the object-oriented image processing approach. It proposes an innovative composite segmentation approach that combines a multiresolution image segmentation method with other algorithms for watershed transformation and grow region, as standard versions available in the IDE. This process is to evaluate the potential of using a combination of image segmentation methods that could consider spectral and shape features of objects to improve zone management delineations, besides solving over-segmentation problems and seeding definitions when using the watershed and grow region segmentations.

Unsupervised multiresolution object segmentation was executed with process parameters that could generate small size objects preserving general patterns on the input (Definiens®, 2007). A multiresolution segmentation can be implemented with different scale parameters and segment homogeneity criterion (i.e. shape and compactness). This image segmentation method (Baatz & Schäpe, 1999) is an effective, but proprietary, technology whose full details haven't been public yet (Wang, 2008). By definition, the multiresolution algorithm applies an optimization procedure which locally minimizes the average heterogeneity of image objects for a given resolution that is determined by scale parameter constraints. The scale parameter is used to control the pixel merging process creating primitive objects, which stops a merge when the minimal parcel merging cost exceeds its power (Baatz & Schäpe, 2007). A given scale determines the maximum allowed heterogeneity for the resulting image objects. Consequently, for a given scale parameter more heterogeneous data will result in objects smaller than in more homogeneous data. By modifying the scale parameter value, the size of image objects will vary. The idea was to generate primitive image objects out of minimum homogeneous areas representing the related agronomic process involved (i.e. yield monitoring, approximately 100 m^2). This pre-processing step was expected to restrict the break down of areas bellow the smallest primitives when applying the following segmentation process. The use of the multiresolution segmentation was taken as the first step in the composite process for image information extraction, which would avoid over-segmentation issues as reported when using the standard watershed algorithm to zone management partitioning (Roudier *et al.*, 2008).

Settings for the next process using the watershed transformation algorithm have considered the minimum length factor that could further split sub-objects already generated by the multiresolution process, as generating sub-watersheds within broader image objects. After class assignments and merging procedures as required for the proper segmentation workflow in Developer 7©, a final grow region algorithm is applied to generalize and produce the final object-oriented segmentation results for zone managements considering 2, 3, and 4 classes.

7.3.3 – Advantages and penalties to zone management using a net worth analysis

Economic advantages and penalties to zone management of Nitrogen are suggested in Australian dollars per hectare ($/ha) by class for procedures that consider 2, 3, and 4 clusters of management classes. A criterion of different benefit values by management class follows the concepts in Robertson *et al.* (2008). Robertson *et al.* (2008) suggest that the economic advantage to zone over uniform management can be expressed as a continuous function of the yield difference between the lowest and highest yielding zones in a field, where the middle zone is equal to the mean of the low and high zones.

After the execution of the MZs delineation procedures zone areas and border lengths were extracted from object-feature tables obtained as result of the rule set work flow in Definiens Developer 7.0, which were used for the overall net worth computation of each delineation process detailed in **Section 7.3.2**. Finally, the net worth of variable Nitrogen application is simply calculated as the difference between advantages to zone management and penalty costs of Nitrogen interventions in relation to the number of times fertilizer rates are changed.

Advantages to zone management

Benefits considered in this investigation also assumed different classes, as shown in **Tables 7.1**, **7.2**, and **7.3**, and uses financial values as given in Robertson *et al.* (2008) for the financial significance of the variation in potential yield of wheat crops in Western Australia. Their evaluation estimates the potential benefits from yield monitor data in 199 fields and suggests economic advantage to three-class zone segmentation (i.e. low, standard, or high yield zones), in which standard figures are assumed (i.e. nitrogen cost = $1.2/kg & wheat price = $175/t).

Figures for the advantage to zone management in Robertson *et al.* (2008) considered a sensitivity analysis of the impact of relative sizes of management zones on the economic benefit ($/ha) to zone management for Nitrogen and Phosphorus on a three-class basis. Scenarios are then simulated suggesting different benefits ($/ha) to equally distributed area percentages between zones (33:33:33), a low class area predominance (70:15:15), or a high class area predominance (15:15:70). Sensitivity analysis relative to starting soil fertility status have also suggested different net benefits to four scenarios for starting soil fertility differences between zones. To keep coherence with segmentation processes that have only used multi-year yield inputs, benefits suggested in this work (**Tables 7.1**, **7.2**, and **7.3**) refer to the minimum ($0) and the maximum ($8) values for the advantages to zone management (Robertson *et al.*, 2008) found for the two scenarios in which no soil difference in nutrition (i.e. N and P) between the zones is incorporated. Results in Robertson *et al.* (2008) have shown that the larger the difference in potential yield between zones, the greater the economic benefit from zone management. These findings may support variable price assumptions in this investigation, such as detailed in **Table 7.1**, for a 2 class; **Table 7.2**, for a 3 class; and **Table 7.3**, for a 4 class scenario.

Table 7.1: The advantage to zone management considering 2 management classes.

Class	No predominance (AU$/ha)	Low yield predominance (AU$/ha)	High yield predominance (AU$/ha)
ZH (higher yields)	8	5	6
ZL (lower yields)	0	2	0

Table 7.2: The advantage to zone management considering 3 management classes.

Class	No predominance (AU$/ha)	Low yield predominance (AU$/ha)	High yield predominance (AU$/ha)
Zone 1 (higher yields)	8	5	6
Zone 2 (average yields)	4	3	3
Zone 3 (lower yields)	0	2	0

Table 7.3: The advantage to zone management considering 4 management classes.

Class	No predominance (AU$/ha)	Low yield predominance (AU$/ha)	High yield predominance (AU$/ha)
Very High	8	5	6
High	6	4	4
Low	2	3	1
Very Low	0	2	0

Penalties to zone management

Penalties attributed to differential crop management are estimated using the cost of VRT services as per meter ($/m) based on the required change in application rates when the machinery footprint crosses boundaries between different zone classes. Therefore, the overall penalty for a single field operation of variable Nitrogen application accounts for the number of machinery crosses over the total length of borders between management zones. For this, the total sum of the border length, in metres, between all zones of a segmentation process is divided by a operational swath width, assumed as 10m in this instance, and multiplied by the cost of a VRT consultancy service for N intervention as given by Bongiovanni *et al.* (2007) in US dollars for a protein content experiment in Argentina. The cost of US$ 6.00/ha for the VRT service is first converted to Australian dollars (AU$), in current exchange rates, and square metres (m^2), and further square rooted to provide figures in metres (AU$/m). A resulting price of AU$ 0.25 is then assumed per crossing of borders between different zone classes.

7.4 – Results for proposed methods

Results for the economic evaluation comparing the net worth to zone management have considered thresholding-based and morphology-based delineation methods with inputs of multiple-year crop production maps. Multiple-year crop information was considered as an effective source of strong spatial and temporal variations in crop yield, considering median yield and first principal component maps as reflecting different aspects of crop production factors and spatial crop variation patterns.

Although preliminary in nature, the proposed objective function characterizing the net worth of variable-rate Nitrogen management interventions has proved robust across different segmentation approaches and price assumptions. The idea to consider a simple net balance model which would consider the financial advantages, in relation to the contrast between yield means, initial soil fertility conditions and the relative size of each zone management classes, against the penalty for an increased number of times in which variable-rate equipment is activated to change fertilizer application rates has proved efficient. Prices given to the cost of VRA services are related to the overuse of variable-rate machinery associated with a larger total border length between different zones, which were easy to compute and could be directly related to a greater number of zone segments and/or an increased shape contours.

Outcomes from the three delineation procedures and net worth analysis are shown for 2, 3, and 4 classes by individual fields, as for: i) field Road (112 ha), SPAA, in **Figure 7.2** for median yield, **Figure 7.3** for PC1, and **Table 7.4**; ii) field WA (81 ha), Riverine, in **Figure 7.4** for median yield, **Figure 7.5** for PC1, and **Table 7.5**; and iii) field BT (135 ha), CFI, in **Figure 7.6** for median yield, and **Figure 7.7** for PC1, and **Table 7.6**.

Inputs for net worth analysis

The median yield map appears to preserve some zoning artefacts that can be related to procedures during field interventions (e.g. central line in field Road preserved by clustering outcomes, **Figure 7.2**). Such patterns are often associated with harvesting operation techniques (e.g. machinery footprints), adding inappropriate inputs for the delineation of crop production homogeneity. These zoning artefacts are not present in the PC1 input, as they are clearly isolated in the second component of the PCA (**Figure 7.1**).

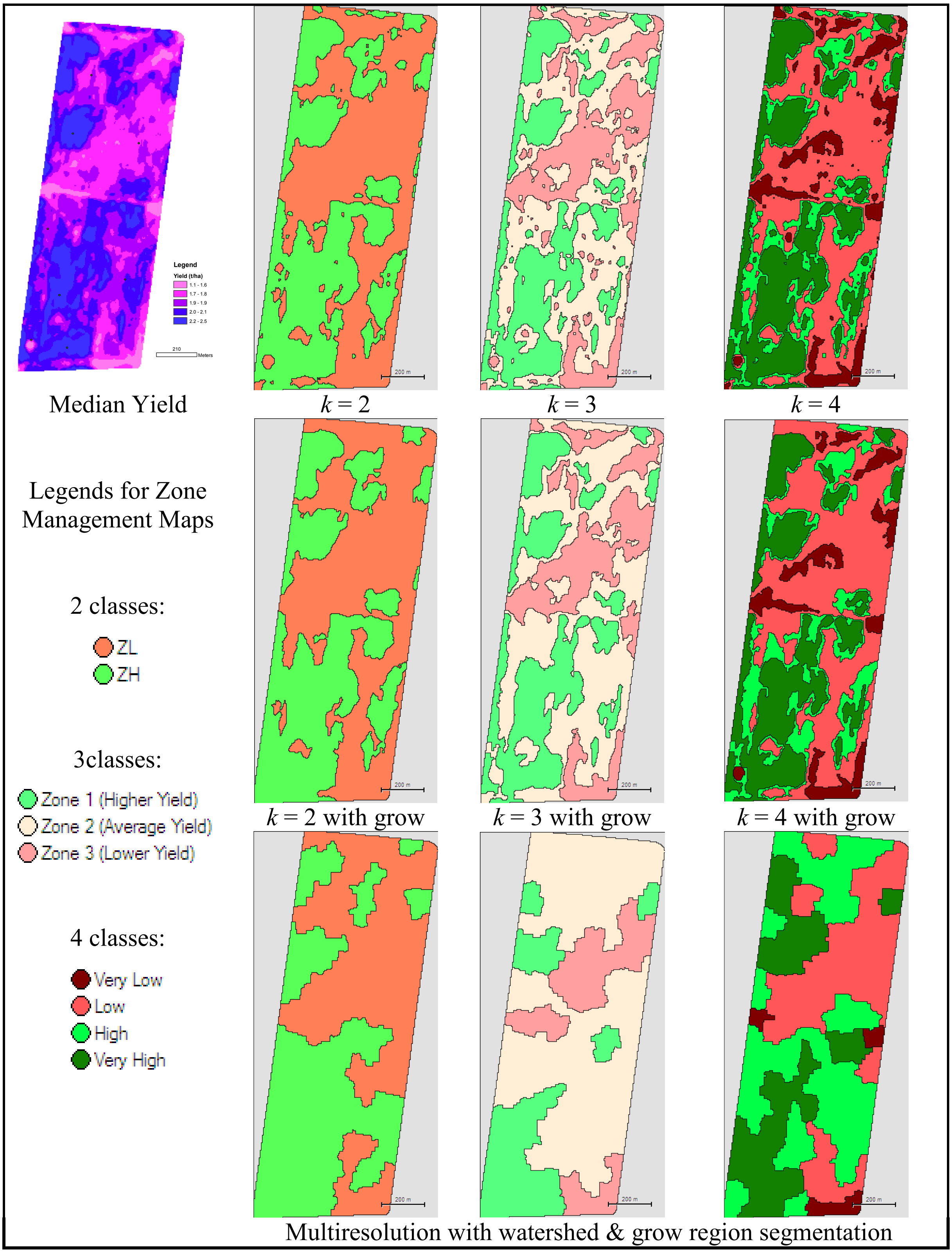

Figure 7.2: Management zones obtained by different delineation process for 2, 3, and 4 classes at field Road, using the median yield input map.

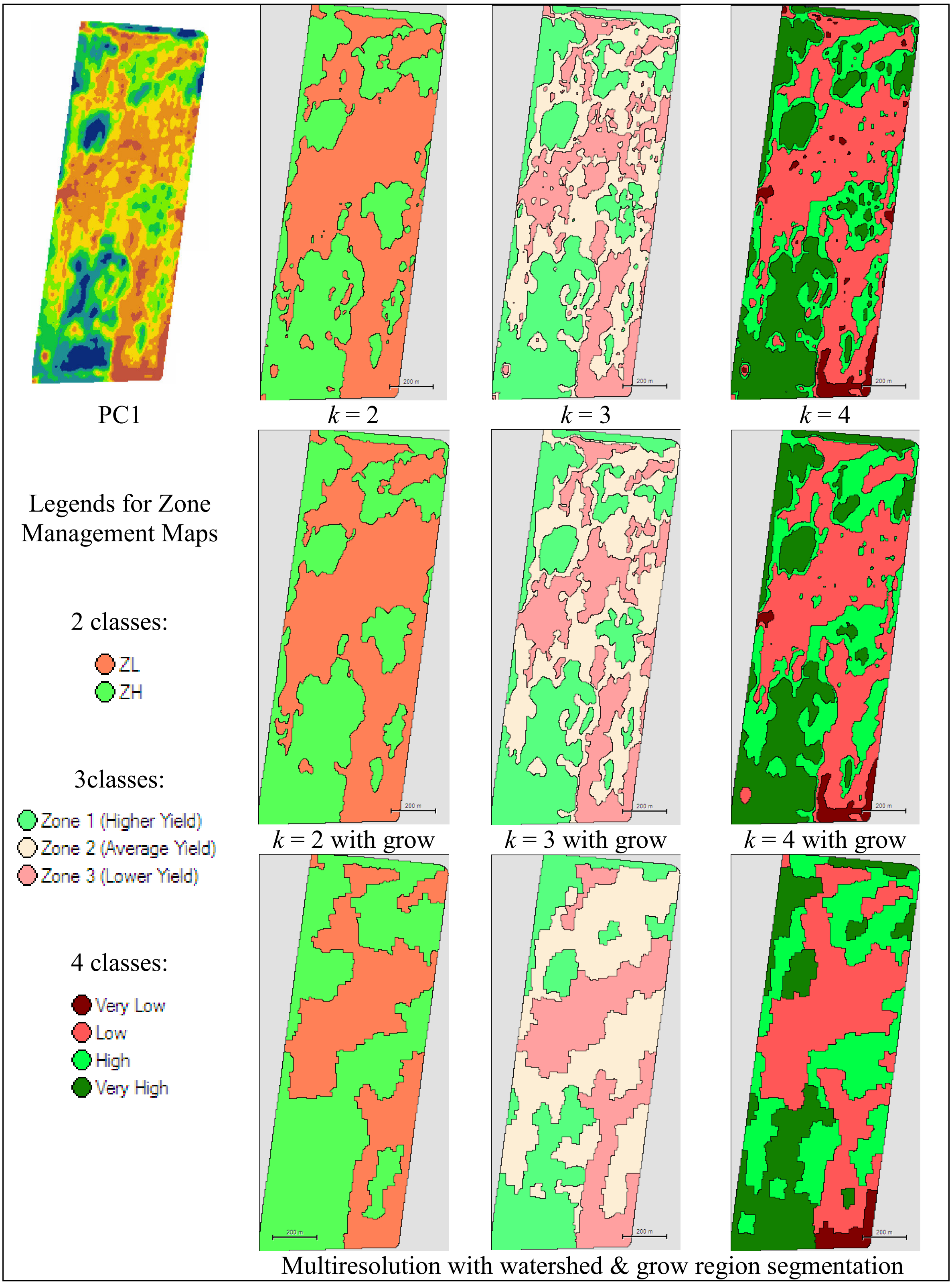

Figure 7.3: Management zones obtained by different delineation process for 2, 3, and 4 classes at field Road, using the PC1 input map.

Table 7.4: Net worth evaluation using the proposed method in this work when applied to management zones obtained from different clustering and segmentation outputs for field Road.

Input	Delineation		2 Classes	3 Classes	4 Classes
Median Yield	***k*-means**	**Advantage**	$ 410.40	$ 471.20	$ 347.30
		Borders (m)	16,200	26,650	30,255
		Penalty	$ 405.00	$ 665.13	$ 756.38
		Net Worth	$ 5.40	- $193.93	- $409.67
	***k*-means with grow region**	**Advantage**	$ 412.80	$ 476.00	$ 346.80
		Borders (m)	13,410	24,155	26,900
		Penalty	$ 335.25	$ 603.88	$ 672.50
		Net Worth	$ 77.55	- $127.88	- $325.70
	Multiresolution Watershed Segmentation	**Advantage**	$ 450.40	$ 466.40	$ 566.00
		Borders (m)	6,020	7,980	11,600
		Penalty	$ 150.50	$ 199.50	$ 290.00
		Net Worth	**$ 299.90**	$ 266.90	$ 276.00
PC1	***k*-means**	**Advantage**	$ 395.20	$ 480.00	$ 528.60
		Borders (m)	10,980	31,755	31,675
		Penalty	$ 274.50	$ 793.90	$ 791.88
		Net Worth	$ 120.70	- $313.88	- $263.28
	***k*-means with grow region**	**Advantage**	$ 397.60	$ 484.00	$ 531.20
		Borders (m)	9,215	23,820	22,196
		Penalty	$ 230.38	$ 595.50	$ 554.90
		Net Worth	$ 167.22	- $115.50	- $ 23.70
	Multiresolution Watershed Segmentation	**Advantage**	$ 524.80	$ 438.00	$ 535.60
		Borders (m)	9,355	13,500	15,735
		Penalty	$ 233.88	$ 337.55	$ 393.38
		Net Worth	**$ 290.93**	$ 100.50	$ 142.23

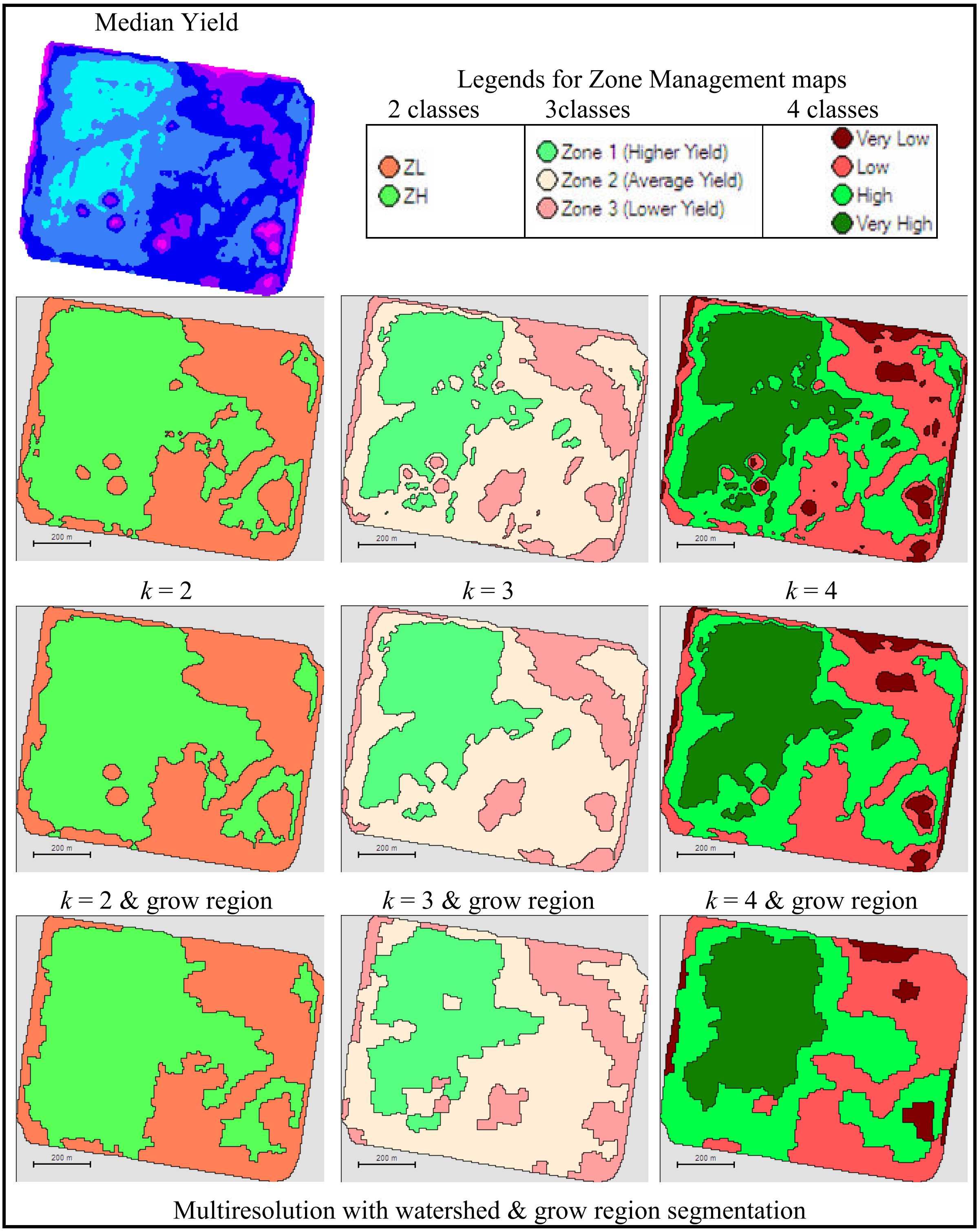

Figure 7.4: Management zones obtained by different delineation process for 2, 3, and 4 classes at field WA, using the median yield input map.

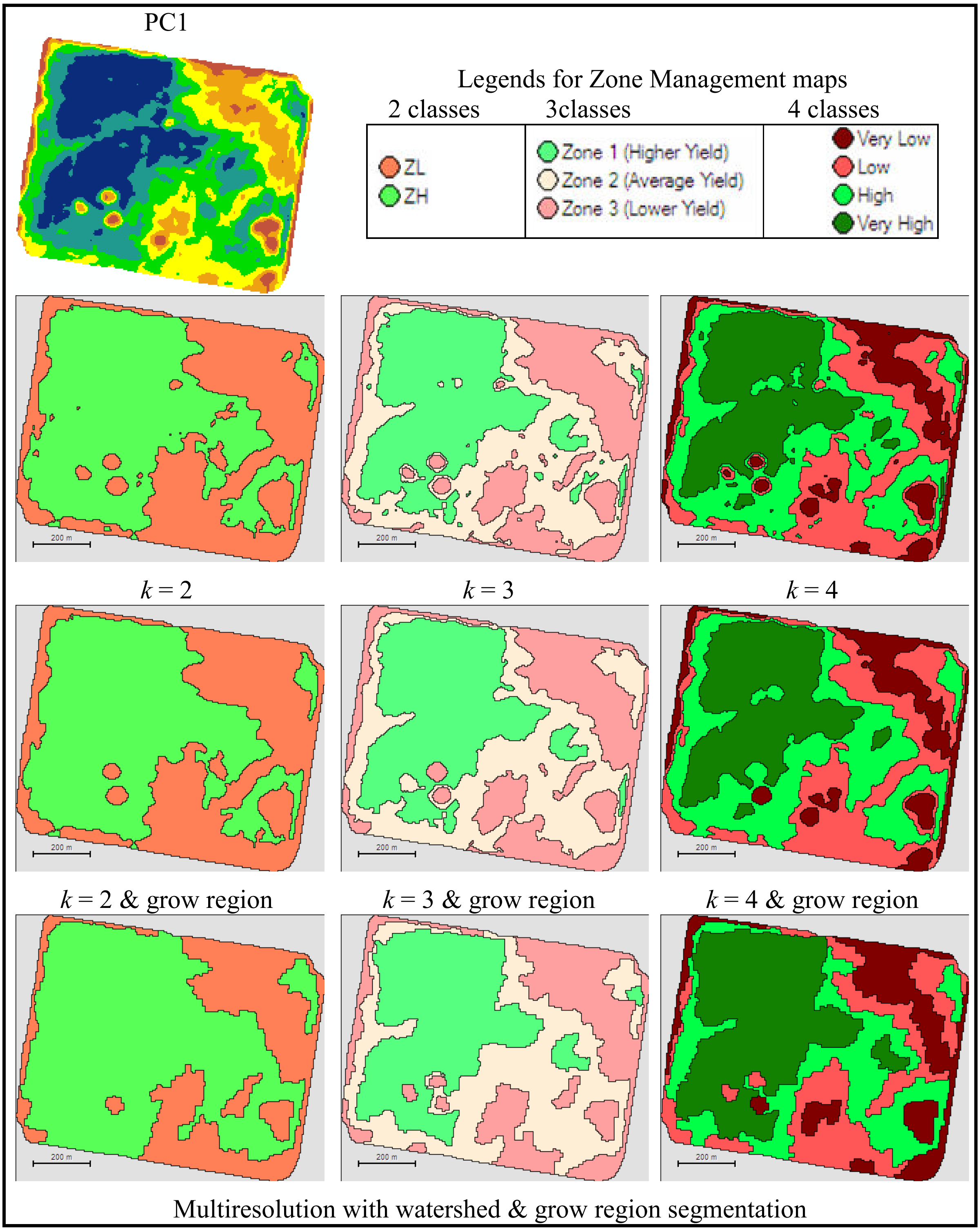

Figure 7.5: Management zones obtained by different delineation process for 2, 3, and 4 classes at field WA, using the PC1 input map.

Table 7.5: Net worth evaluation using the proposed method in this work when applied to management zones obtained from different clustering and segmentation outputs for field WA.

Input	Delineation		2 Classes	3 Classes	4 Classes
Median Yield	*k*-means	**Advantage**	$ 360.80	$ 348.40	$ 396.20
		Borders (m)	8,990	14,835	17,255
		Penalty	$ 224.75	$ 370.88	$ 431.38
		Net Worth	$ 136.05	- $ 22.48	- $ 35.18
	k-means with grow region	**Advantage**	$ 372.00	$ 353.20	$ 402.00
		Borders (m)	8,170	9,685	14,330
		Penalty	$ 204.25	$ 242.13	$ 385.25
		Net Worth	$ 167.75	$ 111.07	$ 16.75
	Multiresolution Watershed Segmentation	**Advantage**	$ 369.60	$ 356.80	$ 398.60
		Borders (m)	6,815	8,950	9,130
		Penalty	$ 170.38	$ 223.88	$ 228.25
		Net Worth	$ **199.22**	$ 132.92	$ 170.35
PC1	*k*-means	**Advantage**	$ 408.00	$ 342.80	$ 376.60
		Borders (m)	9,120	15,185	17,895
		Penalty	$ 228.00	$ 379.63	$ 443.38
		Net Worth	$ 180.00	- $ 36.83	- $ 66.78
	k-means with grow region	**Advantage**	$ 410.40	$ 341.20	$ 380.00
		Borders (m)	8,250	13,575	16,275
		Penalty	$ 205.37	$ 339.38	$ 406.87
		Net Worth	$ 205.03	$ 1.82	- $ 26.87
	Multiresolution Watershed Segmentation	**Advantage**	$ 428.80	$ 345.20	$ 387.80
		Borders (m)	6,905	11,830	15,210
		Penalty	$ 172.63	$ 295.75	$ 380.25
		Net Worth	**$ 256.17**	$ 49.45	$ 7.55

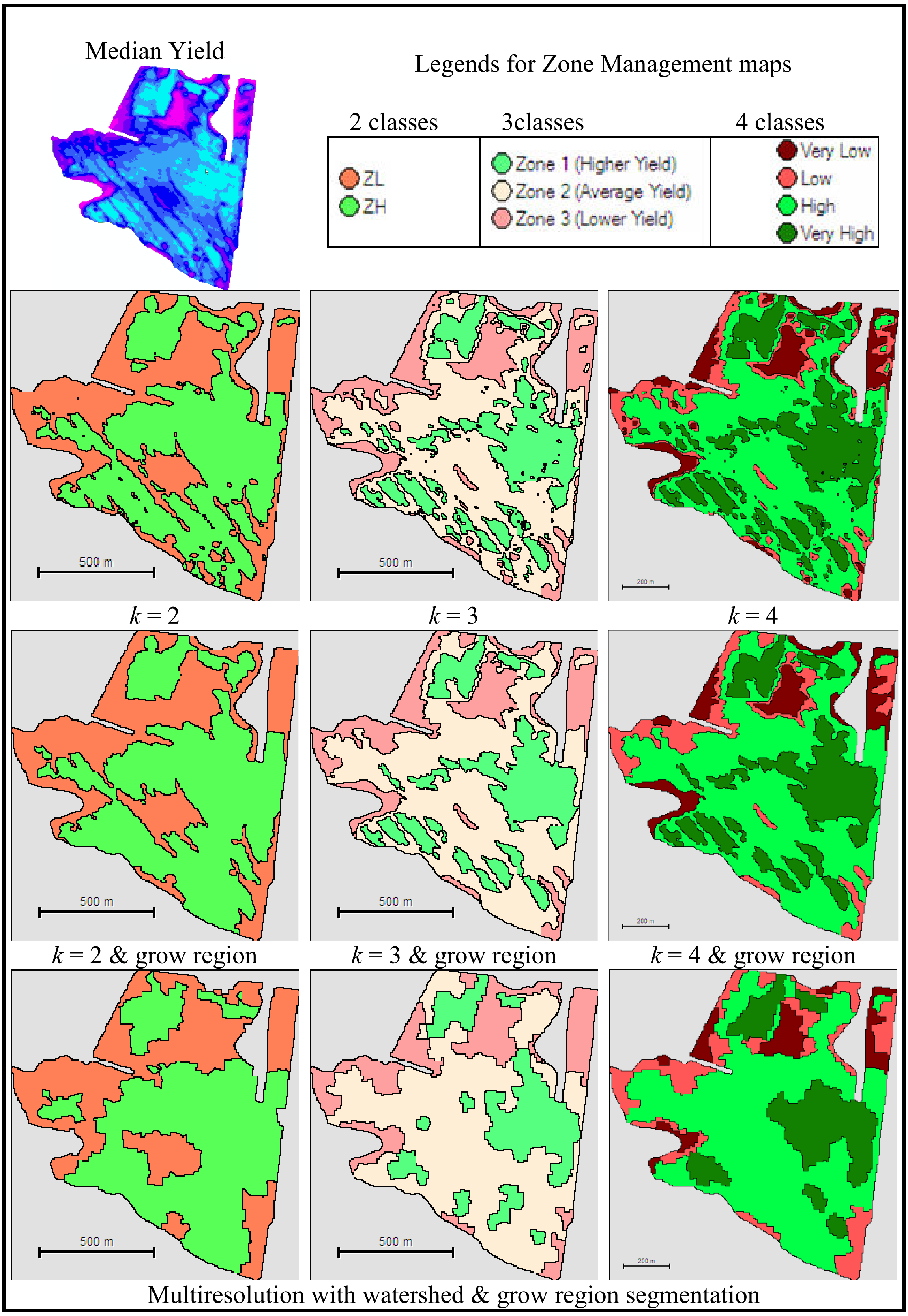

Figure 7.6: Management zones obtained by different delineation process for 2, 3, and 4 classes at field BT, using the median yield input map.

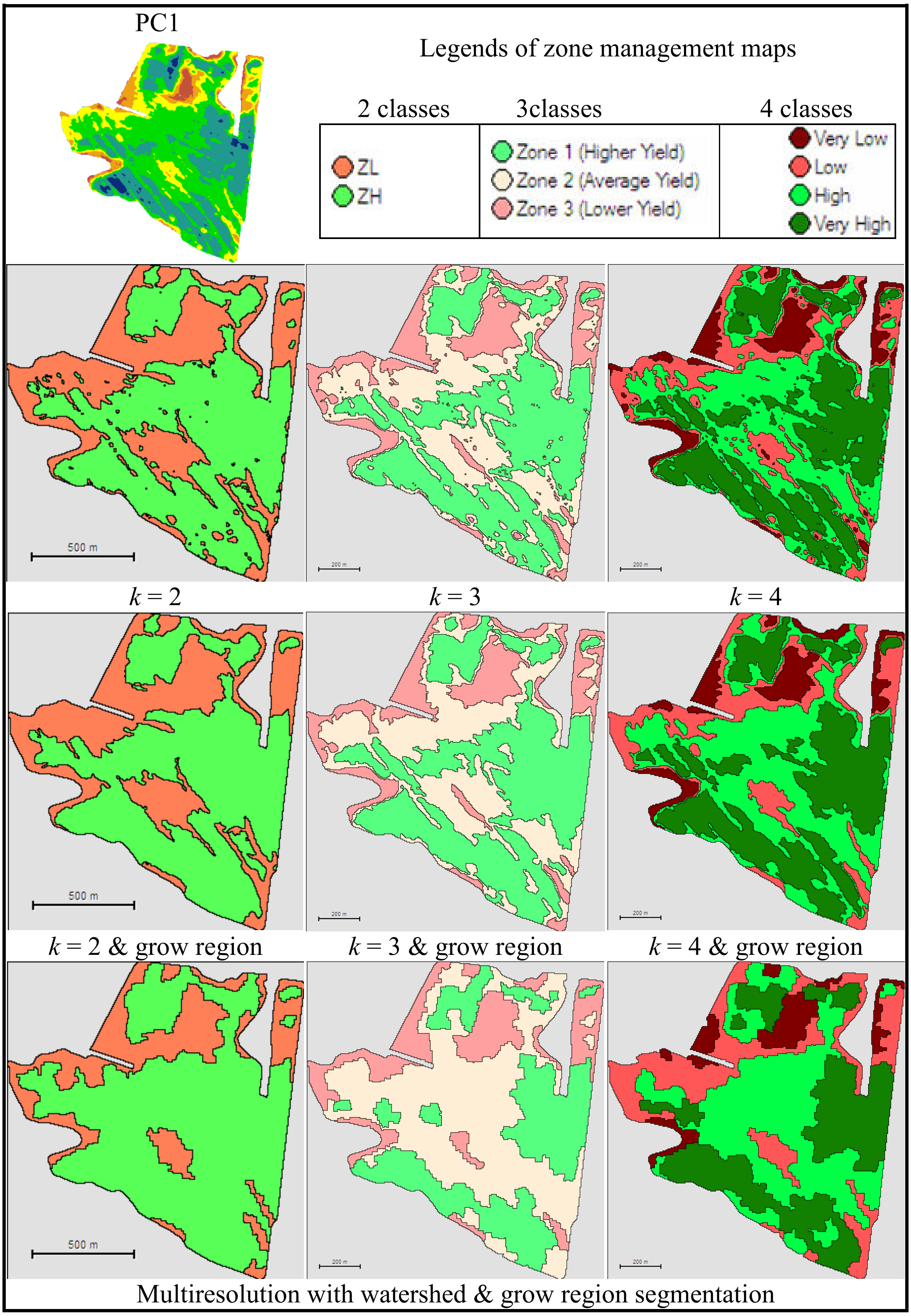

Figure 7.7: Management zones obtained by different delineation process for 2, 3, and 4 classes at field BT, using the PC1 input map.

Table 7.6: Net worth evaluation using the proposed method in this work when applied to management zones obtained from different clustering and segmentation outputs for field BT.

Input	Delineation		2 Classes	3 Classes	4 Classes
Median Yield	*k*-means	**Advantage**	$ 444.80	$ 411.20	$ 371.80
		Borders (m)	26,865	32,697	39,632
		Penalty	$ 671.62	$ 817.43	$ 990.80
		Net Worth	-$226.82	-$406.23	-$619.00
	k-means with grow region	**Advantage**	$ 460.00	$ 407.60	$ 370.84
		Borders (m)	13,955	25,520	27,632
		Penalty	$ 348.87	$ 613.00	$ 690.80
		Net Worth	$ 111.13	-$205.40	- $319.80
	Multiresolution Watershed Segmentation	**Advantage**	$ 455.20	$ 389.60	$ 359.20
		Borders (m)	9,700	12,015	13,085
		Penalty	$ 242.50	$ 300.38	$ 327.13
		Net Worth	**$ 242.50**	$ 89.23	-$ 32.08
PC1	*k*-means	**Advantage**	$ 652.00	$ 678.56	$ 506.00
		Borders (m)	18,895	26,449	29,166
		Penalty	$ 472.38	$ 661.23	$ 729.15
		Net Worth	$ 179.62	$ 17.34	-$223.15
	k-means with grow region	**Advantage**	$ 663.20	$ 688.00	$ 539.60
		Borders (m)	16,355	24,060	28,395
		Penalty	$ 408.88	$ 601.50	$ 709.88
		Net Worth	$ 254.32	$ 86.50	-$170.28
	Multiresolution Watershed Segmentation	**Advantage**	$ 784.80	$ 609.76	$ 518.00
		Borders (m)	11,976	14,575	18,170
		Penalty	$ 299.41	$ 382.38	$ 454.25
		Net Worth	**$ 485.39**	$ 227.38	$ 63.75

Clustering and segmentation methods

Segmentation methods applied to delineate site-specific management zones have shown that morphology-based techniques have brought some improvement in generating contiguous within-field zone segmentations. Overall results for the economic evaluation using the composite segmentation approach, multi-resolution segmentation grow region with watershed transformation, have shown a greater opportunity for the delineation of management zones using the first principal component (PC1) as input (**Figures 7.2** to **7.7**). Outcomes have also indicated that the commonly used thresholding-based histogram clustering (*k-means*) may have improved results when combined with reshaping techniques, such as the grow region algorithm, which are available in the object-oriented image processing IDE used (Definiens Developer®, 2007).

Median yield inputs have systematically responded with less lengthy zone borders than inputs of PC1 for the same segmentation process of each field, as shown in **Table 7.7** for the minimum and maximum length range by field and number of classes for the best delineation process indicated by the net worth analysis. This response may be also associated to the fact that segmentation processes using median yield as input have shown to be more sensitive to the calibration of parameter sets for the composition of homogeneity criterion (e.g. colour, shape, smoothness, and/or compactness). It was observed that scale parameters defined with median yield inputs systematically required smaller values for best results, ranging from 1 to 5, when compared with scale parameters for PC1 inputs, ranging from 5 to 8.

The scale parameter is an abstract term which determines the maximum allowed heterogeneity for the resulting image objects in the multiresolution segmentation process. According to concepts of the multiresolution segmentation algorithm used (Definiens, 2007), the use of smaller segmentation scale parameters for the desired spatial generalization suggests that median yield inputs have provided a more spatially homogeneous source of information, when compared with principal component inputs.

In contrast, the more heterogeneous character of PC1 inputs has supported segmentation of zones in which the advantage to zone management has been maximized for two class segmentations, mostly promoting the best economic net worth for fields of strong spatial and temporal variation such as field BT ($\tilde{\mathbf{Y}}_i$ = 8.3). In this case, the optimized distribution of zone areas promoted by the PC1 input for multiresolution segmentation has provided increased advantage with the preponderance of high yield areas (**Figure 7.7**).

Table 7.7: Minimum and maximum border length ranges obtained by field and number of management classes with the associated best delineation processes.

Field	Classes	Range	Best Delineation	Associated Input	Border Length (m)
Road	2	Min.	Segmentation	Median Yield	4,113
		Max.	*k-means*	Median Yield	16,200
	3	Min.	Segmentation	Median Yield	7,980
		Max.	*k-means*	PC1	31,755
	4	Min.	Segmentation	Median Yield	11,600
		Max.	*k-means*	PC1	31,675
WA	2	Min.	Segmentation	Median Yield	6,815
		Max.	*k-means*	PC1	9,120
	3	Min.	Segmentation	Median Yield	8,950
		Max.	*k-means*	PC1	15,185
	4	Min.	Segmentation	Median Yield	9,130
		Max.	*k-means*	PC1	17,895
BT	2	Min.	Segmentation	Median Yield	9,700
		Max.	*k-means*	Median Yield	26,865
	3	Min.	Segmentation	Median Yield	12,015
		Max.	*k-means*	Median Yield	32,697
	4	Min.	Segmentation	Median Yield	13,085
		Max.	*k-means*	Median Yield	39,632

The multiresolution with the watershed and grow region segmentation has provided better net worth across all fields for all class numbers according to net worth results shown in **Table 7.8**.

Table 7.8: Best net worth from all delineation processes of selected fields.

Field	Classes	Delineation Method	Input	Net Worth ($/ha)
Road	2	Segmentation	Median Yield	**$ 3.10**
	3	Segmentation	Median Yield	$ 2.38
	4	Segmentation	Median Yield	$ 2.46
WA	2	Segmentation	PC1	**$ 3.16**
	3	Segmentation	Median Yield	$ 1.64
	4	Segmentation	Median Yield	$ 2.10
BT	2	Segmentation	PC1	**$ 4.92**
	3	Segmentation	PC1	$ 2.31
	4	Segmentation	PC1	$ 0.65

The net worth analysis

The economic evaluation was mostly meant to support a simple way of looking at comparing segmentation methods at this preliminary stage. Although using suggestions from actual economic evaluations for site-specific management zones in Western Australia (Robertson *et al.*, 2008), assumptions of net benefits as shown in **Tables 7.4**, **7.5**, and **7.6** may have little bearing on the real world. For this reason, prices for the advantage to zone management by class (**Tables 7.1** to **7.3**) have been also considered at a 50% higher level than in Western Australia. This revised net worth evaluation is shown in **Tables 7.9** and **7.10**, summarizing results from median yield and PC1 inputs respectively, and it may offer a more relevant reference for higher value crops, as for agronomic areas considered in this research (i.e. NSW, SA, and VIC). Still, final values per field have somehow approach previous reports (Whelan, 2008). In addition, it could be argued that crops in the Eastern Australia production systems are associated with a higher grain production advantages.

Although following minimum and maximum references for advantages to zone management as suggested by an economic assessments of actual crop production systems (Robertson *et al.*, 2008), price assumptions in this work may have produced net worth results that have little support in the real world. Alternative advantage figures, as related to higher value crops in Eastern Australia, may be still fictitious, but have reproduced the same best net worth results by field and input (**Tables 7.9** and **7.10**), as for prices given for Western Australian production systems (**Tables 7.4** to **7.6**). This mostly supports the sensitivity analysis of the proposed model in relation to price variances, to show the robustness of the simple economic model suggested as a function of total border length by zone classes.

Also, price references were considered from a scenario in which no soil difference in nutrition between the zones was initially incorporated (i.e. N and P). This scenario was considered adequate for this work since segmentation inputs have not considered soil electrical conductivity (EC_a) or elevation data in the PCA. However, there are clear evidences of improved zone partitioning by means of multivariate analysis combining crop yield, soil EC_a, and terrain attributes (Whelan & McBratney, 2003; Whelan *et al.*, 2007). For this reason, further net worth analysis combining these production factors is considered for the field Road, for which previous work on management zones has been conducted and soil sampling data is available. A new net worth scenario considering soil related variation is summarized in **Table 7.11**, showing a better evaluation over simulations only considering yield inputs on both economic advantage and practical management purposes, with output patterns better matching general aspects in the input map (**Figure 7.8**).

Table 7.9: Revisited net worth summary for Eastern Australian crops considering the best segmentation results with median yield inputs and 50% higher level prices than suggested for Western Australia.

Field	Delineation		2 Classes	3 Classes	4 Classes
Road	*k*-means	Advantage	$ 615.60	$ 706.80	$ 520.95
		Penalty	$ 405.00	$ 665.13	$ 756.38
		Net Worth	$ 210.60	$ 41.16	- $235.43
	k-means with grow region	Advantage	$ 619.20	$ 714.00	$ 520.20
		Penalty	$ 335.25	$ 603.88	$ 672.50
		Net Worth	$ 283.95	$110.12	- $152.30
	Multiresolution Watershed Segmentation	Advantage	$ 675.60	$ 699.60	$ 849.00
		Penalty	$ 150.50	$ 199.50	$ 290.00
		Net Worth	**$ 525.10**	$ 500.10	$ 559.00
WA	*k*-means	Advantage	$ 541.20	$ 522.60	$ 594.30
		Penalty	$ 224.75	$ 370.88	$ 431.38
		Net Worth	$ 316.45	$ 151.72	$ 162.92
	k-means with grow region	Advantage	$ 558.00	$ 529.80	$ 603.00
		Penalty	$ 204.25	$ 242.13	$ 385.25
		Net Worth	$ 353.75	$ 287.67	$ 217.75
	Multiresolution Watershed Segmentation	Advantage	$ 554.40	$ 535.20	$ 597.90
		Penalty	$ 170.38	$ 223.88	$ 228.25
		Net Worth	$ **384.02**	$ 311.32	$ 369.65
BT	*k*-means	Advantage	$ 667.20	$ 616.80	$ 557.70
		Penalty	$ 671.62	$ 817.43	$ 990.80
		Net Worth	$ 4.42	- $200.63	- $433.10
	k-means with grow region	Advantage	$ 690.00	$ 611.40	$ 556.20
		Penalty	$ 348.87	$ 613.00	$ 690.80
		Net Worth	$ 341.13	- $ 1.60	- $134.60
	Multiresolution Watershed Segmentation	Advantage	$ 682.80	$ 584.40	$ 538.80
		Penalty	$ 242.50	$ 300.38	$ 327.13
		Net Worth	**$ 442.30**	$ 284.02	$ 211.67

Table 7.10: Revisited net worth summary for Eastern Australian crops considering the best segmentation results with PC1 inputs and 50% higher level prices than suggested for Western Australia.

Field	Delineation		2 Classes	3 Classes	4 Classes
Road	***k-means***	Advantage	$ 592.80	$ 720.00	$ 792.90
		Penalty	$ 274.50	$ 793.90	$ 791.88
		Net Worth	$ 318.30	- $ 73.90	- $ 1.02
	***k-means* with grow region**	Advantage	$ 596.40	$ 726.00	$ 796.80
		Penalty	$ 230.38	$ 595.50	$ 554.90
		Net Worth	$ 366.02	$ 130.50	$ 241.90
	Multiresolution Watershed Segmentation	Advantage	$ 787.20	$ 657.00	$ 803.40
		Penalty	$ 233.88	$ 337.55	$ 393.38
		Net Worth	**$ 553.32**	$ 319.45	$ 410.02
WA	***k-means***	Advantage	$ 612.00	$ 514.20	$ 564.90
		Penalty	$ 228.00	$ 370.88	$ 443.38
		Net Worth	$ 384.00	$ 143.32	$ 121.52
	***k-means* with grow region**	Advantage	$ 615.60	$ 511.80	$ 570.00
		Penalty	$ 205.37	$ 339.38	$ 406.87
		Net Worth	$ 410.23	$ 172.42	$ 163.13
	Multiresolution Watershed Segmentation	Advantage	$ 643.20	$ 517.80	$ 581.70
		Penalty	$ 172.63	$ 295.75	$ 380.25
		Net Worth	**$ 470.57**	$ 222.05	$ 201.45
BT	***k-means***	Advantage	$ 978.00	$1017.84	$ 759.00
		Penalty	$ 472.38	$ 661.23	$ 729.15
		Net Worth	$ 505.62	$ 356.61	$ 29.85
	***k-means* with grow region**	Advantage	$ 994.80	$1032.00	$ 773.70
		Penalty	$ 408.88	$ 601.50	$ 709.88
		Net Worth	$ 585.92	$ 430.50	$ 63.82
	Multiresolution Watershed Segmentation	Advantage	$1177.20	$ 914.40	$ 732.00
		Penalty	$ 299.41	$ 382.38	$ 454.25
		Net Worth	**$ 877.79**	$ 532.02	$ 227.75

7.5 – General discussion

The results suggest that scenarios considering advantages with differences in starting soil fertility status between zones are worth investigation. Maximum and minimum values as given for this scenario by Robertson *et al.* (2008), from 21 to 44 ($/ha) in Western Australia (WA), contrast a lot with figures previously used, from 0 to 8 ($/ha), as a reference for the advantage to zone management (**Tables 7.1** to **7.3**). New figures for higher level prices in Eastern Australian (EA) crops suggest a greater economic significance as shown in **Table 7.12** for net worth of best process by field. These results also appear to correlate with a study of financial wastage from uniform fertilizer on 17 field experiments (Whelan, 2008). Whelan (2008) suggests an average wastage of fertilizers of $33/ha, which comes close to the average net worth obtained for the three selected fields ($29.50/ha), when considering the scenario of differences in the starting soil fertility status between different management zones.

Results show a great potential for the use of new segmentation algorithms for delineation of MZs, in particular to fields with strongly segmented spatial patterns as in the case of field BT in this investigation. The multiresolution watershed segmentation has systematically resulted in greater net worth for differential zone management, with the PC1 input and 2 zone class outputs likely to characterize greater net advantages for single intervention for variable-rate Nitrogen application.

The availability of soil core sample information and the site-specific management knowledge acquired on previous studies on field Road has offered good means to evaluate delineation outcomes in relation to soil attributes. Investigations on management zones for 2 and 3 cluster classes have been conducted by means of multivariate analysis (Whelan & McBratney, 2003), whereby soil sampling strategies were developed and field segmentation was analysed in combination to soil, yield and terrain variations. Some of the soil attributes that support the characterization of two main soil types are shown in **Table 7.13**, where detailed on field trials have required additional sampling strategies (Whelan *et al.*, 2007). Soil information has characterized the field Road in two major soil types with differing top soil texture (i.e. Sandy Loam and Sandy Clay Loam). This core sample information taken from sample sites stratified using the previous management zones analysis in 2003 (**Figure 7.8d**), has been mostly matched by several segmentation results, as further discussed in relation to **Figure 7.8**. This comparison between unsupervised segmentation and legacy information about practical knowledge on site-specific crop management gives the opportunity to validate the spatial response of the composite segmentation processes introduced in this work.

Table 7.11: Net worth with different inputs for 2 classes processes in field Road.

	Median Yield	PC1 for Yield	PC1 for Yield, Soil EC_a & Elevation
Advantage	$ 450.40	$ 524.80	$ 468.00
Borders (m)	6,020	9,355	4,683
Penalty	$ 150.50	$ 233.88	$ 117.08
Net Worth	$ 299.90	$ 290.93	**$ 350.93**

Table 7.12: Best net worth for different scenarios for the advantage in zone management.

Field	Net Worth in WA ($/ha)	Net Worth in EA ($/ha)	Net Worth with soil variation ($/ha)
Road	2.60	4.54	20.77
WA	3.16	5.81	26.98
Bt	4.92	8.90	40.70

Figure 7.8 shows different segmentation outcomes for field Road, as overlayed with locations of soil samples to demonstrate the spatial fit of unsupervised zone partitions with actual soil distribution. **Figure 7.8a** illustrates the response of the hybrid segmentation when applied to PC1 data that combines (38.8%) information from crop yield, soil electromagnetic induction, and elevation data. This process has yielded the best net worth result ($350.93) for field Road with 2 classes (**Table 7.8**), and its associated map (**Figure 7.8a**) has conformed all soil samples within the appropriate lower or higher soil related yield potential zone. This performance has improved the results obtained for the same segmentation process ($290.93) in which PC1 was limited to multi-year crop yield information (**Figure 7.8b**). Another good boundary delineation response is observed for the same process with the input of median yield for 3 class segmentations. Again the unsupervised hybrid segmentation has shown a response for 3 zone classes which managed to precisely contour soil sample locations (**Figure 7.8c**) pertaining to higher yield potential zones (red dots representing Sandy Clay Loam soils). **Figure 7.8d** illustrates legacy knowledge on zone management for this crop production system (Whelan & McBratney, 2003; Whelan & Taylor, 2005; Whelan *et al.*, 2007), as a means of comparison for results in this work.

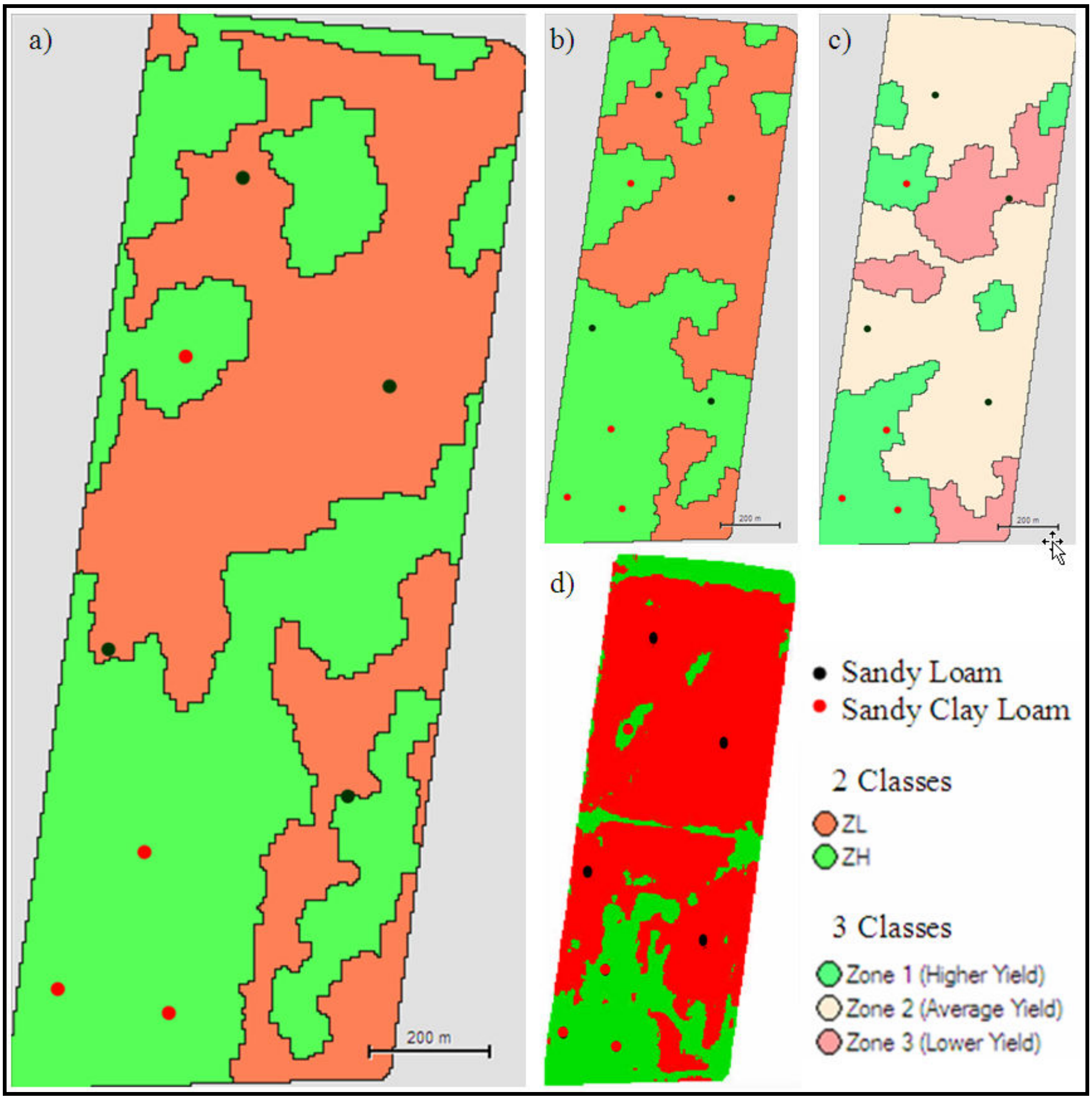

Figure 7.8: Multiresolution watershed segmentation match using existing soil information, for processes of: a) PC1 yield & soil information; b) PC1 yield 2 Classes; c) PC1 yield 3 classes; and d) *k*-means zone delineation 2003 (Whelan *et al.*, 2007).

The typical effect of random, small and non-contiguous zones as a result of *k-means* clustering is observed. In their threshold segmentation, Whelan *et al.* (2007) suggest zones of high yield class which are mostly contained in equivalent areas of high yield in the morphological segmentation. In addition, Whelan *et al.* (2007) report figures of potential wastage of fertilizers for this field that varies from \$8.22/ha to \$65.02/ha, a range which involves the net worth evaluation for variable-rate Nitrogen applications (\$20.77/ha) when incorporating differences in starting soil fertility conditions (**Table 7.12**)

Table 7.13: Soil characteristics for 2 classes of zone management in field Road.

Soil Attributes	Lower Yield Zones	Higher Yield Zones
Texture (0-10cm)	Sandy Loam	Light Sandy Clay Loam
Texture (10-30 cm)	Clay Loam	Sandy Clay Loam + Lime
Texture (30-60 cm)	Clay	Clay Loam + Lime
CEC (0-10 cm)	16	21
CEC (10-60 cm)	26	21
pH(CaCl) (0-10 cm)	6.3	7.8
$NO3^-$ (0-10 cm)	17.5	12.3
$NO3^-$ (10-30 cm)	5.2	7.5
P (0-10 cm)	57	27

Alternatively, PC1 appears to be more useful for discriminating hot spots of image objects, which characterizes big differences between mean yields of boundary neighbours. Therefore, soil sampling strategies may be oriented to regions which are characterized by abrupt changes in the mean yield of image objects, potentially indicating locations in which further soil investigations need to be conducted. This would be the case for the selection of new sampling locations not yet considered in previous zone segmentation exercises of advanced PA adopters.

Finally, all findings relative to the investigation of the hybrid segmentation process here introduced have added some important points to the extension of current knowledge supporting the delineation of site-specific crop management zones. Key factors from the segmentation processes here investigated, which can be considered as candidate condition supporting decision process flow include: the total border length between zones, zone area predominance, and positive net worth balances. Perhaps, it seams premature at this stage to establish threshold values for conditional factors influencing decision processes supporting the adoption of management zones. Still, a synthesis of the observations in this work has allowed the suggestion of additional decision-making steps for management zone delineations, which extends the decision-tree diagram proposed in **Section 6.3.2** (**Figure 6.2**) for the opportunity for adoption of SSCM. Decision-tree branches extending the support to opportune within-field partitioning are shown in the diagram of **Figure 7.9**.

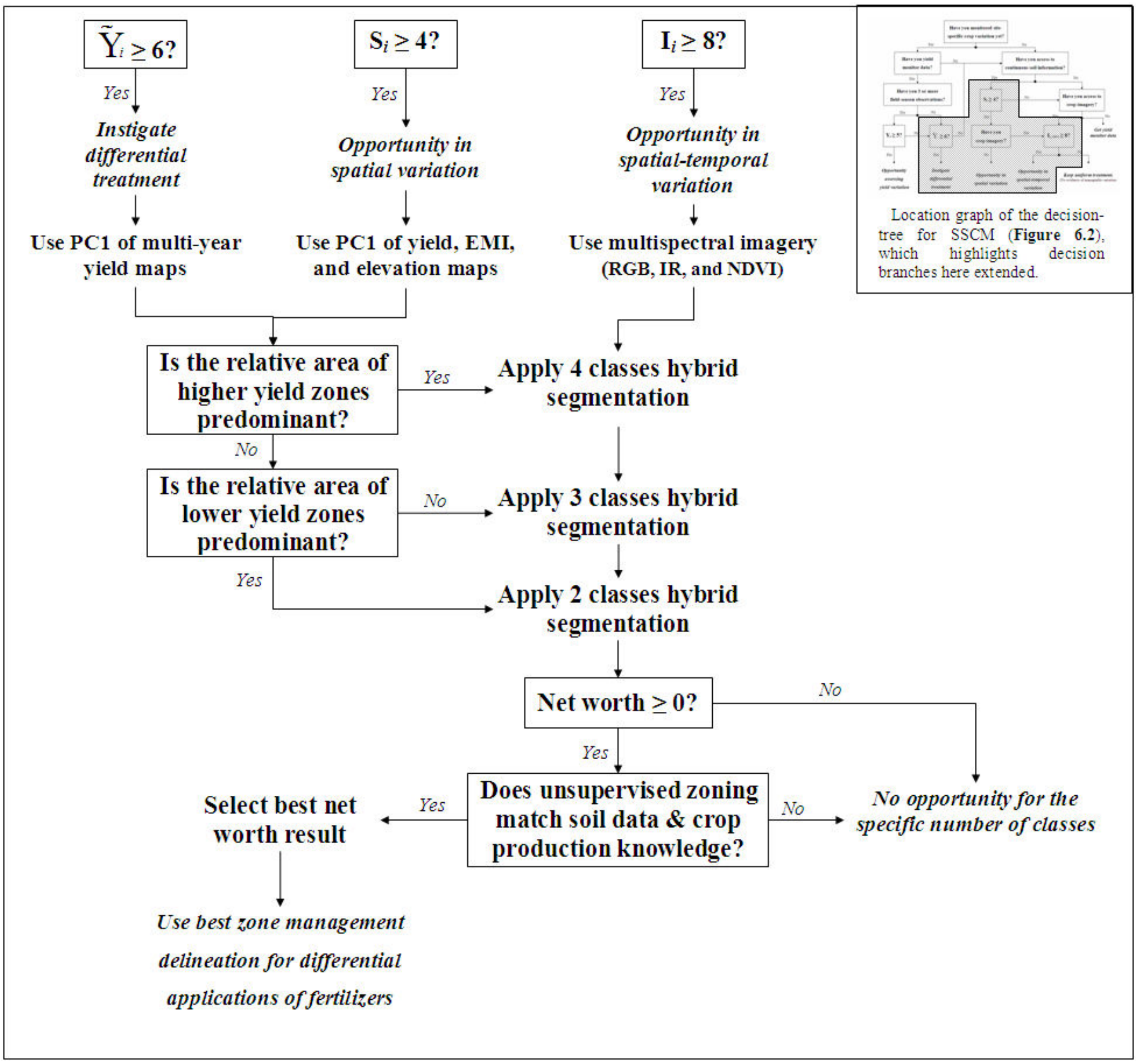

Figure 7.9: Extension of the opportunity decision-tree to support zone segmentation.

7.6 - Concluding remarks

Within an empirical study on object-oriented image segmentation algorithms, a simple economic objective function has been proposed and applied as a mean to evaluate different approaches for the delineation of management zones for SSCM. The use of an interactive development environment for the analysis of several image processing workflows has proved effective when applying the proposed economic net worth analyses for the opportunity to zone management. Commonly applied to the delineation of site-specific management zones, two thresholding-based classification algorithms, based on histogram clustering methods (*k*-means), are compared with a new segmentation workflow as composed of multiresolution, watershed transformation, and grow region segmentation algorithms.

This investigation has shown that use of object-oriented concepts has brought semi-automatic amendments to image segmentation procedures that mostly require expertise supervision for parameter settings and statistical interpretations.

Given image object features from site-specific crop monitoring, the use of image segmentation techniques to evaluate zone management segmentation can be viewed as a problem of continuous spatial pattern delineation and the optimization of borders between management zones. Classic clustering algorithms may support precise statistical class partitioning, perhaps hardly conforming to grain field management zones that are operationally feasible. Results show that thresholding classification approaches, which take no account for spatial dependencies of image features, generally produce random and unstructured spatial patterns. This solution does not match requirements of a few homogeneous and continuous management zones that may minimize investment risk to farmers.

Datasets from selected fields are of strong non-stationarity behaviour, on both spatial and temporal dimensions. This means the optimal delineation of crop management zones for site-specific differential applications is a challenging process, which is also difficult to evaluate. Still, overall results in this investigation have suggested that object-oriented image processing may offer new and efficient approaches to better segmentation of a field into spatially contiguous sub-areas of homogeneous yield potential across several crop seasons.

The combination of segmentation methods by means of an interactive workflow of image processing techniques applied to image objects, rather than to image pixels, has provided an effective approach to evaluated zone management delineations using hybrid segmentation procedures. In particular, the combination of morphological- and topological- based segmentation algorithms has shown potential to support decisions on the opportunity for the adoption of site-specific zone management in an unsupervised and semi-automated fashion. A simple hybrid solution using multiresolution, watershed, and grow region techniques have consistently responded better to PCA inputs characterizing multi-year yield data. Also, this new object-oriented approach has shown results with contiguous zones that have also conformed to local agronomic knowledge and soil characteristics previously reported.

What the composite method of multiresolution with the watershed transformation and grow region segmentation has brought new traditional image clustering algorithms is that the delineation of more continuous and agronomic-based zones may rely on functions that can use image object features as a source of information (i.e. spectral, shape, and hierarchical characteristics). In addition, the proposed compounded segmentation workflow has addressed issues about over-segmentation usually observed when using solo watershed transformation or training seed-objects for grow region algorithm

Several object features are available supporting the functional and spatio-temporal relationships in site-specific crop management zones. This type of segmentation response may be more appropriate for operational field interventions and whole-farm PA assessments, while reducing the investment risk associated with the adoption of SSCM. The use of object-oriented concepts for image segmentation using morphology-based segmentation algorithms seems appropriate for the support of zone management decisions. The potential in future work using hybrid or customized object-oriented segmentation involves the description of behavioural relationships (e.g. spatial, functional, and/or agronomic) which depends on agronomic and managerial knowledge on site-specific zone management that is still under investigation. Descriptive object features may also be used to support improvements in the economic model by considering shape related features to establish different penalties when crossing borders between zone classes with large differences between yield means.

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PART III

Closing Remarks,

Bibliography & Appendices

Chapter 8

Overall discussion, conclusions & future work

Summary

Complementing the detailed discussion specifically provided to each chapter, general aspects of decision support for PA are considered within the overall context of exploring simple means to characterize the opportunity for the adoption of site-specific differential crop management. An evaluation of the applicability of the proposed quantitative methods for characterizing within-field variability within a conceptual framework for system design and development of decision support systems directly available to farmers and farm management advisors is provided. This evaluation adds general points about the implications of this work in the development of automated methods for spatio-temporal analysis of site-specific data. Overall conclusions are summarized in reference to each chapter, and major aspects regarding future work are suggested.

8.1 - Overall discussion

Agricultural decision support was originally conceived as a process modelling solution that mostly considered discrete descriptions of major production factors (e.g. soil, terrain, and climate) as related to single plant development processes. This analytical approach has certainly promoted a better understanding about agronomic interactions in crop production, even if no or limited spatial and temporal considerations have been incorporated. Typical simulations generate precise quantifications at the plant process level, which are assumed as averages of homogeneous fields. This information may have already added great support to farmers with generic estimations and qualitative conclusions, but proper farm management decision support requires more comprehensive evaluations that would incorporate simulation models as a decision calculus component of a knowledge intensive management system.

In contrast to the fast technological improvement in the automation of field operations and intensive field monitoring, a technological gap exists in the use and interpretation of site-specific information. The direct interpretation of field monitoring outputs was not feasible as initially expected, with an increase of information layers mostly promoting a decision paralysis due to information overload. Beyond the technological appeal for field operations, SSCM is still missing a great deal of research to build up specific knowledge on how to properly manage and automate the interpretation of intensive multiplatform-monitor data. Methods to promote the proper understanding of the space-time tradeoffs in crop production variability are still missing.

There is a clear need for a better understanding of DSS components, where some of the issues involve questions such as: what is a decision tool for farmers?; which questions are important for the adoption of site-specific farm management?; how is spatio-temporal variation best measured?; and what information technology is available to match system requirements? The quantitative models proposed in this thesis may serve as building blocks towards the solution of some of these critical questions in SSCM decision support, and opportunely some of the conceptual aspects of system development discussed will bring attention to a new generation of IT standards potentially useful in farm management decision support.

The body of this research concerns building the bridge between measures for spatio-temporal analysis, as required to support agronomic decisions in SSCM, and the opportunity given by new IT open standards, as required for the effective development of software tools which are accessible and directly available to farmers. These requirements have been obtained in a truly historical review on agricultural decision support solutions (**Chapter 1**), which has revealed not only typical environmental and economic aspects, but in fact an increased concern with social and human factors as affecting farm-knowledge management. In addition, the analysis of generic DSS typologies has shown that contemporary IT approaches are still limited in use by the PA community. This research has extended the literature review through a software development perspective (**Chapter 2**), in which available solutions have shown that even with the recently increased focus given to Web solutions, there is still limited compliance with a minimum set of basic system design standards and modest investigation on up-coming software engineering (e.g. ontologies, knowledge management, and autonomic agents).

In a very general picture of the outcomes of this work, specific hypothesis are drawn on why site-specific datasets have been poorly taken up by the farming community. Investigations suggest that the low adoption of SSCM technology is mostly due to agronomic and system development knowledge gaps, when searching for methods and processes for integrating site-specific datasets in the mainstream farm management decision process. As a result, a new method of application is used to propose a conceptual framework for the generic concept of knowledge intensive management (**Chapter 3**), in which building blocks for decision support relating to the opportunity for SSCM are suggested. The critical issue of assessing the opportunity given by within-field spatio-temporal variations is addressed using parametric methods from variogram analysis to measure the magnitude and the spatial structure of crop production variation (**Chapter 4**). This yield variability index has proved robust dealing with non-stationary variation and was further applied to soil electrical conductivity and crop reflectance imagery (**Chapter 5**), showing potential to support pre-season ($\mathbf{S}_i$), in-season ($\mathbf{I}_i$), post-season ($\mathbf{Y}_i$) evaluations. Results from these investigations have determined threshold values for crop related variability indices (i.e. $\mathbf{Y}_i$, $\mathbf{S}_i$, and $\mathbf{I}_i$) that could be used to systematize the integration of site-specific datasets into management knowledge by means of an opportunity decision-tree for the adoption of SSCM technology (**Chapter 6**). The final investigation on the direct and unsupervised use of SSCM datasets (**Chapter 7**) is conducted using methods partitioning contiguous areas of similar yield potentials, addressing the optimal number of management classes for the delineation of manageable zones. An economic model is proposed as a simple means of assessing the best delineation approach. Object-oriented image segmentations introduced by a combined process of morphologic-based algorithms appears to show the best potential.

The overall flow of decisions and processes investigated are summarized in the activity diagram (**Figure 8.1**), which provides a broad picture of the methods introduced in this thesis as a module to support decisions about the opportunity for strategic investments and tactical changes to field operation. The use of freeware tools supporting prototyping design and code implementation (i.e NetBeans IDE and Java SDK) has proven effective, once providing costless development means and facilitating model documentation and decision-knowledge interchange.

Figure 8.1 shows an upper-level diagram which is related to detailed activities introduced in the diagram for the opportunity of SSCM adoption (**Figure 6.4**), and incorporates activities related to the extension of the opportunity decision-tree to support management zone segmentation (**Figure 7.12**). The "*Variability Index*" object of the diagram in **Figure 8.1** is a super-class object for the "*Soil Variation*", "*Yield Variation*", and "*Crop Variation*" objects in **Figure 6.4.** The general expectation is that these solutions may lead to improvements in the agronomic management of farms (e.g economic and environmental) once they have incorporated spatial and temporal considerations from the analysis of information on production variation.

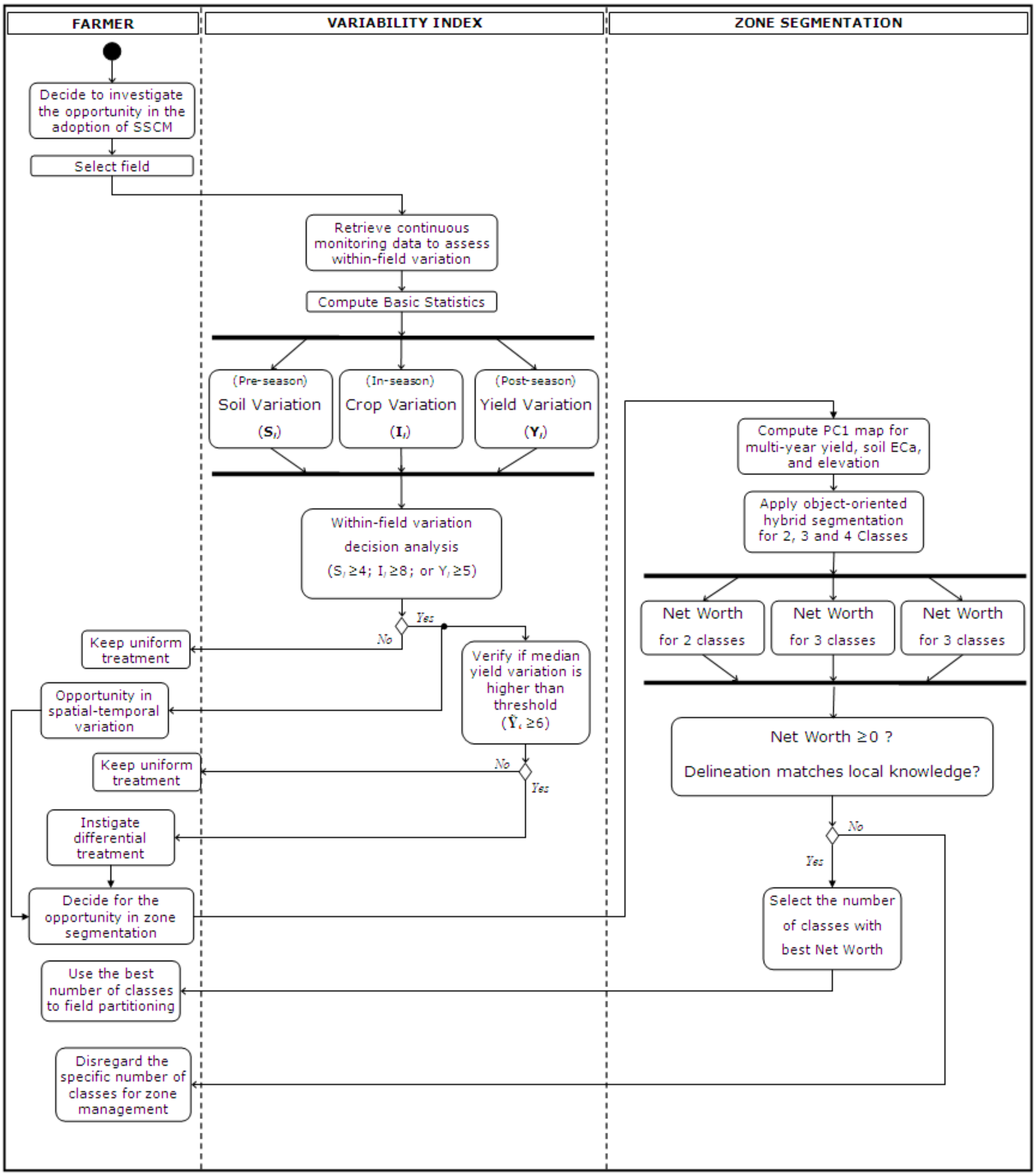

Figure 8.1: Top-level activity diagram for the opportunity of SSCM adoption.

Considering the potential given by multilayered continuous information, decision tools for SSCM should be conceived as a knowledge intensive management and adaptive learning environment. This idealistic solution would help farmers to link between local production knowledge and agronomic models. Knowledge-based frameworks underlying routine decision-making would incorporate autonomic storage, management and analysis of historical data, simulated scenarios, and decision outcomes. Specific decision tools would interoperate with these distributed frameworks via accessible interfaces which would favour the interpretation of scientific-based solutions through a farm management perspective. In reality, there is more to the overall solution than just system development issues, and it may be not clear the amount of agronomic and managerial knowledge that is still missing for a full understanding of spatio-temporal interactions between SSCM data layers.

Some of the important findings and major observations collected during the research to fulfil the specific aims of each chapter are summarized in the following paragraphs. Aiming to understand what is actually required for a conceptual framework and implementation of decision tools supporting the adoption of SSCM technology, the literature review in **Chapter 1** shows that site-specific decision-making operations need a means to convert the present opportunity analysis into a scientifically-sound, farmer-oriented, and knowledge-based decision tool. It is clear that unrealistic expectancies in the technology may have mislead farmers' perceptions about which analytical tools would be actually and timely available for SSCM decision support.

In general, DSS concepts and development approaches involve different operation levels, which require several aspects of farm management to be considered. The challenge for SSCM supporting tools is to couple several data types and sources, analysis tools, and domain specific knowledge, while continuously enabling adaptive change. Although within-field intensive data from one field survey may give us a good insight to the contributing factors of final production variation in a crop-season, it often doesn't stand by itself to support next season or long term management decision processes. Inconclusive returns at initial adoption phases may have contributed to loss or isolation of a great number of single field surveys. Negative impacts may have been promoted by this ambiguous situation affecting the perceived usefulness of the technology as a decision support.

The consequent low adoption means less data is available to enable research. In addition, a lot of what was gathered has been wasted by the inexperienced use of computer or monitoring devices and faulty monitoring interventions. Furthermore, useful raw yield data may have been mostly underused, as only a few formal protocols have addressed the proper characterization of the magnitude and spatial structure of variation and the opportune segmentation of site-specific management zones. In 10 years of data collection for 3 agronomic regions investing in PA there are still few datasets homogeneously distributed across crops, farms, and regions. A reason why results in this work have faced some limitation for the determination of index thresholds and significance in correlations. Only 5 farms in SPAA, 7 in CFI, and 3 in Riverine could provide consistent historical data on PA adoption. And, for 218 field-year samples, from 79 broad acre crop fields, 32 fields have one year of yield monitoring, and only 25 with more than 3 years.

The extended literature review in **Chapter 2** illustrates that several methods and tools have been successfully used to match some requirements of decision tools for SSCM. Still, long term use of those tools has mostly failed. Given the comprehensive PA requirements for decision support, it is suggested that the technological tool box providing the required functionality has only recently improved to the level of providing composable and integrated software solutions. The object-oriented approach has proved to persist as a basis for new open developments towards knowledge-based Web services for PA. Current WWW paradigms are a definitive trend for the new generation of knowledge-based supporting tools that can aid integrated, educative, and adaptive farm management; but the attention given to emerging areas like knowledge management, ontologies and autonomic agents is limited. In addition, available decision tools lack a minimum of development standards that could sustain effective information extraction supporting the build up of agronomic and managerial knowledge about the opportune adoption of SSCM technology. OO is a programming standard but proper modelling activity is very limited, in particular in the use of UML. Evolutionary software development techniques have shown successful applications in support of broad agricultural analysis and crop modelling, but have not been systematically applied in relation to differential management decision processes.

Current DSS overload a farmer with computer work, lack spatial reasoning for quantitative assessments of environmental-economic factors, and do not provide integrated analysis capabilities which couple scientific methods and actual farm business processes. Therefore, a conceptual framework using a platform independent design has been introduced for a new method of application (**Chapter 3**) of the UML to the opportunity for adoption of SSCM technology, which has proven to be accessible and effective in mapping object class relationships.

It is expected that this model can be broadly used or extended as a template either for design or code implementation, since it is developed using an evolutionary, general-purpose and standardized modelling architecture. The reuse of this design to support the development of SSCM tools will also enable the realization of benefits associated with this modelling technology.

The rationale for an opportunity index (**Chapter 4**) is to determine whether the observed variability warrants differential crop treatment. It is clear that this quantitative approach may support threshold information as a useful reference to identify the areas of a farm where investments in SSCM are likely to be best matched by economic and environmental outcomes. Additionally, it can also give extra insights into factors affecting variability.

The yield variation index (Y_i) simplifies the parameterization of the magnitude and spatial structure of yield variability components; however it still does not address any aspect of the opportunity associated with the economic-environmental cost/benefit of SSCM adoption. The Y_i provided robust results across the entire dataset, though perhaps not systematically supporting the ranking of individual season samples per field as initially expected. The method can respond to strong non-stationary data and once automated can provide simple references that may facilitate decision processes. On the other hand, the multi-year analysis of average Y_i per field has shown the ability to support different levels of farm management decisions in relation to investments in SSCM technology. The field median Y_i could prove to be useful for whole-farm investment strategy, with the allocation of production alternatives using the ranking of opportunity by fields per farm. If a fair distribution of samples by crop and region becomes available, the farm median Y_i can also be used to rank the opportunity of farms per region per season that may be used for regional agro-systems planning and environmental regulations. Crop rotation and differential management strategies for a single field will be possible when a minimum number of samples per crop type are available allowing the ranking of crops per field. Further, crop suitability per field and detailed operational plans may be possible if the ranking of single crops per season per field can be established. Greater data availability by crop type can additionally support index thresholds by crop in the opportunity decision tree. An example of this applicability is given in Chapter 4, where the amount of available data for wheat has indicated that at least 30 field-years is required to characterize a median Y_i value that could be used to compare indices in terms of crop per field per season (**Figure 4.7**).

The extraction of management information from remote and proximal fine-scale data monitoring activities is fundamental to the adoption of PA and proved useful for measures of within-field variability. The opportunity index method was further applied to soil EC_a (S_i) and crop reflectance imagery (I_i), and have shown promise to support farmer's decisions in instances where spatially dense data on crop yield are unavailable (**Chapter 5**). Promising results are also suggested for index evaluations using alternative vegetation indices suggested (e.g. GNDVI, TRVI, and PVR).

The decision model introduced in **Chapter 6** has shown that it is possible to incorporate simple quantitative methods within main stream farm decision processes to assess the opportunity for the adoption of PA technology. Strategic adoption pathways could be associated with index thresholds (i.e. Y_i, S_i, and I_i) for the opportune use of several field monitoring technologies that may support optimal investments in differential crop management.

The decision-tree model separates particular adoption phases and describes the associated decision strategy alternatives that may minimize investment risks, when accounting for the spatial and temporal variation in crop production. The opportunity index method is used as a utility function when determining the expected value of specific decision nodes, addressing questions pertaining to different phases of adoption. Results have mostly matched the actual potential for SSCM adoption as observed in spatial-temporal variations and estimated economic returns in the literature. In addition, a tentative table is suggested quantifying the minimum requirements for different types of SSCM monitoring observations, which can support decision making at different decision scales.

A simple net worth analysis has been applied and proved robust when evaluating different image processing techniques used to delineate management zones (**Chapter 7**). This approach has shown that object-oriented segmentation could bring amendments to previous procedures using clustering analysis. Results from histogram threshold algorithms also applied have supported precise class clustering, but perhaps not producing continuously operational management zones. In this case, the use of image segmentation techniques is understood as a potential solution for continuous spatial field partitioning and border optimization for crop management zones. Object-oriented image processing proved to be an efficient approach to improve the delineation of spatially contiguous areas of homogeneous yield potential.

A composite solution using multiresolution segmentation, watershed, and grow region techniques have shown potential to support decisions on the opportunity for the adoption of site-specific zone management in an unsupervised and semi-automated fashion. The segmentation has consistently responded better to PCA inputs, in particular when considering soil EC_a and elevation as well as multi-year yield maps. This new segmentation approach has also shown results that have also conformed to local agronomic knowledge and soil characteristics previously reported. In addition, the object-oriented segmentation approach may additionally rely on extra agronomic functions, which could be defined as object's behavioural features (i.e. spectral, topological, and/or hierarchical processes).

8.2 - Conclusions

Final conclusions are here summarized in a single sentence by chapter, followed by a short explanatory paragraph as listed below:

1. A lot of well designed decision support solutions have been developed in the past which are very useful to research, but not directly available to farmers.

Specific and tailored agricultural decision tools have been mostly directed at general farm accounting or crop yield simulations, neither supporting spatio-temporal analysis nor fully representing actual decision pathways for the adoption of SSCM technology. The increasing demand for human-social and environmental-economic aspects in agricultural DSS development contrast with the availability of interoperable tools that could interact and provide user-friendly interface. Simple quantitative models are required that could represent the existing agronomic knowledge and facilitate direct access to farmers. In particular for SSCM, these quantitative models need to consider the spatial and temporal characterization of crop yield variability.

2. There is still limited use of new software technology which can potentially provide more accessible tools to users.

Some of the new recommendations and standards in the software industry have had limited use in PA solutions. Few examples can be found for practical farm operations and they are mostly related to site-specific data gathering processes. Although system developers have considered user participation in development and recognized the present trend in Web related solutions, few practical analysis tools are directly available to farmers or have conformed to open and evolutionary system development approaches.

3. It is clearly possible to create cooperative, and easy to read system designs for SSCM that make use of IDE's and UML, but the implementation phase is challenging and requires advanced object-oriented concepts.

The multidisciplinary aspect in SSCM often requires the collaborative development of decision support modules that need to interoperate. Several examples in PA related areas have shown potential application for semantically oriented developments, but no specific model for decision processes in SSCM has been conceptualized. The conceptual framework introduced in this work may support platform independent developments and serve as a guide for the proposal of new object classes composing an integrated farm knowledge management. In addition, it has provided an easy means to identify parts of the system which are dependent on the solution of gaps in agronomic knowledge.

4. As an aid to decision support for site-specific management, an index for assessment of yield variation is devised, this takes into account the magnitude and the spatial structure of yield variation.

The proper characterization of crop yield variation is vital to support decisions regarding spatial and temporal crop differential management. Few attempts have been made to establish measures for yield variation that could be used as an index ranking the opportunity to SSCM. The revised opportunity index suggested in this work has proved robust when considering non-stationary yield variations and efficiently ranked fields by farm with the current available data. The importance of considering components such as the magnitude of variation and the spatial structure of variation is clear, as is addition to the economic and environmental considerations. The empirical investigation of the Y_i has shown the potential of several other uses at different scales from field to whole-farm and regional management, such as: i) crop suitability per field and directing detailed soil sampling; ii) field specific crop rotations and differential management strategies; iii) whole-farm investment strategy and allocation of production alternatives; and iv) environmental regulations and agricultural system planning.

5. Besides crop yield, data from Soil EC_a and airborne imagery are useful for assessing the opportunity for SSCM, particularly supporting temporal and within-season management decisions.

Another aspect in the investigation of the opportunity index is the potential use of alternative index components or input data sources, perhaps especially when considering index components from production systems other than grain crops (e.g. viticulture, sugar-cane, and apples). In this study, the use of different inputs has proved the potential to characterize other crop production factors at different time spans (i.e. soil attributes and crop vigour) and given alternative means of analysis for pre-season and within-season decision support. The response of multi-year yield data and alternative input sources has potentially added a temporal perspective to the use of the opportunity index, which is still dependent on greater data availability for its potential to be fully realised.

6. Given the opportunity indices (Y_i, S_i, I_i), it is possible to propose a tree structure that farmers can use to decide whether there is an opportunity to invest in SSCM at different scales (i.e. crop season, single field and whole-farm).

Simple solutions that include quantitative indices summarizing scientific knowledge and support optimized pathways for the adoption of SSCM technology are urgently required,. A simple decision tree using field variation measures is expected to add value to the information flow for site-specific decision-making by defining pathways for the opportunity to adopt different monitoring technologies (i.e. yield monitor, EMI, and airborne imagery). The application of the decision model to historical datasets has provided opportune pathways for adoption that have matched actual production responses, validating the potential in the systematic use of indices for adoption decisions such as: i) Should I go for PA?; ii) Which technology should I use?; and iii) Where should I apply differential crop management?

7. Based on an objective economic criterion, a combination of multiscale segmentation with region growth and watershed transformation algorithms appears to be a very useful way for segmenting continuous field areas for zone management.

The use of object-oriented concepts for image processing has added a valuable approach for the specific application in the segmentation of within-field management zones. Morphology-based segmentation algorithms could be effectively combined through image-object IDE, to highlight the potential use in this type of model development technology. The simple economic model used to evaluate segmentation outcomes has introduced the concept of border crossing amongst different management zones, in which the preliminary computation may be further refined. The effective partitioning of selected fields into contiguous areas of strong contrast between yield means has mostly matched the actual production knowledge of these fields, thereby suggesting a new approach to zone management investigations.

8.3 - Future work

As extensively discussed, there are several issues requiring attention in future work. Several aspects in SSCM decision support are still in the infant phases of conceptualization and prototyping. As a consequence of a greater availability of data, preliminary approaches in this work could be revisited for extended conclusions. In this case, it is expected that the conceptual models suggested in this work, using standardized UML diagrams, will facilitate specific knowledge transfer as well as the reuse of the model for either insertion of revisions or the implementation of applied software. Among the most important points to be addressed in future investigations, four have been selected as requiring special and more immediate attention:

- Some detailed work on ABM is required for implementation of tools that may facilitate practical farm decisions supported by autonomous agents embedding agronomic research knowledge.

- To implement a Web decision support service that may use the conceptual models introduced in chapters 3 and 6 as a base to automate the computation of the variation indices and the segmentations for zone management and to offer to farmers an accessible tool for SSCM decision support.

- To improve steps of the decision trees proposed in chapter 6 and 7, more on-farm data and experimentation is required to provide a more homogeneous distribution of variation observations.

- Segmentation procedures should be further considered with descriptions of object spatial, temporal, and functional behaviours which are based on agronomic relationships which are still under investigation.

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Appendix 1

Prototype experimentation source codes

A1.1 – A Java object class for average covariance of the total field (A_C)

```
import java.io.*;
                                                  // (The TextReader class must be available to this program.)
public class AveVarioFile {
public static void main(String[] args) {
   TextReader data;                               // Character input stream for reading data.
   PrintWriter result;                            // Character output stream for writing data.
   double[] number = new double[180000];          // An array to hold up to 180,000 records within 1 file.
   double sum, sumNugOff;                         // Total sum of Yield Semivariance.
   double ave, aveSumOff, aveNugOff;              // Average Yield Semivariance.
   String inFile = args[0];                       // Input File Name from Execution Arguments
   String OutFile = args[1];                      // Output File Name to Execution Arguments
   int numberCt,nRows,nCols;                      // Number Counter of records actually stored in the array.

   try {                                                    // Create the input stream.
     data = new TextReader(new FileReader(inFile));
   }
   catch (FileNotFoundException e) {
     System.out.println("Can't find file "+ inFile + " !!");
     return;                                                // End the program by returning from main().
   }
   try {                                                    // Create the output stream.
     result = new PrintWriter(new FileWriter(OutFile));
   }
   catch (IOException e) {
     System.out.println("Can't open file " + OutFile + " !!");
     System.out.println(e.toString());
     data.close();                                          // Close the input file.
     return;                                                // End the program.
   }
   System.out.println("file in / Out OK:  " + inFile + "  &  " + OutFile +" !!");        // control
   try {                                          // Read the input data file into an input record array.
     numberCt = 0;
     while (data.eof() == false) {                // Read until end-of-file.
            number[numberCt] = data.getlnDouble();
       numberCt++;
     }
   System.out.println(" Number of Records = "+ numberCt +" !!");                           // control
   System.out.println("In file has been dimentioned "+ inFile +  " !!");                   // control
     // Calculating Sum of Variances.
      sum = sumNugOff = nCols = nRows = 0;
                   for (int i = 0; i < numberCt; i++) {
                          for (int j = 0; j < numberCt; j++) {
                                 sum += (Math.pow((number[i] - number[j]),2)/2);
                                 sumNugOff += (Math.pow((number[i] - number[j]),2)/2) - 0.1565;
                            nCols = j;                                                     // control
                          }
                          nRows = i;                                                       // control
                   }
   System.out.println(" i  =  "+ nRows +" !!");                                            // control
   System.out.println(" j  =  "+ nCols +" !!");                                            // control
   System.out.println("Sum Done !");                                                       // control
   System.out.println(" Sum  =  "+ sum +" !!");                                            // control
```

```
                                        // Calculating Average of Total Field Variance.

      ave = sum / Math.pow(numberCt,2);
      aveNugOff = ave - 0.1565;
      aveSumOff = sumNugOff / Math.pow(numberCt,2);
      result.println(" Number of Input Records  =  "+ numberCt);
      result.println(" _________________________________________________________________");
      result.println(" ");
      result.println(" Total Sum of Variance  =  " + sum);
      result.println(" Total Sum of Variance - Co =  " + sumNugOff);
      result.println(" _________________________________________________________________");
      result.println(" ");
      result.println(" Total Average Semi-Variance  =  " + ave);
      result.println(" Average Semi-Variance - Co =  " + aveNugOff);
      result.println(" Average Semi-Variance (Sum - Co) =  " + aveSumOff);

      System.out.println("Done!");
      }
      catch (TextReader.Error e) {
                                          // Some problem reading the data from the input file.
        System.out.println("Input Error: " + e.getMessage());
      }
      catch (IndexOutOfBoundsException e) {
                                          // Must have tried to put too many numbers in the array.
        System.out.println("You have more than 50,000 records in data file.");
        System.out.println("Processing has been aborted.");
      }
      finally {
                                          // Finish by closing the files,
                                          //     whatever else may have happened.
        data.close();
        result.close();
      }
   }                                      // end of main()
}                                         // end of class
```

A1.2 – The Yieldex (Y_i) computation in Splus© script

```
##########################################################################################
#                                   Yieldex.SSC           March  2007                   #
#  Ronaldo P. Oliveira                                                                  #
#   Last review for 218 yield maps on Final Set                                         #
#  Program for numerically turning variogram parameters into an Integral Scale         #
#  of Yield Variability .                                                               #
##########################################################################################
##    Input Data:
##############
     j<-read.table("C:\\Documents and Settings\\roli7539.AGRICULTURE\\My Documents\\Research\\Data\\Final_Set\\Yldx\\Yldx_218_In.TXT", header= T, as.is=T, sep="\t")

##    Set Integral Scale Result Matrix:
####################################
     JaIntegr<-matrix(ncol=11, nrow=nrow(j))
     dimnames(JaIntegr)<-list(NULL,c("Farm","Field","Year","Crop","MeanYld","CVyld","Model","MagFields","IntScale","SpatStruc","YldEx"))

## Processes Row by Row (All Models from All Fields):
###########################################################
for(i in 1:nrow(j))
{
##    Reads Parameters from InFile:
##################################################
          Model       <-   j[i,7]
          C0          <-   j[i,8]
          C1          <-   j[i,9]
          A1          <-   j[i,10]
          Alfa     <-   j[i,11]
          MaxLag      <-   j[i,12]
          GamStar  <-   j[i,13]
          MagFields <-  j[i,14]
          sVRate      <-   sqrt(0.036)
##    Selects Model for Integration:
     ##    Spherical:
     ##################################################################
     if(Model=="Spherical")
     {
          GammaS      <-   C0+C1
          StrucDist  <-   A1
          #     just the Range
     }
     ##    Exponential:
     ##################################################################
     if(Model=="Exponential")
     {
          GammaS      <-   C0+0.95*C1
          StrucDist  <-   3*A1
```

```
        # or
        # StrucDist        <-    log(1/(1-(0.95*GamStar-C0)/C1))*A1
        #       just the Range (3*A1) if R <= MaxLag, else (R>MaxLag) ==>       Log(1/(1-(:Name("1999")-C0)/C1))*A1
    }
    ##    Gaussian:
    #############################################################
    if(Model=="Gaussian")
    {
        GammaS          <-    C0+0.95*(GamStar-C0)
        StrucDist   <-    sqrt(log(1/(1-(GammaS-C0)/C1)))*A1
        #                         Root(Log(1/(1-(:Gauss00-C0)/C1)),2)*A1
    }
    ##    Stable:
    #############################################################
    if(Model=="Stable")
    {
        GammaS          <-    C0+0.95*(GamStar-C0)
        StrucDist   <-    ((log(1/(1-(GammaS-C0)/C1)))^(1/Alfa))*A1
        #                         Root(Log(1/(1-(:Stable_00-C0)/C1)),Alfa)*A1
    }
    ##    Generalised Cauchy:
    #############################################################
    if(Model=="Generalised Cauchy")
    {
        GammaS          <-    C0+0.95*(GamStar-C0)
        StrucDist   <-    sqrt(1/((1-(GammaS-C0)/C1)^(1/Alfa))-1)*A1
        #                         Root(1/Root(1-(:Name("2000")-C0)/C1,Alfa)-1,2)*A1
    }
##  YieldEx Business:
#####################
    SpatVar         <-    StrucDist/sqrt(10000)
    DYieldex        <-    SpatVar/sVRate
    Yieldex         <-    sqrt(MagFields*DYieldex)
##    Populates Result Matrix:
###########################
        JaIntegr[i,1]     <-    j[i,1]
        JaIntegr[i,2]     <-    j[i,2]
        JaIntegr[i,3]     <-    j[i,3]
        JaIntegr[i,4]     <-    j[i,4]
        JaIntegr[i,5]     <-    j[i,5]
        JaIntegr[i,6]     <-    j[i,6]
        JaIntegr[i,7]     <-    j[i,7]
        JaIntegr[i,8]     <-    MagFields
        JaIntegr[i,9]           <-    StrucDist
        JaIntegr[i,10]    <-    DYieldex
        JaIntegr[i,11]    <-    Yieldex
}
##    Creates Output File:
    write.table(JaIntegr,file="C:\\Documents and Settings\\roli7539.AGRICULTURE\\My Documents\\Research\\Data\\Final_Set\\Yldx\\Yldx_218_Out.TXT",sep="\t",dimnames.write="colnames")
```

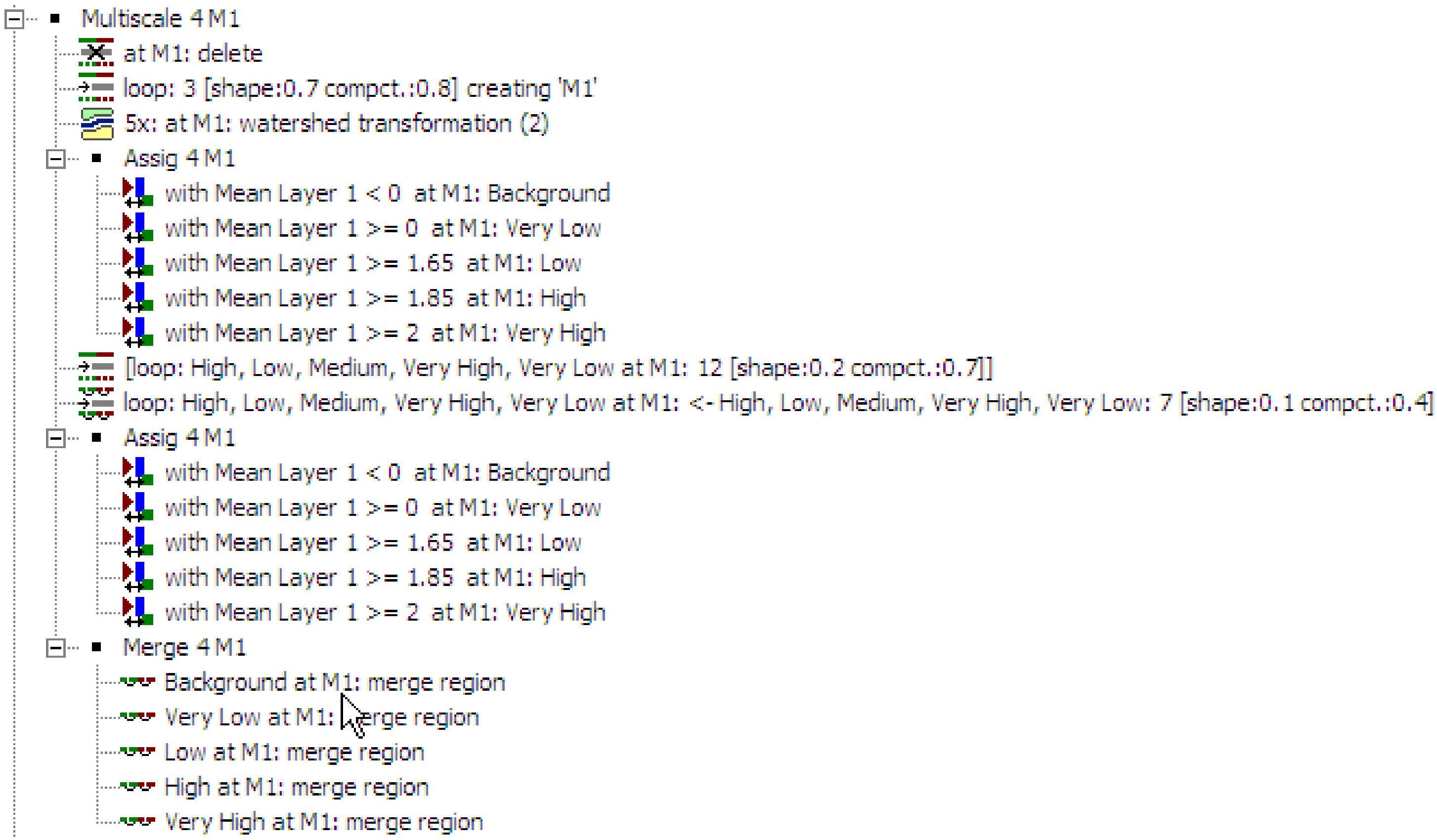
A1.3 – The object-oriented delineation of management zones in Developer 7©

- ***Multiresolution with watershed transformation and grow region segmentations***

Process tree for 2 Zones:

***Process tree for 3 Zones*:**

Process tree for 4 Zones:



- ***k-means Clustering***

Process tree for 2 Zones:

- Chess (1) + K-means
  - at M1: delete
  - chess board: 1 creating 'M1'
- Assig 2 M1
  - with Mean Layer 1 < 0 at M1: Background
  - with Mean Layer 1 >= 0 at M1: ZL
  - with Mean Layer 1 >= 1.9 at M1: ZH
- Merge 2 M1
  - Background at M1: merge region
  - ZL at M1: merge region
  - ZH at M1: merge region

Process tree for 3 Zones:

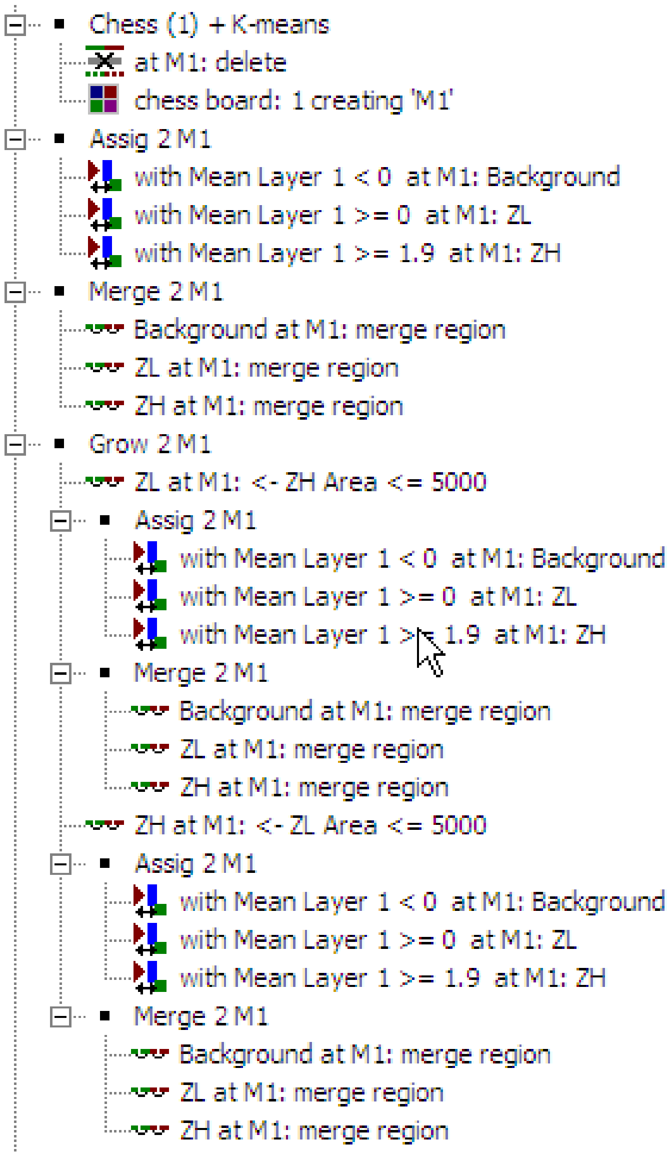
- Chess (1) + K-means
  - at M1: delete
  - chess board: 1 creating 'M1'
- Assig 3 M1
  - with Mean Layer 1 < 0 at M1: Background
  - with Mean Layer 1 >= 0 at M1: Zone 3 (Lower Yield)
  - with Mean Layer 1 >= 1.78 at M1: Zone 2 (Average Yield)
  - with Mean Layer 1 >= 1.99 at M1: Zone 1 (Higher Yield)
- Merge 3 M1
  - Background at M1: merge region
  - Zone 1 (Higher Yield) at M1: merge region
  - Zone 2 (Average Yield) at M1: merge region
  - Zone 3 (Lower Yield) at M1: merge region

Process tree for 4 Zones:

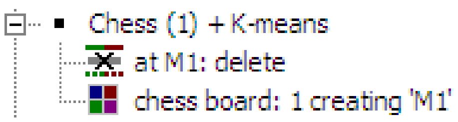
- Chess (1) + K-means
  - at M1: delete
  - chess board: 1 creating 'M1'
- Assig 4 M1
  - with Mean Layer 1 < 0 at M1: Background
  - with Mean Layer 1 >= 0 at M1: Very Low
  - with Mean Layer 1 >= 1.7 at M1: Low
  - with Mean Layer 1 >= 1.9 at M1: High
  - with Mean Layer 1 >= 2 at M1: Very High
- Merge 4 M1
  - Background at M1: merge region
  - Very Low at M1: merge region
  - Low at M1: merge region
  - High at M1: merge region
  - Very High at M1: merge region

- ***k-means Clustering with grow region***

Process tree for 2 Zones:



Process tree for 3 Zones:



- Assig 3 M1
  - with Mean Layer 1 < 0 at M1: Background
  - with Mean Layer 1 >= 0 at M1: Zone 3 (Lower Yield)
  - with Mean Layer 1 >= 1.78 at M1: Zone 2 (Average Yield)
  - with Mean Layer 1 >= 1.99 at M1: Zone 1 (Higher Yield)
- Merge 3 M1
  - Background at M1: merge region
  - Zone 1 (Higher Yield) at M1: merge region
  - Zone 2 (Average Yield) at M1: merge region
  - Zone 3 (Lower Yield) at M1: merge region
- Grow 3 M1
  - Zone 3 (Lower Yield) at M1: <- Zone 2 (Average Yield) Area <= 2500
  - Assig 3 M1
    - with Mean Layer 1 < 0 at M1: Background
    - with Mean Layer 1 >= 0 at M1: Zone 3 (Lower Yield)
    - with Mean Layer 1 >= 1.78 at M1: Zone 2 (Average Yield)
    - with Mean Layer 1 >= 1.99 at M1: Zone 1 (Higher Yield)
  - Merge 3 M1
    - Background at M1: merge region
    - Zone 1 (Higher Yield) at M1: merge region
    - Zone 2 (Average Yield) at M1: merge region
    - Zone 3 (Lower Yield) at M1: merge region
  - Zone 2 (Average Yield) at M1: <- Zone 3 (Lower Yield) Area <= 2500
  - Assig 3 M1
  - Merge 3 M1
  - Zone 2 (Average Yield) at M1: <- Zone 1 (Higher Yield) Area <= 2500
  - Assig 3 M1
  - Merge 3 M1
  - Zone 1 (Higher Yield) at M1: <- Zone 2 (Average Yield) Area <= 2500
  - Assig 3 M1
  - Merge 3 M1
  - Zone 1 (Higher Yield) at M1: <- Zone 3 (Lower Yield) Area <= 2500
  - Assig 3 M1
  - Merge 3 M1

Process tree for 4 Zones:

- Chess (1) + K-means
  - at M1: delete
  - chess board: 1 creating 'M1'
- Assig 4 M1
  - with Mean Layer 1 < 0 at M1: Background
  - with Mean Layer 1 >= 0 at M1: Very Low
  - with Mean Layer 1 >= 1.7 at M1: Low
  - with Mean Layer 1 >= 1.9 at M1: High
  - with Mean Layer 1 >= 2 at M1: Very High
- Merge 4 M1
  - Background at M1: merge region
  - Very Low at M1: merge region
  - Low at M1: merge region
  - High at M1: merge region
  - Very High at M1: merge region

- Grow 4 M1
  - Very Low at M1: <- Low Area <= 2500
  - Assig 4 M1
    - with Mean Layer 1 < 0 at M1: Background
    - with Mean Layer 1 >= 0 at M1: Very Low
    - with Mean Layer 1 >= 1.7 at M1: Low
    - with Mean Layer 1 >= 1.9 at M1: High
    - with Mean Layer 1 >= 2 at M1: Very High
  - Merge 4 M1
    - Background at M1: merge region
    - Very Low at M1: merge region
    - Low at M1: merge region
    - High at M1: merge region
    - Very High at M1: merge region
  - Low at M1: <- Very Low Area <= 2500
  - Low at M1: <- High Area <= 2500
  - Low at M1: <- Very High Area <= 2500
  - Merge 4 M1
    - Background at M1: merge region
    - Very Low at M1: merge region
    - Low at M1: merge region
    - High at M1: merge region
    - Very High at M1: merge region
  - Assig 4 M1
  - High at M1: <- Low Area <= 2500
  - Assig 4 M1
  - Merge 4 M1
    - Background at M1: merge region
    - Very Low at M1: merge region
    - Low at M1: merge region
    - High at M1: merge region
    - Very High at M1: merge region
  - High at M1: <- Very High Area <= 2500
  - Assig 4 M1
  - Merge 4 M1
    - Background at M1: merge region
    - Very Low at M1: merge region
    - Low at M1: merge region
    - High at M1: merge region
    - Very High at M1: merge region
  - Very High at M1: <- High Area <= 2500
  - Assig 4 M1
  - Merge 4 M1
    - Background at M1: merge region
    - Very Low at M1: merge region
    - Low at M1: merge region
    - High at M1: merge region
    - Very High at M1: merge region

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Appendix 2

Concepts in object-oriented development and Web environments

A2.1 - Languages for human-computer interactions

Programming language typologies can be difficult to establish. They commonly arise from combining elements of predecessor languages, being categorizable along multiple axes (Binstock, 2005). For example, Java has at least two interpretations, as OOP for reinforcing behaviour, or as a concurrent language for managing parallel threads. Mixed classifications are also given for scripting languages (*e.g.* VB, Perl, Python, and Ruby) and markup languages (HTML, XML, and GML), being object-oriented as well as domain-specific languages. Further references of programming languages can be found on Web sites for the evolution of software technology (e.g. O'Reill Media, 2008 - the History of Programming Languages Wiki; Nierstrasz and Meijler, 1995 - the Software Composition Portal; Ducasse et al., 2005 - the SmallWiki; Rigaux, 2001 - Pixel's home page in the SourceForge.net Portal). Web mark-up languages have a layered topology and are conceived as extensions of basic layers of consortia certified standards and specifications which are further introduced in **Section A2.4**. Although a rigid programming categorization has become less relevant, a resilient and commonly used classification for procedural, imperative, and declarative languages is briefly introduced (**Table A2.1**).

Procedural languages specify the explicit sequences of individual steps to follow in order to produce an algorithm changing the system state, as an example of structured programming languages (e.g. Fortran, Cobol, Pascal). Imperative languages specify the explicit manipulations of the system state by describing an input algorithm. The algorithm language (Algol) is an example of imperative languages designed for syntax and semantics (van Wijngaarden et al., 1973), fitting a wider scope of applications. These concepts are supported by languages like C, C_{++}, Java, Ruby, and Phyton (Stroustrup, 2000; Binstock, 2005).

Table A2.1: Programming language chronology (modified from Nierstrasz, 2008).

Year	Programming Language	Team Development Leaders	Language Innovative Characteristic
Early 50's	Assemblers	-	Machine code languages
1957	Fortran	Backus	Procedural high-level language
1958	Algol	Dijkstra and Naur	Imperative language
1960	LISP[*]	McCarthy	Procedural/Imperative language
1960	Cobol	Hopper	Business oriented language
1962	APL[*]	Iverson	Array Programming
1962	Simula	Dahl & Nygaard	First OOP key concepts
1964	Basic and PL/I	Kemeny; IBM Labs.	Interactive O/S[*] languages
1966	ISWIM[*]	Landin	Abstract/Functional language
1970	Prolog[*]	Colmerauer & Warren	First Logic Language
1972	C	Ritchie	O/S[*] medium-level language
1975	Pascal and Scheme	Wirth; Steele	Educational languages
1977	FP[*]	Backus	Function programming proposal
1978	CSP[*]	Hoare	First concurrency concepts
1983	Smalltalk and Ada	Kay; Ichbiah	OOP revisited for Interoperability
1984	ML[*]	Backus & Milner	First polymorphism concepts
1986	C++	Stroustrup	OOP version for C
1986	Eiffel	Meyer	Design by contract concepts
1988	CLOS and R	Keene; Ihaka	Domain Specific OOP
1990	Haskell	Curry	Non-strict semantics' proposal
1990s	Python and JavaScript	(Various)	Scripting as a mainstream
1995	Java	Gosling	OOP revisited for the WEB
2000	C#	Hejlsberg	Microsoft .NET version of C$_{++}$

[*] O/S acronym stands for Operating Systems; CSP for Communicating Sequential Process; LISP for List Programming; FP for Function Programming; ML for Modular Language; Prolog for Program Logic, and ISWIN for "If you See What I Mean".

[**] Underlined names are development leaders who have received the annual A. M. Turing Award by the Association for Computing Machinery (ACM); recognized as the Nobel Prize in computer science.

Declarative languages specify neither explicit sequences nor state manipulations, rather focusing on behavioral relationships between variables. They are understood as a composition of logic and control, where only the logic is supplied in the source code and the execution control is given by the system. Most declarative languages are branches of artificial intelligence and automation, including logic lists (LISP), functional (Smalltalk), constraint (Prolog), relational (SQL), and definitional (PL/I).

In fact, all object-oriented approaches are an ultimate language multi-paradigm mix. According to Mangold (1996), they can be considered as strongly-typed languages (imperative style) of structured constructs (procedural style), also supporting behavioral abstractions (declarative style). This actually reflects a cumulative aspect in the evolution of programming which was firstly suggested by Backus (1977): "*Each successive language incorporates, with a little cleaning up, all the features of its predecessors plus a few more*".

A2.2 - What languages do we speak now?

As seen in the previous section, programming languages are in a constant and dynamic update that is difficult to cope with. In parallel to the natural processes of maintenance or improvement of specific application tools, the surging and retreat of proprietary (and some times passionate) coding formats have trapped many research driven developments in the past. Over the years, an increasing concern with data compatibility and open system interoperability (Ramsin and Paige, 2008) has improved system flexibility and code reuse for agricultural tools (Kitchen, 2008).

It is well accepted by the software engineering research community that the object-oriented approach has represented the ultimate evolutionary and open architecture development. Probably not representing either the ultimate solution for all types of requirements, or the final step in the evolution of methodologies (Ramsin and Paige, 2008). It is recognized that many areas - *e.g.* Graphical User Interfaces (GUI's), multi-format spatial data handling (GIS), and distributed Web services (SOA) - can be supported by object-oriented methods rather efficiently. In addition, there are clear evidences in specialized computer magazines and online developer communities that OOP is increasingly popular in the software industry (**Table A2.2**). Similar figures are difficult to draw for agriculture, in particular for SSCM, where information mostly accounts for computer usage.

Table A2.2: The increasing adoption of the OO paradigm.

Category	Ratings Feb. 2008	Delta Feb. 2007	Ratings Jul. 2008	Delta Jul. 2007
Object-Oriented Languages	54.8%	+3.1%	56.6%	+3.9%
Procedural Languages	42.9%	-1.9%	41.1%	-2.3%
Functional Languages	1.4%	-0.4%	1.7%	-0.3%
Logical Languages	0.9%	-0.8%	0.7%	-1.2%

*** source:** The online TIOBE programming community index.

As previously detailed in **Section 2.2**, the effective use of the object-oriented approach has been reported in agricultural system developments, with an overall recognition of facilitated system integration by simplifying system abstractions and increasing code flexibility. The relevance of the approach in simulation research has been evaluated for crop models (Beck et al., 2002) with flexible ways of model integration improving quantitatively based cropping decisions (Hayman, 2003) using specific development protocols for composable simulation frameworks (Tolk, 2003; Moore et al., 2007).

Among object-oriented languages, the popularity of Java is heavily based on open and free software communities, who have thoroughly tested, refined, and extended its functionalities. In a recent monthly rank of an independent software community (TIOBE Programming Community Index, 2008), 8 languages out of the top 10 involved OO architectures, with the Java programming language leading the rank (**Table A2.3**). Other known programming languages lower ranked in this survey and their respective usage percentage are as follows: Delphi (2.0%, 11th), SQL (0.74%, 13th), SAS (0.63%, 14th), Pascal (0.43%, 16th), Cobol (0.42%, 17th), Ada (0.41%, 19th), Fortran (0.29%, 25th), MatLab (0.25%, 27th), and LabVIEW (0.16%, 31st).

The recent increase of PHP and Python popularity can also be highlighted as examples of the popularity of a rapid prototyping offered by Web scripting languages, which promote dynamic capabilities for animation and data exchange within Web pages. Although offering powerful Web interfacing for server centred models, as used in the Yield Prophet solution (Hunt et al., 2006), these development approaches do not support further semantic extensions and model composability as required for integrated analysis.

Table A2.3: Top 10 leading programming languages.

Programming Language	Position Jul 2008	Ratings Jul 2008	Delta Jul 2007
Java	1	21.35%	+0.33%
C	2	15.95%	-0.42%
C_{++}	3	10.69%	+0.19%
(Visual) Basic	4	10.45%	+0.72%
PHP	5	9.53%	+0.87%
Perl	6	5.13%	-0.20%
Python	7	4.97%	+1.95%
C#	8	4.00%	+0.29%
JavaScript	9	2.76%	+0.24%
Ruby	10	2.735%	+0.64%

* **source:** http://www.tiobe.com

These trends are in agreement with other market related publications that report a software developer's review. Binstock (2005) indicates that long-term trends are clearly in favour of object-oriented languages, although this tendency appears not be influencing developments like C and C_{++}. In comparison, classic programming languages (e.g. Fortran, Ada, and Assembly) and proprietary fourth-generation languages (4GLs) are expected to continue to decline, though the market share of these products has been in steady decline for years. Additional figures on the adoption of Java are given with reference to uploaded software projects in an open development repository (Sourceforge.Net® FLOSSmole, 2005). For a better understanding of aspects in the Java technology, a brief introduction of this environment is presented in the next section.

A2.3 - Using objects

Object-oriented technology is a general tool that can be used to model domain-specific problems ranging from software interactions or control of communication protocols to physical agronomic processes or scientific methods for data analysis and interpretation.

Abstractions are centred on objects and the dynamics of message passing among them. Booch (1994) gives a classic definition: "abstraction denotes the essential characteristics of an object that distinguish it from all other kinds of object and thus provide crisply defined conceptual boundaries, relative to the perspective of the viewer".

Object-oriented fundamentals

Although it is commonly suggested that OOP languages would offer faster learning, these claims are often too vague and difficult to evaluate in relation to previous approaches (Marston, 2007). The comprehensive set of object-oriented concepts may require some time to be properly understood and practiced. Therefore, this section aims at a brief introduction to key concepts that are understood as being break-through points in OOP. A simple and straight forward definition of OOP is given by Marston (2007): "a programming stile which is oriented around objects, thus taking advantage of encapsulation, polymorphism, and inheritance to increase code reuse and decrease code maintenance". These three concepts have also been suggested as central to supporting flexibility in advanced simulations (Ascough II et al., 2001), GIS applications (Wood, 2002). A summary review of the main object-oriented concepts is given in **Table A2.4**.

Table A2.4: Fundamental concepts supporting object-oriented architectures.

Concept	Concept Definition
Class	A class is a blueprint, or prototype, that defines the variables and the methods common to all objects of a certain kind.
Object	An instance of a class. A class must be instantiated into an object before it can be used. More than one instance of the same class can be in existence at any one time.
Encapsulation	The act of placing data and the operations that performs on that data in the same class. The class becomes a container for data and operations.
Inheritance	The reuse of a base class (superclass) to derived new classes (subclasses). In the class hierarchy, methods and properties of a superclass are automatically shared by any subclass, which may also add other more specific methods.
Polymorphism	The ability to process objects differently depending on their data type or class, thus same interface for different implementations. It allows substituting one class for another. Different classes may contain the same method names, but the result which is returned by each method will be different as the code behind it is different in each class.

*** sources:** Wood, 2002; Berard, 2006; Marston, 2007.

An object is a uniquely identifiable instance of a class which defines both the properties (data) and the methods (functions) related with that type of programmatic entity. Object classes are simplified representations of specific parts of a larger complex system, which are usually built up by several class libraries. Neither the object characteristics (properties) nor the object behaviour (methods) should exist outside of its class definition. Class and class hierarchy constructs are defined with private and public class interfaces for class security management. Published interfaces define the class methods that can be either accessed by message passing from other object classes, or extended by class inheritance of new object classes, without worrying about the hidden details.

A strong aspect in OOP is the typing style in which programmers are not limited to the definition of variables using classic data types (e.g. integer, float, double, character). It means that new types can be created out of specific functions, other object classes, or even existing legacy systems (*e.g.* dynamic link library – DLL's) that can be required by the system structure. In this way, data structures can handle both data and functions.

Marston (2007) lists distinguishing OOP features centred on the implementation of methods contrasting with functions in non-OOP languages, emphasizing that they are defined and accessed differently, they have different numbers of entry points and working copies, and they use different methods to maintaining the space state. In OOP the system flow is controlled through message passing between objects, being executed in synchronous and/or asynchronous ways. Object behaviour (methods) and class relationships are the key elements defining the system dynamic flow (Tracy, 2001).

Another OOP aspect is related to modular communication and data transactions over the Web, which relies on concepts of encapsulation and polymorphism (Weisfeld, 2008). In this case, objects that are remotely used encapsulated their data and behaviours (algorithms that manipulate the data) are both transported across a network and executed in the client machine, facilitating the construction of platform-independent structures with polymorphic interfaces (Papajorgji and Pardalos, 2006). In procedural architectures the data involved in the execution is separated from their operations, when information is sent across a network only the relevant data is sent expecting that the remote client knows how to process it.

Objects in Java

In terms of platform-independent languages, Java is among the latest in pure object-oriented programming designed to meet this goal, particularly in communication between systems via the internet. Often mistaken with the Netscape Web scripting language (JavaScript ®, 1995), Java (Sun Microsystem's ©, 1991) provides a general purpose and comprehensive software development capability that is centred on open platform concepts (e.g. machine independent, reusable, and distributed computing) under the slogan "Write once, run anywhere, and reuse everywhere". Also designed for strong typing functionality, Java facilitates the construction of objects within higher levels of abstraction which contain in itself small Java applications specifically designed to be called from or to be executed in Web servers. These smaller applications are respectively denominated as Applets and Servlets. These specific network driven functionalities have made Java the most utilised development language for Internet and intranet applications (Tracy, 2001). A summary of the Java technology advantages include the given ability for developers to:

- Write platform independent software;
- Create programs to run within a web browser and web services;
- Develop server-side applications for online interoperability;
- Create highly customized applications or services; and
- Write applications for mobile phones, remote processors, or network controllers.

The Java Virtual Machine (JVM) is an abstract computer architecture designed within the Java Runtime Environment (JRE) to run an architecture-neutral bytecode (".class" extensions) translated from a Java source code (".java" extensions) by JRE interpreters (Tracy, 2001; Nierstrasz, 2008). A compiled Java byte code can run on any computer with an installed JRE which is freely available for all standard operating systems (e.g. UNIX, Macintosh OS, Windows, and Linux).

Java classes can be accessed by other object classes by exposing its public methods and attributes across the Internet. The Javadoc program takes Java source codes and creates a Web page representing the class application programming interface (API), known as Java API. This interface allows public navigation on the exposed parts of a class structure and supporting class reuse. In Java, methods of an object class are the core elements for execution control. The execution control features are then coordinated by the semantic definition of class relationships (Wood, 2002; Horstmann, 2005; Weisfeld, 2008). Class relationships are mostly established through three main constructs: i) inheritance ("is a" relationship – class and super-class); ii) aggregation ("has" relationship – generalization or specialization); and iii) association ("uses" relationship – functional interactions).

Java was developed with a unique set of Internet/intranet primitive classes from which programs can be designed for use on the World Wide Web. This construct allows Java Applets to be developed for downloading from a Web server and run on any Web browser client (e.g. Netscape, Internet Explorer, Mozilla). The disadvantage of using Applets is the slow processing in relation to programs that are native in the client machine. Servlets which are newer developments, have the same function as the Applets, but they are executed at the remote Web server (Nierstrasz, 2008).

Several Java-centric development platforms and software artefacts from Sun Microsystem's are available for developing, building and deploying different types of platform-independent architectures. They range from compact operating systems for mobile-devices or desktop stand-alone solutions to huge and decentralized enterprise Web service solutions. Some of these construction tools are summarized in **Table A2.5**.

Additional development support is given by Java Interactive Development Environments (IDE). Java IDE's are software applications designed for facilitating programming and maximizing productivity. An IDE may offer a source code editor, a compiler and/or interpreter, a debugger, a version control system, a visual GUI design, a class browser, an object inspector, and other built in code generation automation tools. Several other specialized development tools, plug-in technologies, and educational documentation sources are also offered by active open communities. Open communities offer a comprehensive list of development initiatives options and supporting tools (e.g. java-source.net, gnu.org, sourceforge.net, javaworld.com, junit.org, developer.com).

Table A2.5: Main Java related technologies.

Technology	Summary Definition
J2SE	The Java Standard Edition is an environment for developing applications on desktops and servers. The J2SE platform includes several component libraries to improve cross-platform performance and interoperability (e.g. AWT, JAXP, CORBA, VisualVM).
J2EE	The Java Platform Enterprise Edition is an environment for developing Web-based applications. It consists of services, APIs, and protocols that providing multilayered development, including HTML code creation, the Enterprise JavaBeans (EJB's), the Java Database Connectivity (JDBC), and the Java Servlet API.
J2ME	The Java Platform Micro Edition developing applications running on mobile and other embedded devices (e.g. mobile phones, PDA's, TV set-top boxes, printers) that includes flexible user interfaces, robust security, built-in network protocols, and support for networked and offline applications that can be downloaded dynamically.
JFX	The Java Platform Enterprise Edition is an environment for creating dynamic applications for the next generation of web delivered content.
JSP	The Java Server Pages is a server-side technology for developing web applications with rich user interfaces. JSP technology is a user interface framework for building Java-based web server applications rending the user interface back to the client.
JDMK	The Java Dynamic Management Kit is a toolkit that allows developers to rapidly create smart agents based on the Java Management Extensions (JMX) specification.
JADE	The Java Agent Development Environment is for agent-based developments.
JESS	The Java Expert System Shell is an environment for automating domain specific rule-based decision trees. The JESS rule engine evaluates and executes rules expressed as *if-then* statements, separating knowledge from its implementation logic.
Applet	A small Internet-based program written in Java that can be downloaded by any computer and executed within a Web browser.
Servlet	A small Internet-based Java program, which can be remotely executed on a Web server from any client computer, and, if required, downloads the output to the client.
JavaBeans	A specification that defines how Java objects interact. An object that conforms to this specification is called JavaBeans.

* **source:** Sun Microsystem's (http://java.sun.com/; last accessed 12/08/08).

Abstracting objects

Some distinguishing advantages confered on OOP were never in fact unique to OOP languages. These techniques have been in fact inherited from previous programming styles, therefore they cannot be used to differentiate them. If OOP improves code reuse and software modularity, it does not imply that code reuse is not possible using other languages. The advantage of class reuse depends more on the proper coding than on the language in which it is written (Marston, 2007). Modularity is another concept that has been used in procedural languages for many years. The ability given by OOP to perform individual object code maintenance without imposing revisions in other parts of the system, does not assure that the class abstractions have been done in a way to facilitate a modular maintenance (Berrard, 2006). Therefore, ideas around the "off the shelf" components for evolutionary developments with customized solutions are more likely to be related with the quality of system design phases, than with the choice of programming.

It is actually possible to implement a procedural algorithm design (like classic Fortran routines) by means of any object-oriented language, whether or not making use of the specific OO functionalities is relevant to the system design (Wood, 2002). Still, there is a common agreement on the high suitability of the OO architecture for network developments, and it has been suggested (Binstock, 2005) that OOP languages are among the few programming languages which are likely to keep a net increase in investment (*e.g.* Java, PHP, C#, Python, and Ruby).

Finally, OO design methods, such as the Unified Modelling Language (UML; Rumbaugh et al., 1999), in association with integrated development tools (e.g. Java NetBeans IDE) are expected to work in achieving development benefits, in particular for spatio-temporal analysis. These methods are further detailed and used in Chapter 3 for in an innovative method of application design supporting SSCM decision-making processes.

A2.4 - The Web world

The growth of the World Wide Web (WWW) can be measured by the number of Web pages that are published; 176,000,000 web sites (Netcraft, 2007); and the number of links between pages. This fast growth is associated with the effective, relatively easy, and free form way in which a Web page can be written, maintained, and linked to other pages. (Sheth and Miller, 2003; Baer, 2007). A Web page has no formal coordination from central authorities over the open HyperText Transfer Protocol (HTTP) which allows information flow regardless of volume, content or ownership (Bell, 2007).

The HyperText Markup Language HTML (Berners-Lee, 1989) is a tagged text document format that represents the foundation of the WWW. This foundation is appropriate for presenting a multitude of Web pages of static content, but problems arise when large volumes of data need a consistent look and feel with variable content (Williams, 2007). Initially, the HTML had only a small, fixed set of tags, which has been extended and applied to several problem solving domains (Wilson, 2005).

The exponential growth of the WWW has created the challenge of how to get meaningful information and knowledge out of a dynamic, free and open media. The issue is that meaningful discovery varies according to the structure, type and content of the resource, and also on the individual interests and beliefs of the information service. An integrated farm resource management requires the retrieval of information to be drawn from distributed and heterogeneous knowledge domains. This may have motivated the perception of necessary semantic representation in Web developments, which was documented in early initiatives of integrated, participative, and adaptive farm management DSS (e.g. Gauthier et al., 1996; Lewis et al., 1998; Shaffer et al., 2000; Argent and Grayson, 2001). These requirements are in fact part of the general directives of the original Web proposal (Berners-Lee, 2007).

A summary overview of standards related to Web technologies are introduced in the next sub-sections as background to these evolutionary and multilayered solutions. The principal concepts introduced here are focused on current industrial standards in software developments which adhere to technologies aimed towards Web Services. New developments are conceived as extensions of embedded functionalities from basic layers of the Web multilayered architecture (**Figure A2.1**). This common and expandable media, “One Web”, is centred on certified standards and specifications from consortiums like W3C and OpenGIS.

It is believed that many of the Web technologies may represent new opportunities to diminish technical barriers to data and systems integration in SSCM decision support. Emerging technologies underlying the next semantic Web generation, refereed as “Web 2.0” or “Web of knowledge”, are also introduced later in this section (*The Semantic Web*). These semantic architectures have concepts centred on ontology mapping and autonomous agents, aiming to further extend the present Web functionality (the Web 1.0). They may potentially address advanced levels of knowledge integration supporting SSCM decision processes. Examples from the Web technology offered for agricultural decision support are discussed. System solutions for other application domains closely related to site-specific management (e.g. climate, soil, environment, simulation models, and GIS) are also illustrated for means of highlighting the relative limited attention given to Web solutions by the PA research community.

A multilayered architecture

The development of the Web was rolled out over the existing Internet without requiring any changes to it. Its architecture is depicted as a series of layers, each building on top of the other. This technology stack is built according to standards and recommendations given by the World Wide Web Consortium (W3C). This separation in layers of concerns (**Figure A2.1**) allows each component of the Internet and the applications that run on top of it to be capable of development and improving independently (Berners-Lee, 2007).

In this technology stack there are six major development activities: Web application, mobile, voice, Web services, semantic Web, and privacy-security (W3C, 2005). The evolution of this stack is realized through the extendibility of markup languages. The first IBM Generalized Markup Language, GML (Goldfarb et al., 1969) was extended by the ISO 8879 standard metalanguage, the Standard Generalized Markup Language – SGML, and after that descendant markup languages (e.g. XML) have been compliant with the rules for tagging elements recommended by the SGML, while establishing different ways in which tags can then be interpreted within rules of a specific application or business process.

Because of the open nature of the Internet's design, this layered architecture allows simultaneous but autonomous innovation to occur at many levels (Berners-Lee, 2007). Within a higher level of abstraction, Web related packages and technologies replicate the concept of “self-describing” and “self-contained” distributed components as part of a multi-tiered architecture to enable flexible interoperability of links, composability of services, or autonomic computing (Barry, 2003; Papazoglou and Georgakopoulos, 2003; Baer, 2007; Bloomberg, 2007; Berners-Lee, 2007).

The Web is now more than a practical media for document exchange. It has also been a platform for innovative commercial applications based on open standards and royalty-free technologies (e.g. J2EE and .NET) that underpin the Web (e.g. the eBay online auctions, the Google Earth Web GIS, Yahoo, Amazon.com selling platform). Innovation in the research and government areas has been equally robust. Leading efforts to make the process more open and transparent (e.g. Wiki and Grid Computing Communities) have pioneered new collaborate styles of information sharing (Pullen et al., 2005; Berners-Lee, 2007).

One of the potentials for changes to the Web service standard is apparent on applications called "mash-ups", which involve the ability to automatically match and mix multiple sources into one dynamic entity. Business locators (e.g. Yellow- and White- pages.com) and hotel booking services (e.g. lastminute.com, wotif.com) are a few examples where a search for a service returns the requested information, business address or accommodation prices, with additional value added by matching other relevant references, a location map or room pictures respectively. This type of functionality illustrates initial endeavours within the concept of "smart services", where information is automatically selected and tailored to suit specific needs of a consumer request.

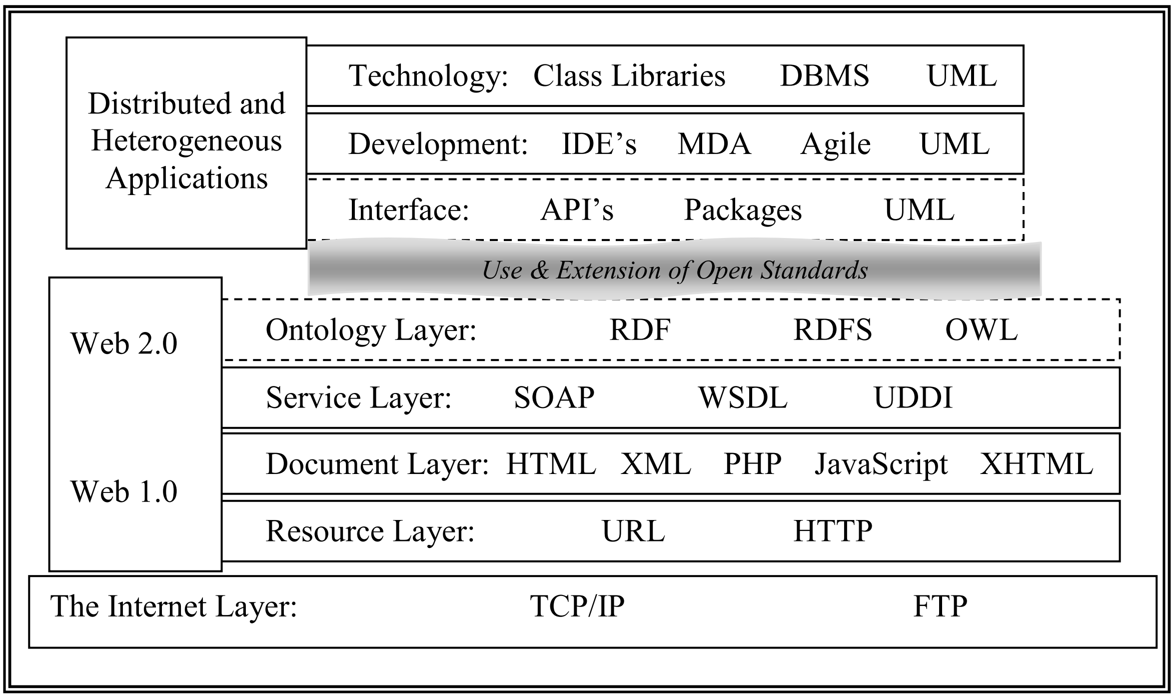

Figure A2.1: The integrative and multilayered architecture of the Web evolution.

*** source:** http://www.w3.org/Consortium/technology.html#techstack and http://www.service-architecture.com/web-services/articles; last accessed 12/08/08).

Web services

The W3C defines web services as "a software application identified by a Universal Resource Identifier (URI), whose interfaces and bindings are capable of being defined, described, and discovered as XML artefacts" (Bell et al., 2007). Less technical definitions are given in Papazoglou and Georgakopoulos (2003) and Sommaruga (2003), the former defined services as ''self-describing, open components supporting rapid low-cost compositions''. Web services are many times referred to as an information bus, in analogy to the data bus of a personal computer where various different hardware devices and circuit boards can be plugged in and exchange data in a common way.

To support robust, composable, and reusable integration, Web services consist of a set of universally agreed standards and specifications, which are summarized in **Table A2.6**, including XML, SOAP (Simple Object Access Protocol), WSDL (Web Services Description Language) and UDDI (Universal Description, Discovery and Integration) (Tsalgatidou and Pilioura, 2002; Ferris and Farrell, 2003). The self-describing nature of XML and WSDL allows dissimilar software components to understand each other. The messaging protocol SOAP supports the interaction between software components. The UDDI represents a set of protocols for the description, registration, lookup and integration of software components (Zhao et al., 2005)

Table A2.6: Main standards of Web services.

Standard	Summary Definition
WSDL	An XML-based language protocol developed by Microsoft and IBM describing service's abilities as collections of communication endpoints capable of exchanging messages.
XML	The eXtensible Markup Language, a specification by the W3C, is a pared-down version of SGML, designed especially for Web documents. It allows designers to create their own customized tags, enabling the definition, transmission, validation, and interpretation of data between applications.
SOAP	An XML-based messaging protocol used to encode the information contained in a service request and response messages before sending them over a network. Encoded messages are platform independent and transported via Internet protocols (e.g. SMTP, MIME, and HTTP).
UDDI	A public registry that enables services to list themselves on the Internet and discover, serving as a means of obtaining contact information for available WSDL described services.

*** sources:** Ferris and Farrell (2003); Tsalgatidou and Pilioura (2002); Bell et al., 2007.

The term Web service describes a standardized way of integrating Web-based applications using the XML, SOAP, WSDL and UDDI open standards over an Internet protocol backbone. In this approach services can be thought of as remote procedure calls over the web. The messaging is XML-based conforming to the SOAP protocol. SOAP essentially provides the envelope for sending the Web Services messages, generally using a HTTP connection. The form and structure of this service communication is described in the WSDL. The discovery of web services is typically carried out using the public UDDI registry, which provides a yellow page style lookup on available services. There are specific discovery directories dedicated to agriculture, like the Finnish Agronet (www.agronet.fi) and the German DAINet (www.dainet.de), where reliable information services from independent organizations are made available within the same web site.

In short, XML is used to tag the data, SOAP is used to transfer the data, WSDL is used for describing the services available and UDDI is used for listing what services are available. The approach relies on common business and service categorizations having utility across a community (Bell et al., 2007). The core technology has been driven by three communities: (1) The standards groups of the W3C, the Organization for the Advancement of Structured Information Standards (OASIS) and the Global Grid Forum (GGF); (2) Middleware vendor adoption and; (3) The open-source community.

The five steps involved in providing and consuming a Web service are: i) a service provider describes his service using WSDL, publishing it to a directory of services (e.g. UDDI, ebXML Registry); ii) a service consumer issues one or more queries to the directory of services, locating a service and communicating with that service; iii) part of the provided WSDL is passed to the service consumer, telling what the requests and responses are for that service; iv) the consumer uses the WSDL to send a request to the provider; and v) the service provides the expected response to the service consumer. The use of XML and web service developments is suggested as providing a low learning curve and slowing the prospect to faster a wider technology (Sheth & Miller, 2003) adoption.

Finally, distributed program-to-program interactions add extra threads on top of current Web security schemes (e.g. the secure sockets layer - SSL). As a result, The Web service technology has been proposing new XML-based security schemes on top of existing structures (e.g. digital signatures, key specification, ebXML Message Service).

The semantic Web

Ontological analysis has been shown to be an effective first step in the construction of robust knowledge based systems. The use of these techniques over the open Web media has been supporting developments towards intelligent systems. Among an outstanding range of applications, biosystem design (Priami and Quaglia, 2004) and mechanistic simulation models (Benjamin et al., 2006) are likely to take advantage of semantic development standards, re-usable application and domain reference models.

In a simple sentence, the Semantic Web makes use of tagged text documents representing knowledge of a specific domain. This paradigm was first proposed by Berners-Lee et al. (2001) as the ultimate goal of the WWW, in which information is given well-defined meaning, better enabling computers and people to work in co-operation. This ontology layer has been added to the classic Web stack (**Figure A2.1**) by means of semantic languages which enabled the relation between web resources to be made explicit (Bell et al., 2007).

Cesare et al. (2007) suggested that Semantic Web initiatives have introduced a new set of concepts and tools aiming to facilitate and/or enable the dynamic integration between different representations (and understandings) of real world phenomena, usually denominated as “ontology mapping”. In brief, the required support for semantic driven technology is given by structures such as the Resource Description Framework (RDF), the Resource Description Schema (RDFS), and the Web Ontology Language (OWL). Such semantic Web system architecture is referred to as "ontology services".

One of the central aspects in the development and use of ontology acquisition methods is the build up of a wide range of domain ontologies (Benjamin et al., 2006). These ontology libraries aim to reduce inefficient knowledge management, where redundant efforts are expended in capturing or recreating information that has already been encoded elsewhere. The idea underpinning the build up of ontology libraries is to offer a large and revisable collection of knowledge-bases of structured, domain specific, meaningful information which can be put to several uses for multiple application situations.

According to Benjamin et al. (2006), this information infrastructure is essential for enabling intelligent system developments, being the core component of software systems searching to facilitate knowledge sharing. The importance of knowledge sharing is evidenced by the large body of research directed toward the development of tools and methods to support a knowledge sharing approach to integration (Neches 1991; Gruber 1992; Benjamin et. al

2006). They discuss specific roles played by ontologies in a distributed simulation modelling framework, further detailing activities associated with multiple levels of abstraction, integration of tools, and development of component based virtual repositories.

The generic reuse of simulation models via semantic Web service architectures has been proposed in Bell et al. (2007), who provided a novel approach that explores the evolutionary and cooperative development of simulation components. They use WSDL (**Table A2.6**) and OWL for an ontology mapping of the health service simulation domain comprising remote access to hospital procedures and national blood service databases. This type of solution can potentially support generic DSS requirements related to human-computer interactions and system interoperability between heterogeneous data structures.

The semantic approach potentially supports requirements from several farm management decision support studies such as: for intelligent DSS (Ginzberg and Stohr, 1982; Kozai and Hoshi, 1989; Leung and Leung, 1993; Deursen, 1995; Stein et al., 1995; Smaalen, 1996; Petrov and Stoyen, 2000; Recio et al. 2003), knowledge-based systems (Jacucci and Uhrik, 1993; Cloutier et al., 1998; Sonka and Coaldrake, 1997; Button, 2001), and integrated farm management analysis and simulation (Steyaert and Goodchild, 1994; Egenhofer, 1996; Gauthier and Néel, 1996; Lewis, 1998; Sheffer et al., 2000; Kelly et al., 2001).

Ontology reference models such as the Suggested Upper Merged Ontology (SUMO - http://www.ontologyportal.org/) are available on the Internet. SUMO forms a free formal public ontology with 20,000 terms and 70,000 axioms from all its domain ontologies, being the first merged ontology mapped to the entire WordNet® (http://wordnet.princeton.edu/) lexical database of English. Similar models in agriculture involve endeavours such as the Agricultural Ontology Service (AOS), from FAO, and other PA relevant ontology services as previously discussed in **Section 2.4**.

A2.5 - Survey form on methods for DSS developments in SSCM

Introduction

Gaining views on your effort and experience developing software applications in Precision Agriculture (PA) is an important part of a research thesis aiming to evaluate present implementation standards and foresee potential pathways in software design. Results of this survey will be used in formulating a conceptual system framework to serve as a reference for near-future improvements in applied software. There will not be any individual evaluation or comparative matrix compiled as result, as only summary information will be used for reference and this will also be fed back to you. The underlying motivation is to identify and report common requirements to promote better standards of software accessibility, modularity, composability and reverse engineering. We believe that identifying these requirements could help the development of more pragmatic tools for decision support in the adoption and operation of site-specific management, if they are matched with both commercial implementation and process modelling research. Please take a few minutes to complete this survey form and return it to the address below.

Section A: Aims to compile a contact list of PA software which will be posted (with links) on the ACPA website.

Company Name:
Contact Name:
Address:
Tel: Fax:
eMail: URL:

Section B: Aims to identify present patterns and approaches in PA software development.

Software Name(s)	Software Version(s):

1. Has your software development process used object-oriented design methodologies (OOD)?

☐ 1 = Yes ☐ 2 = No

If "Yes", please indicate the method(s) from the options below:

- ☐ UML (Unified Modelling Language)
- ☐ OMS (Object Modelling System)
- ☐ SOA (Service-Oriented Architecture)
- ☐ Visual DFD (Data Flow Diagram)
- ☐ Visual ADE (Application Development Environment)
- ☐ Semantic or Ontology Representation Schemes
- ☐ Other: ____

If "No", which design approach was used?

____

2. Has your software development used object-oriented programming languages (OOP)?

☐ 1 = Yes ☐ 2 = No

If “Yes”, please indicate the language(s) selecting from the options below:

- ☐ JavaScript
- ☐ Perl, PHP or Python
- ☐ Ruby
- ☐ Java
- ☐ C++
- ☐ Visual Basic
- ☐ XML
- ☐ Other: ____

If “No”, which programming language was used?

____

3. Have you made use of any IDE (Interactive Design Environment) in your PA software?

☐ 1 = Yes ☐ 2 = No

If “Yes”, mark the concept(s) which you considered most useful.

- ☐ Encapsulation
- ☐ Prototyping
- ☐ Inheritance
- ☐ Class Interface
- ☐ Other: ____

4. Do you use open-source code in your PA applications?

☐ 1 = Yes ☐ 2 = No ☐ 3 = Plan to within a year ☐ 4 = Don’t know

5. Have you developed PA applications for Linux operating system?

☐ 1 = Yes ☐ 2 = No ☐ 3 = Plan to within a year ☐ 4 = Don’t know

6. Do you develop Web-Service application?

☐ 1 = Yes ☐ 2 = No ☐ 3 = Plan to within a year ☐ 4 = Don’t know

7. Did your application involve the canvassing of user requirements?

☐ 1 = Yes ☐ 2 = No

If “yes”, please indicate the user profile(s) from the options below.

- ☐ Farmer
- ☐ Agronomist /Consultants
- ☐ Other Technology Providers

- ☐ Researcher
- ☐ Other: ____

8. What type of decision support modules are already implemented in your solution?

(Please, indicate the analysis capability from the option(s) below)

- ☐ Crop Management & Proximal Sensor Record-keeping
- ☐ Spatial Information Management & GIS
- ☐ Economic Analysis
- ☐ Variogram Analysis and Kriging
- ☐ Crop Growth Simulation
- ☐ Image Processing
- ☐ Input Recommendations & Prescription Mapping
- ☐ Analysis of Management Zones
- ☐ Analysis of Production Logistics
- ☐ Other: ____

Section C: Aims to summarise future trends in Decision Support Systems (DSS) architecture.

1. What type of upcoming technology could influence future developments of your software solution?

- ☐ SOA
- ☐ Semantic Web
- ☐ Knowledge Engineering
- ☐ MABM (Multi-Agent Based Modelling)
- ☐ Grid Computing and Simulation
- ☐ Open Source Development
- ☐ Other: ____

2. Do you have active communication with users via a proprietary Web site?

☐ 1 = Yes ☐ 2 = No

If "yes", please indicate the user profile(s) from the options below.

- ☐ Farmer
- ☐ Agronomist /Consultants
- ☐ Other Technology Providers
- ☐ Researcher
- ☐ Other: ____

3. Indicate which type of Internet resources are used for client interactions and data exchange:

☐ 1 = eMail ☐ 2 = FTP ☐ 3 = P2P ☐ 4 = cooperative data warehouse ☐ 5 = not relevant

4. Where has the use of your software solution been reported?

(Please, indicate publication type(s) and media from the options below.)

- ☐ Agribusiness Magazines
- ☐ Software Magazines
- ☐ Technical Consultancy Reports
- ☐ Workshop or Field Day Reports
- ☐ Conference Proceedings
- ☐ Scientific Journals
- ☐ Press
- ☐ Web
- ☐ eMail

5. Comparison of your software with other products in the marketplace is useful in evaluating and upgrading your product.

(Please, choose an answer to indicate which statement best matches your opinion.)

☐ 1 = strongly agree ☐ 2 = agree ☐ 3 = disagree ☐ 4 = strongly disagree ☐ 5 = not relevant

6. The opportunity to interact with users, about changes and new implementation requirements, is or will be better facilitated by a Web-Service application.

(Please, choose an answer to indicate which statement best matches your opinion.)

☐ 1 = strongly agree ☐ 2 = agree ☐ 3 = disagree ☐ 4 = strongly disagree ☐ 5 = not relevant

A2.6 - List of software companies collaborating to the survey

Table A2.7: List of software companies supporting DSS for SSCM.

Company Name	Contact	Address	eMail	Software	Phone	Fax
PCI Geomatics	Kerry Chan	490 St. Joseph Blvd.,Gatineau, Quebec,J8Y 3Y7	chan@pcigeomatics.com	Geomatica 10.1.2 (Focus, OrthoEngine, Modeler, EASI); LidarEngine; Definiens eCognition Suite; FeatureObjeX; Geoconference; Summit Evolution; ProLines; ProSDK, ProPacks; Imagery Appliance	819-770-0098	819-770-0022
MapShots, Inc.	Tim Taylor	4610 Ansley Lane Cumming, GA 30040	trtaylor@mapshots.com	EASi Suite Farm Edition & EASi Suite Professional Edition		
ProducePak Solutions / W.I.S.H. Co S.A.	Jason Merricks	PO Box 489 , Collins Street West, Melbourne 3000	infoATproducepak.com	ProducePak Farm ERP & Management, ProducePak Packhouse, ProducePak Food Manufacturing, ProducePak Quality Management	03 8648 5899	(03) 9015 9743
Texas A&M University System AgriLife Research and Extension Center at Beaumont	Yubin Yang	1509 Aggie Drive, Beaumont, Texas 77713, USA	yyang@aesrg.tamu.edu	Available at: http://beaumont.tamu.edu/eTools/eTools_default.htm	409 752 5560	409 752 2741
Fairport Farm Software	Colin Booth	17 Charles St., SOUTH PERTH, WA, 6151	sales@fairport.com.au	PAM Farmstar & Farmstar Lite	+61 (0)8 93675823	+61 (0)8 93675814
Leica Geosystems Pty Ltd	Rob Kiernan	19 Lyall Street, South Perth, WA, 6151	rob.kiernan@leica-geosystems.com	GuideTRAX ver3.2 PlanIT ver1.1	(08) 9474 4772	(08) 9474 4771
FarmPlan	Robbie Scott	PO. Box. 236 Molong, NSW, 2866	Robbie.Scott@redriver.com.au	Farm Accounts V.4.162; Farm Stok; Farm Mapping V1.15	+63 (02) 63668512	+63 (02) 63668262

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Appendix 3

Basic concepts in current system development standards

A3.1 - System Development Methodologies (SDM)

System development may be characterized as a general problem solving activity, ideally including system analysis, requirement engineering, system design and implementation. As for any other knowledge domain, biosystems tools are first modelled (hypotheses), then implemented and tested (experiments) to refine/validate the model (feedback loop) (Priami and Quaglia, 2004). System design includes the understanding or conceptualization of a given problem and the abstraction of a desired solution. Implementation refers to physical manipulation of the problem abstraction, realizing and constructing a solution.

Analogous to current methods used for DSS design and development, Swedlow et al. (2003) describe biological and environmental models as a means to capture knowledge (semantics) about problems and solutions. Architectural views are abstractions of the model implementation used to organize the problem domain (business) knowledge in accordance with a specific programming language syntax. Diagrams are graphical projections of sets of model elements, which are used to depict different views of the domain knowledge about problems and solutions.

In software development, modelling is the designing of applications before coding. Models aim to raise the level of semantic representation facilitating the prototyping of different architectural aspects (e.g. business rule representation, process requirement and distribution, event synchronism and change in system state). Core design considerations which directly influence the final software functionality are given in **Table A3.1**.

System design methodologies have progressed from representations of pure software programming and data structures to semantic design patterns and comprehensive technology supporting business models as well as functional algorithms with reverse engineering. The increasing accessibility of these tools and the standardization of concepts and methods is strongly related to improvements in software quality and composability (Tolk, 2003; Baxter et al., 2006, Ramsin and Paige, 2008).

The process of gathering, analysing, and incorporating unstructured managerial knowledge and decision support requirements into a program design is a complex one that has persisted through the evolution of several modelling methodologies (Mintzberg et al., 1976; Ariav and

Ginzberg, 1984; Langley et al., 1995; Nakamori et al., 2007). From the engineering perspective, software versatility and composability have been a common goal to all system design methodologies such as: structured programming (Dijkstra, 1972), functional decomposition and object-oriented design (Booch, 1986); Unified Modelling Language (UML – Rumbaugh et al., 1999); the model-driven architectures (MDA - OMG, 2001); and agile developments (Ambler, 2002).

Design notations for stronger semantic representations have become central to proper system developments, overcoming code and data centred programming approaches (Abrahamssosn et al., 2003). The focus on pure object implementation techniques has only become more effective with the adoption of object-oriented methods for analysis (OOA) and design (OOD), which offer new standards in system development efficiency. Object-oriented design techniques were originally conceived with the potential to represent domain-specific hierarchical categorizations (Booch, 1994), which is typical of biophysical taxonomies. They can improve the way in which environmental and agricultural models are designed (using rich semantic representations) and implemented (using modularity and reuse capabilities) (Papajorgji, 2005).

A chronology of general aspects considered in system design methodologies shows that the present standards are mostly aligned with semantically rich architectures (**Table A3.2**), which have been associated with significant gains in development quality and efficiency. Only recently, design activity has emerged from academia and government projects into the mainstreams of business development, due to increasing complexity of today's enterprise applications (Binstock, 2005). Data modeling and process modeling have become popular development trends which diminish the gap between user requirements and developer specifications.

A3.2 - The Model Driven Approach (MDA)

A great deal of wasted investments in software development has been endured due to continual changes in technology which have required complete recoding of systems (Dalgarno and Fowler, 2008). Approaching the accessibility of open standards, the Object Management Group (OMG) has brought some structure to this arena by creating overarching architectures such as the Common Object Request Broker Architecture (CORBA) and the Model Driven Architecture (MDA). The MDA merges different OMG standards that have been developed and used separately into a common view by applying common meta-models.

Table A3.1: Design aspects directly influencing final software functionality.

Aspect	Characteristic & Resulting Functionality
Cohesion	Describes the contents of a module and its degree of interaction. The higher the cohesion the simpler to reuse and to extend a method,.
Coupling	Describes module interaction by the degree of mutual interdependence between components. Lower coupling tends to create more reusable methods, and completely decoupled methods can not be executed.
Visibility	The ability to assess parts of an imported object. Any method or property marked as 'public' is visible, while parts of a class marked as 'private' can not be directly accessed. Visibility requires parsimony with class re-use.
Dependency	The degree in which one component relies on another to perform its responsibilities. High dependency limits code reuse and makes moving components to new projects difficult.

*** sources:** Ramsin and Paige, 2008.

Table A3.2: A brief chronology of the evolution in system design methodologies.

Time Frame	**General Aspects of Design Methodologies**
1970 to 1980	The software lifecycle concept; programming and design methodologies; requirement engineering and description technologies; and project management. The goal is high software reliability and productivity with easy-to-change structure.
1980 to 1990	Prototyping technologies; process formalization; analysis of dynamic methods; and automated development tools (CASE).
1985 to 1995	Software Process Model, this includes process programming, CMM, integrated environment, and analysing and supporting human factor.
1999 to 2004	Network age; object-oriented technologies; distributed and heterogeneous computing; open source software development; and Web engineering.
2002 to Present	Interoperability (e.g. MDA); Composability (e.g. SOA, Agile); Machine Learning; Semantic Web; Autonomic Agents; and Grid computing.

*** sources:** Impagliazzo, 2004; Bernard, 2006; Ramsin and Paige, 2008.

The idea behind the meta-model is: "to use a common stable model, which is language-, vendor- and middleware-neutral: a meta-model of the concept" (OMG, 2007). It basically means that a conceptual model solving the general problem in the form of a "Meta Model" is established first, instead of directly approaching a given problem with a coded solution. The MDA comprises standards to address the various facets of interoperability, where the UML also serves as a conceptual design solution mostly providing harmonization of processes and interfaces

In agriculture, useful simulation models have been redesigned several times, to suit changing hardware configurations, or simply failed over time due to lack of system maintenance. A set of methodological recommendations from the OMG have been applied to separate the functional specification for soil-water balance and irrigation scheduling models from their coding specification on a specific technology platform (Papajorgji and Pardalos, 2006). The system functionality specification, called Platform Independent Model (PIM), for those domain models are introduced using UML models (Papajorgji and Shatar, 2004). The specification of a system implementation on a particular platform is called Platform-Specific Model (PSM). The PSM is usually generated by automatic procedures within Integrated Development Environments (IDE's) (e.g. Eclipse, NetBeans, ,NET), which can be further interpreted by code developers and provide guidance for final code generation.

The final set of MDA standards was only recently completed (MDA™ OMG, 2007). These standards are strongly supported in grid simulation (Pullen et al., 2005) and Defence sectors (Nunrich et al., 2004), where they frame the development of component tools as part of large projects for operational and logistic field control. To give an independency of solutions from a variety of vendors, MDA uses the UML as a foundation (OMG, 2001) to transform popular code-driven UML models into comprehensive business workbench systems. This has reinforced the UML as a "de facto" solution in software developments, which are also integrated with Web concepts. This new standardized development context strengthens the use of UML in this research as a foundation for an evolutionary development of SSCM knowledge support tools.

A3.3 - UML basics

The UML emerged from the merger of several object-oriented design methodologies proposed in late 1980's (e.g. Booch, 1986; Jacobson, 1986; Rumbaugh, 1987; Loomis et al., 1987), and unified several modelling concepts and design notations (Rumbaugh et al., 1999). Because of its original lower level modelling (code driven perspective), UML could not give business benefits when applied to integrated management systems. The use of more specialised and abstract modelling elements were introduced by the OMG as part of the MDA standard (OMG, 2001). Progress beyond abstractions of "coding objects" has now encompassed thirteen standard diagrams, covering architectural, business process and rules, and operational aspects considered in different computer, management, and business disciplines.

UML diagrams describe several functional and structural aspects of a system. These aspects were initially described through four views (e.g. use-case, logical, component, deployment) of the development process (Rumbaugh et al., 1999). Recently, a UML version (UML v.2.1) has been split into two complimentary specifications: the infrastructure and the superstructure specifications (OMG, 2007). The infrastructure specification is divided into three main design categories: six diagram types representing the static application structure; three representing the general types of behaviour; and four representing the different aspects of interactions. Structure diagrams emphasize what things must be in the system being modelled. They include the class diagram, object diagram, component diagram, composite structure diagram, package diagram, and deployment diagram. Behaviour diagrams emphasize what must happen in the system being modelled. They include the Use Case Diagram; the Activity Diagram, and the State Transition Diagram. The Interaction Diagrams emphasize the flow control of data in the system being modelled, being derived from more general behaviour diagrams. They include the sequence diagram, communication diagram, timing diagram, and interaction overview diagram. A functional description of the diagrams which were considered relevant to the design for knowledge support in SSCM is presented in **Table A3.3**.

A3.4 - UML related technology

Several related technologies have used basic UML applications, which further improve the interoperability between development methods and tools. Some have been identified as of relevance towards the idea of an integrated knowledge suite supporting SSCM.

Design frameworks

A framework is a conceptual skeletal solution defining the overall structure of parts and their relationships (D'Souza, 2000). It has been suggested for use in agriculture since the early phases of integrated system design (e.g. Hodges et al, 1992; Waldman and Rickman, 1996). A framework helps define and enforce some aspect of architecture, supporting the reuse of software constructs as in **Table A3.4**. Two further properties of frameworks are: i) frameworks can be described at different levels of refinement; and ii) frameworks themselves are composed of smaller frameworks.

According to D'Souza (2003) the systematic reuse of frameworks can include applications with diverse domain models (e.g. design patterns, architectural connectors, JavaBeans frameworks, or layered frameworks). An example of applied frameworks in PA is given by the stepwise evolution of the precision agriculture markup language (PAML; Murakami et al., 2007). The PALM vocabulary conforms to AGROVOC (FAO, 2006) and extends the eMOSAICo Web service (Murakami et al., 2002), which was based on the MOSAICo object-oriented framework described in UML class diagrams (Saraiva, 1998). The PAML is designed for operational management of intensively monitoring georeferenced datasets and has been used in a prototype for a yield monitor data filtering service implementing a legacy algorithm (Molin and Menegatti, 2002).

Design patterns

Design pattern is a concept inherited from architectural urban planning, with the idea of describing core solutions to problems which occur recursively. This is mostly applied as a code reuse technique that has the purpose of extending the functionality of basic generalized solutions. Papajorgji and Pardalos (2006) introduce the concept as applied to a plant simulation interface and a decision support system using a water-balance model (Ritchie, 1998). Another template using Ritchie (1998) for simulation of irrigation scheduling is given in Papajorgji and Shatar (2004). Argent and Grayson (2001) have described an interface prototyping for environmental models that is integrated with a water-balance model for farm management planning. In upper levels of

Table A3.3: A description of the function of UML diagrams that were considered in the framework design proposed in this research.

Diagram Type	Diagram Design Function
Use case	Describes the functionality provided by a system. Shows a dialog in terms of actors, their goals represented as use cases, and dependencies between use cases.
Class	Describes the structure of a system. Shows the system structure and hierarchy in terms of classes, interfaces, their attributes, and their different degree of relationships (e.g. generalizations, specialization, associations, and inheritance). They can be considered equivalent to classic entity-relationship diagrams of database structures.
Collaboration	Describes both the static structure and dynamic behaviour of a system. Shows the communication between objects in terms of objects, links of interaction, and messages. They represent the interaction between objects combining information taken from class, sequence, and use-case diagrams.
Activity	Describes the dynamics of a system. Shows the business operational workflow of components in terms of their activities and triggering decisions. They are essentially flowcharts or data flow diagrams used to get the general flow of the system.
State Transition	Describes the dynamic behaviour of objects of a system, Shows a change from an originating state to a successor state for objects with significant dynamic behaviour. They depict statecharts of specific action scenarios during an object lifetime.
Sequence	Describes the sequence of messages exchanged between objects in a system. Shows how processes operate in terms of object interactions and time sequence. They depict the order of invocations as well as the creation of objects.

* **sources:** OMG, 2007; Quatrani, 2000; NetBeans, 2008.

Table A3.4: Characteristics of the reuse of software constructs.

What to reuse	***How to reuse***
Code	Cut and paste
Interfaces	White-box inheritance
Designs	Black-box composition
Problem Domain Models	Code-generation

*** sources:** D'Souza, 2003; Papajorgji, 2005; NetBeans, 2008.

abstraction, a design pattern is understood as a set of interrelated model components defined in a package, some of which will be substituted when imported into another package (D'Souza, 2003).

Design patterns are one of the most visible demands placed on top of the UML by new MDA specifications for proper treatment of class refinement. Refinement is a relationship between two models, one of which is strictly more detailed than the other and which maintains the rules made by the other. D'Souza (2003) suggests that a proper class refinement unifies design concepts such that:

- Systems and subsystems became just objects at different levels of abstraction.
- Use case, action, and activity diagrams realize different abstractions of behavioral interactions.
- Interface, type, and class are established by a realization/abstraction relationship between them.

Object design

There are other specific methodologies for object design which have been proposed in the domain of agriculture in particular to landscape level agroecological models. They usually explore concepts and functionalities in behavioural object design focused on interchange of class libraries or modelling components. Although strongly promoting modular approaches and code-reuse, these solutions support the structural refinement of software functionality, but lack description for knowledge of the applied processes and are hardly ever aligned to Web interoperabity.

van Evert and Campbell (1994) introduced a collection of OO simulation models of agricultural systems. Kage and Stützel (1999) introduced an object component for generic design of dynamic crop systems. As a utility set of mathematical routines facilitating the use of model evaluation, Fila et al. (2003) presents a class library for evaluating numerical estimates. The use of this technique is extensive in process modeling for plant agronomic processes. Some of the examples of modular designs can be found in: Timlin et al. (1996) for a soil-plant modular design; Hodges et al. (1992) and Acock and Reinolds (1997) for crop model; Lewis and Bardon (1998) for environmental management in agriculture; Pan et al. (2000) for Web-based plant growth simulator; Steward et al. (2001) for integrated Web-based data model of a client-property-event agricultural system; Mi et al. (2003) for rice growth model; Donatelli et al. (2003) for crop evapotranspiration; Nute et al. (2004) for integration of components in ecosystem management model.

Knowledge design

The development of knowledge-based methods for decision support and business management have mostly used concepts originating from evolutionary development processes (e.g. objects, unified methods, template design, cooperative components). An overview of this applied technology can clearly illustrate the potential of UML as a basis for knowledge management aid tools.

The CommonKADS methodology introduced in **Section 1.3.4** incorporates a common library of reusable expert problem solving components (Breuker and van de Velde, 1994), with models based on UML diagrams (in particular Class, Activity and State Transition Diagrams) and links to ontology languages like Protégé (2006). This methodology has been used as a reference for the management of large-scale scientific workflows (Deelman and Gil, 2006) and agent-based grid simulation in distributed intelligent management systems (Gil, 2006).

Other knowledge developments strongly based in UML models can be found. Brimble and Sellini (2000) introduce a modelling language for management of engineering knowledge, which has been extended to a knowledge development suit of methodology and tools (Stokes, 2001). These development methods have been well used in mechanical engineering applications (Hunter et al., 2006; Ammar-Khodja et al., 2008), but never addressed in PA robotics. Dijkstra (2001) discuss the development of knowledge engineers and management actors, which offers a combination of methodologies and software tools enabling businesses to electronically capture knowledge processes. This technology was also used to assist mechanistic process-oriented knowledge acquisition (Cottam, 2000), to design knowledge models to map semantic relationships for categorical classifications (Sureephong et al., 2006), and to aid competitive clustering of business markets (Sureephong et al., 2007). The functionality offered by these types of applications can potentially support both the design of agronomic process simulation models and the multidisciplinary integration of those models into mainstreams of the farm business management.

UML parsers

Parsing is a classic technique in computer science disciplines, whereby compilers parse source code to be able to translate it into machine code. Likewise, applications processing complex commands must be able to parse the command parameters. A widely used OMG specification to parse UML models into Web solutions is the XML Metadata Interchange (XMI; OMG, 2008). One of the purposes of the XMI is to enable easy interchange of metadata between UML-based modelling tools and MOF-based metadata repositories in distributed heterogeneous environments. The transfer of UML models across Web services preserves semantics when applied to any metadata expressed in Meta-Object Facility (MOF; OMG, 2008).

Most common uses of XMI include the interchange of UML models and the serialization of metamodels from other languages. XMI is also applied as the medium by which models are passed from modelling tools to software generation tools as part of model-driven engineering. No practical solutions using parsing techniques have been reported for PA, in contrast examples from several other applied domains translating UML and Java into XML, or vice versa have been reported (Grønmo et al., 2004).

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Appendix 4

Best-fit variogram & yield variation index (Y_i) parameters

A4.1 - Variogram parameters for Australian grain crop agriculture

Variogram parameters and components from the computations of the crop yield variation index are detailed in **Table A4.1** for the 218 field-year observations of yield monitor datasets. Best fit parameters were selected and used as described in the Yieldex method (**Section 4.5**).

Table A4.1: Best fit parameters from variogram analysis and resulting components of the yield variation index (Y_i).

Farm	**Field ID**	**Year**	Crop	**Mean Yield**	**CV%**	**Best Fit**	**C0**	**C1**	**A1**	**Practical Range**	**Alfa**	**Maximum Lag**	**C^***	**CV_a**	**M_v**	**Cd**	**S_v**	**Y_i**
Bearbung	Anniies	2004	Wheat	1.8	32.8	Stable	0.261	0.3	260	451	1.99	398	0.50	16.8	1.19	342	18.0	4.63
Bearbung	Camerons	2004	Wheat	2.5	27.6	Stable	0.261	4.8	50000	320231	0.59	630	0.61	18.6	1.31	576	30.3	6.33
Bearbung	Craig	2004	Wheat	3.5	28.8	Exponential	0.678	0.4	107	321	0.00	903	1.08	17.0	1.20	321	16.9	4.50
Bearbung	Creek	2001	Canola	2.7	27.8	Spherical	0.238	0.4	265	265	0.00	1054	0.59	21.2	1.50	265	14.0	3.41
Bearbung	Creek	2002	Wheat	0.5	48.4	Exponential	0.041	0.0	194	581	0.00	1123	0.07	29.9	2.11	581	30.6	8.05
Bearbung	Creek	2003	Canola	0.6	68.9	Spherical	0.062	0.1	671	671	0.00	1054	0.22	56.1	3.95	671	35.4	12.55
Bearbung	Creek	2004	Wheat	4.1	31.7	Exponential	0.690	1.3	253	759	0.00	1054	1.98	24.4	1.72	758	40.0	8.29
Bearbung	Cris	2004	Wheat	0.6	32.2	Stable	0.029	7.3	9863	18086	1.81	539	0.07	16.1	1.13	524	27.6	5.61
Bearbung	Doolies	2000	Canola	1.6	24.0	Stable	0.098	0.1	673	1170	1.99	905	0.21	13.6	0.96	887	46.8	6.70
Bearbung	Doolies	2002	Chickpeas	0.7	58.6	Spherical	0.106	5.7	50000	50000	0.00	886	0.26	36.4	2.57	811	42.7	10.49
Bearbung	Doolies	2003	Wheat	1.1	45.1	Stable	0.101	243.8	31533	59075	1.75	898	0.58	34.8	2.45	872	45.9	10.63
Bearbung	Doolies	2004	Canola	1.2	30.4	Spherical	0.067	0.1	847	847	0.00	891	0.19	22.0	1.55	847	44.6	6.23
Bearbung	Doolies	2005	Wheat	3.8	16.7	Exponential	0.230	0.2	120	360	0.00	893	0.42	10.9	0.77	359	18.9	3.82
Bearbung	Kates	2003	Canola	1.1	19.9	Exponential	0.018	0.0	102	307	0.00	779	0.06	16.1	1.14	306	16.2	4.29
Bearbung	Kates	2004	Wheat	3.9	19.0	Spherical	0.447	0.6	2348	2348	0.00	775	0.71	8.6	0.60	630	33.2	4.49
Bearbung	Kates	2005	Chickpeas	2.3	16.0	Exponential	0.025	0.1	57	172	0.00	781	0.14	14.4	1.01	172	9.1	3.04
Bearbung	Kates	2006	Wheat	1.1	51.2	Stable	0.186	97.3	50000	111620	1.37	775	0.51	32.0	2.25	746	39.3	9.43
Bearbung	Racecourse	2003	Canola	0.6	21.0	Stable	0.011	1.6	50000	129759	1.15	762	0.02	12.7	0.89	729	38.4	5.88
Bearbung	Racecourse	2004	Wheat	3.3	26.2	Stable	0.239	6.5	29531	216165	0.55	766	1.05	21.7	1.53	694	36.6	7.50
Bearbung	Racecourse	2005	Chickpeas	2.6	22.2	Stable	0.070	0.3	127	522	0.78	763	0.36	19.7	1.39	258	13.6	4.34
Bearbung	Racecourse	2006	Wheat	1.4	47.2	Stable	0.035	0.5	110	548	0.69	766	0.53	45.4	3.20	246	13.0	6.45
Bearbung	Top Dam	2004	Wheat	1.8	24.0	Stable	0.161	53.0	18473	32085	1.99	618	0.22	8.2	0.58	602	31.7	4.29
Burrendah	Avenue	2004	Canola	1.5	26.4	Exponential	0.085	8.5	50000	150000	0.00	863	0.23	17.6	1.24	819	43.2	7.32
Burrendah	Bridge	2000	Wheat	3.6	22.2	Spherical	0.354	0.4	518	518	0.00	963	0.72	14.9	1.05	518	27.3	3.97
Burrendah	Bridge	2001	Faba Beans	2.6	25.3	Exponential	0.276	0.3	482	1446	0.00	969	0.52	15.0	1.05	834	44.0	6.83
Burrendah	Bridge	2002	Wheat	1.3	44.8	Spherical	0.187	0.2	765	765	0.00	978	0.41	29.4	2.07	765	40.3	6.79
Burrendah	Bridge	2003	Canola	0.7	27.3	Exponential	0.013	0.1	642	1925	0.00	978	0.06	22.6	1.59	872	46.0	8.58
Burrendah	Bridge	2004	Wheat	3.0	30.8	Stable	0.301	1.1	465	1075	1.31	977	1.29	24.6	1.73	707	37.3	8.05
Burrendah	Glens	2000	Wheat	3.3	22.4	Spherical	0.170	0.4	283	283	0.00	774	0.59	18.7	1.32	283	14.9	3.32
Burrendah	Glens	2001	Faba Beans	2.6	45.0	Stable	0.790	66.4	9672	19749	1.54	776	2.14	28.7	2.02	750	39.5	8.96

Farm	Field ID	Year	Crop	Mean Yield	CV%	Best Fit	C0	C1	A1	Practical Range	Alfa	Maximum Lag	C^*	CV_a	M_v	Cd	S_v	Y_i
Burrendah	Glens	2002	Wheat	0.7	50.8	Stable	0.071	85.1	50000	104311	1.49	774	0.24	35.1	2.47	748	39.4	9.89
Burrendah	Glens	2003	Canola	0.6	22.6	Spherical	0.015	0.3	50000	50000	0.00	777	0.02	10.5	0.74	662	34.9	5.10
Burrendah	Glens	2004	Wheat	1.5	31.6	Stable	0.071	0.3	840	6894	0.52	780	0.27	26.3	1.85	663	35.0	8.06
Burrendah	Glens	2006	Wheat	1.1	66.7	Stable	0.000	0.6	81	540	0.58	786	0.59	66.7	4.70	209	11.0	7.21
Burrendah	House	2005	Wheat	3.9	16.5	Spherical	0.216	0.2	630	630	0.00	1205	0.46	11.5	0.81	630	33.2	3.84
Burrendah	Woolshed	2004	Wheat	1.6	25.3	Stable	0.151	241.6	50000	86842	1.99	704	0.20	7.1	0.50	685	36.1	4.25
Burrendah	Woolshed	2006	Wheat	0.8	52.4	Stable	0.153	157.7	32227	55973	1.99	714	0.23	19.1	1.35	696	36.7	7.04
Connamara	H5	2003	Barley	6.3	13.7	Spherical	0.396	0.4	432	432	0.00	1021	0.78	9.4	0.66	432	22.8	2.87
Connamara	H7	2003	Wheat	5.5	21.8	Stable	0.682	460.6	50000	112686	1.35	1072	2.92	15.8	1.11	936	49.3	7.43
Kiewa	Block 3	2004	Wheat	2.5	31.6	Spherical	0.350	0.5	827	827	0.00	849	0.85	20.4	1.44	827	43.6	5.96
Kiewa	Bottom L	2003	Faba Beans	2.8	21.6	Exponential	0.160	4.4	7357	22071	0.00	718	0.57	16.0	1.13	680	35.8	6.36
Kiewa	Bottom L	2004	Wheat	3.2	22.1	Exponential	0.265	0.3	244	732	0.00	715	0.59	15.1	1.06	560	29.5	5.59
Kiewa	Bottom L	2005	Wheat	3.8	18.6	Spherical	0.357	0.5	1626	1626	0.00	709	0.66	9.9	0.70	568	30.0	4.58
Kiewa	Brick Kiln	2001	Wheat	4.0	23.8	Spherical	0.752	10.4	50000	50000	0.00	1003	1.07	10.3	0.73	832	43.8	5.66
Kiewa	Brick Kiln	2005	Wheat	3.5	16.6	Stable	0.308	84.2	50000	95058	1.71	995	0.41	5.0	0.35	965	50.8	4.22
Kiewa	Diamond	2003	Wheat	1.2	68.9	Spherical	0.152	0.5	129	129	0.00	1214	0.68	60.7	4.28	129	6.8	4.05
Kiewa	Diamond	2005	Wheat	2.9	18.9	Spherical	0.186	0.1	287	287	0.00	1213	0.30	11.5	0.81	287	15.1	2.55
Kiewa	Front	2003	Wheat	2.2	17.7	Stable	0.102	22.1	50000	117174	1.29	870	0.22	9.7	0.69	836	44.1	5.51
Kiewa	Front	2005	Wheat	4.9	13.7	Stable	0.000	0.5	48	3320	0.26	876	0.48	13.7	0.97	398	21.0	4.51
Kiewa	Mugs	2001	Wheat	3.1	39.3	Spherical	0.359	2.0	1079	1079	0.00	1144	2.39	34.3	2.42	1079	56.9	8.84
Kiewa	Mugs	2004	Canola	1.5	19.5	Stable	0.035	0.3	45097	1749698	0.30	1137	0.11	15.3	1.08	929	48.9	7.27
Kiewa	Mugs	2005	Wheat	3.7	14.2	Spherical	0.207	0.1	571	571	0.00	1136	0.29	7.3	0.51	571	30.1	2.80
Kiewa	Ramp	2005	Wheat	4.7	17.8	Spherical	0.265	0.5	272	272	0.00	855	0.75	14.0	0.99	272	14.3	2.82
Kiewa	Swamp	2003	Chickpeas	1.1	35.2	Spherical	0.073	0.1	470	470	0.00	1509	0.15	25.1	1.77	470	24.7	4.90
Kiewa	Swamp	2004	Wheat	2.0	30.1	Spherical	0.150	0.2	364	364	0.00	1507	0.37	23.1	1.63	364	19.2	4.16
Kiewa	Swamp	2005	Wheat	4.0	21.0	Spherical	0.504	0.2	366	366	0.00	1512	0.74	11.5	0.81	366	19.3	2.85
Merinda	Airstrip	2003	Barley	3.3	10.6	Stable	0.051	0.1	261	978	0.83	1802	0.14	8.1	0.57	506	26.6	3.90
Merinda	Hoolahan	2003	Canola	1.5	19.5	Spherical	0.165	10.8	50000	50000	0.00	885	0.45	36.0	2.54	815	42.9	10.45
Merinda	Hoolahan	2004	Wheat	5.0	12.6	Stable	0.329	525.2	36224	62915	1.99	882	0.65	5.4	0.38	860	45.3	4.15
Merinda	KRS 14_16	2003	Wheat	4.1	13.0	Exponential	0.184	0.1	197	591	0.00	2093	0.29	7.7	0.54	590	31.1	4.10
Merinda	KRS 14_16	2004	Barley	3.6	13.1	Spherical	0.107	0.1	564	564	0.00	2088	0.23	9.4	0.66	564	29.7	3.30
Merinda	MRS_A	2003	Chickpeas	2.7	27.8	Exponential	0.231	41.1	50000	150000	0.00	896	0.96	21.2	1.49	851	44.8	8.20

Farm	Field ID	Year	Crop	Mean Yield	CV%	Best Fit	C0	C1	A1	Practical Range	Alfa	Maximum Lag	C^*	CV_a	M_v	Cd	S_v	Y_i
Merinda	MRS_A	2004	Wheat	4.2	17.1	Stable	0.393	162.2	36313	71939	1.61	899	0.82	8.5	0.60	871	45.9	5.25
Merinda	Ramp	2004	Barley	2.8	18.7	Stable	0.172	20.0	50000	132191	1.13	1008	0.41	11.1	0.79	964	50.8	6.33
Merinda	Rosewood	2003	Wheat	3.7	14.2	Spherical	0.178	0.2	1076	1076	0.00	980	0.34	8.4	0.59	579	30.5	4.26
Merinda	Rosewood	2004	Wheat	4.5	22.7	Stable	0.685	4.9	10494	39584	0.83	987	1.33	13.3	0.94	923	48.7	6.76
PineCliff	BackPaddock	2006	Wheat	4.3	22.5	Stable	0.589	3.6	50000	417262	0.52	1374	1.10	13.7	0.97	1235	65.1	7.95
PineCliff	Btm G E East	2005	Wheat	4.5	11.8	Stable	0.244	227.8	50000	86842	1.99	1301	0.40	4.5	0.32	1267	66.8	4.62
PineCliff	Duncans	2004	Wheat	5.8	20.9	Stable	1.203	1389.7	35708	62019	1.99	936	2.19	9.0	0.63	912	48.1	5.50
PineCliff	Glen E West	2005	Wheat	5.8	20.8	Spherical	1.166	0.6	1778	1778	0.00	1748	1.66	9.6	0.67	819	43.1	5.40
PineCliff	LongShinrone	2005	Corn	3.9	12.7	Stable	0.000	0.4	511	70210	0.22	2208	0.27	12.7	0.89	1371	72.3	8.07
PineCliff	Middle Gee	2004	Wheat	5.5	20.7	Stable	0.000	1.6	75	6939	0.24	1706	1.43	20.7	1.46	720	38.0	7.45
PineCliff	Number 2	2006	Wheat	4.3	15.3	Spherical	0.137	0.4	747	747	0.00	1532	0.50	12.6	0.89	747	39.4	4.44
PineCliff	Shinrone	2005	Wheat	4.4	10.6	Stable	0.188	0.5	4850	9395	1.66	1643	0.27	3.6	0.25	1589	83.7	4.58
Romaka	Boomerang	1996	Wheat	2.5	32.8	Exponential	0.586	0.1	101	304	0.00	1424	0.70	12.6	0.89	304	16.0	3.77
Romaka	Bull	1996	Wheat	4.9	18.5	Stable	0.000	0.9	12	111	0.49	361	0.87	18.5	1.30	36	1.9	1.59
Romaka	Lease	1996	Wheat	5.7	14.8	Spherical	0.469	0.3	341	341	0.00	1431	0.72	8.5	0.60	341	17.9	2.38
Romaka	Lease	2000	Sorghum	4.9	25.4	Exponential	0.883	1.0	489	1466	0.00	1606	1.84	16.9	1.19	1464	77.2	9.58
Romaka	Pine	1996	Sorghum	5.3	19.8	Stable	0.806	0.5	430	747	1.99	1091	1.29	10.0	0.71	567	29.9	4.61
Romaka	Pine	1997	Sorghum	12.7	11.2	Stable	1.100	133.5	50000	134407	1.11	1080	2.97	7.6	0.53	1030	54.3	5.36
Romaka	Skurr	1996	Wheat	5.2	19.3	Stable	0.718	0.3	96	167	1.99	780	1.05	10.6	0.75	127	6.7	2.24
Romaka	South Dam	1996	Wheat	5.5	13.3	Spherical	0.408	19.7	50000	50000	0.00	489	0.70	6.5	0.46	429	22.6	3.24
Romaka	Well	2001	Sorghum	4.7	34.1	Exponential	0.998	2.1	193	578	0.00	684	3.04	26.8	1.89	577	30.4	7.58
Romaka	West Creek	1996	Wheat	5.4	12.4	Stable	0.351	776.3	50000	86842	1.99	1015	0.68	5.9	0.41	989	52.1	4.68
Romaka	West Creek	1997	Wheat	3.8	20.6	Spherical	0.112	0.5	228	228	0.00	998	0.61	18.6	1.31	228	12.0	2.99
Romaka	West Creek	1998	Wheat	5.6	16.6	Spherical	0.684	13.3	50000	50000	0.00	1002	1.08	7.7	0.54	866	45.7	4.97
Romaka	West Creek	2000	Wheat	5.3	24.9	Spherical	0.585	1.2	274	274	0.00	1019	1.76	20.3	1.43	274	14.5	3.41
Tarnee	Bc Sth	2006	Wheat	2.1	24.6	Stable	0.192	0.2	749	1393	1.77	1197	0.36	13.7	0.97	1021	53.8	7.23
Tarnee	Birdcage	2004	Barley	3.6	24.3	Stable	0.516	5.1	50000	282522	0.63	1036	0.94	14.1	1.00	952	50.2	7.08
Tarnee	Bt	1998	Sorghum	4.6	29.6	Stable	1.355	528.0	50000	98290	1.63	1342	2.83	15.2	1.07	1300	68.5	8.60
Tarnee	Bt	2001	Sorghum	3.9	33.0	Spherical	1.052	4.5	6983	6983	0.00	1336	2.33	19.5	1.38	1188	62.6	9.29
Tarnee	Bt	2003	Wheat	4.1	30.1	Stable	0.570	4.8	50000	1370719	0.33	1274	1.81	23.6	1.67	1065	56.1	9.68
Tarnee	Bt	2005	Wheat	4.0	24.9	Stable	0.756	201.7	26523	47848	1.86	1279	1.47	12.0	0.85	1244	65.6	7.47
Tarnee	Bt	2006	Wheat	2.5	21.6	Stable	0.238	24.0	50000	109284	1.41	1267	0.37	9.0	0.64	1221	64.3	6.42

Farm	Field ID	Year	Crop	Mean Yield	CV%	Best Fit	C0	C1	A1	Practical Range	Alfa	Maximum Lag	C^*	CV_a	M_v	Cd	S_v	Y_i
Tarnee	Comet A	2006	Wheat	1.7	24.5	Spherical	0.143	1.4	50000	50000	0.00	1797	0.22	9.4	0.66	1540	81.2	7.35
Tarnee	Comet B	1997	Wheat	3.7	33.3	Stable	0.592	1261.3	34095	63784	1.75	1220	4.25	26.2	1.84	1185	62.4	10.75
Tarnee	Comet B	1998	Sorghum	5.4	17.0	Spherical	0.309	0.6	274	274	0.00	1221	0.90	13.6	0.96	274	14.4	3.72
Tarnee	Comet B	1999	Chickpeas	1.3	30.3	Spherical	0.124	2.2	50000	50000	0.00	1193	0.20	14.2	1.00	1041	54.8	7.43
Tarnee	Comet B	2000	Wheat	2.6	28.3	Stable	0.000	1.8	20046	1188649	0.27	1184	0.66	30.8	2.17	931	49.1	10.34
Tarnee	Comet B	2003	Wheat	5.0	23.0	Exponential	1.208	10.6	50000	150000	0.00	1546	1.53	7.2	0.51	1466	77.3	6.26
Tarnee	Comet B	2004	Wheat	4.9	17.8	Spherical	0.403	0.5	998	998	0.00	1515	0.90	12.4	0.87	998	52.6	6.80
Tarnee	Comet B	2005	Sorghum	3.5	19.6	Exponential	0.155	0.3	145	435	0.00	1536	0.50	16.1	1.13	434	22.9	5.11
Tarnee	Comet B	2006	Chickpeas	1.8	23.9	Spherical	0.088	0.1	804	804	0.00	1540	0.20	16.9	1.19	804	42.4	7.13
Tarnee	IXLB	2004	Sorghum	6.6	19.4	Spherical	0.796	0.9	319	319	0.00	856	1.70	15.9	1.12	319	16.8	3.22
Tarnee	IXLB	2006	Wheat	2.2	20.5	Stable	0.169	136.7	28025	48675	1.99	855	0.30	8.7	0.62	833	43.9	5.22
Tarnee	Kerrett	2000	Canola	1.2	30.6	Stable	0.085	6.7	50000	123868	1.21	1819	0.21	18.7	1.32	1744	91.9	11.01
Tarnee	Kerrett	2001	Wheat	4.2	25.3	Spherical	0.824	0.4	1502	1502	0.00	2213	1.24	13.0	0.92	1502	79.2	6.16
Tarnee	Kerrett	2003	Canola	1.9	27.1	Spherical	0.216	0.1	784	784	0.00	2191	0.27	11.9	0.84	784	41.3	4.05
Tarnee	Kerrett	2004	Wheat	3.7	24.1	Spherical	0.347	0.5	522	522	0.00	2196	0.85	18.1	1.28	522	27.5	4.42
Tarnee	Kerrett	2005	Sorghum	4.5	26.0	Exponential	0.247	1.1	125	374	0.00	2154	1.33	23.5	1.65	373	19.7	5.71
Tarnee	Stock Route	2005	Wheat	1.7	34.0	Spherical	0.196	0.1	296	296	0.00	1366	0.33	21.3	1.50	296	15.6	3.53
Tarnee	TC	1996	Sorghum	5.4	18.1	Stable	0.579	2665.3	48776	84716	1.99	990	1.72	11.4	0.80	965	50.9	6.38
Tarnee	TC	1997	Sorghum	5.4	17.0	Spherical	0.309	0.7	514	514	0.00	720	1.05	13.6	0.96	514	27.1	3.82
Tarnee	TC	1999	Sorghum	5.2	22.1	Stable	0.000	1.8	311	3501	0.45	1201	1.52	22.1	1.56	1043	54.9	9.26
Tarnee	TC	2001	Wheat	4.1	24.2	Spherical	0.581	0.6	920	920	0.00	1631	1.14	15.5	1.09	920	48.5	5.38
Tarnee	TC	2005	Barley	2.3	21.6	Stable	0.000	0.3	104	34125	0.19	1427	0.25	21.6	1.53	748	39.4	7.77
Tarnee	TC	2006	Chickpeas	2.2	22.8	Spherical	0.191	2.8	50000	50000	0.00	1413	0.31	11.4	0.81	1226	64.6	7.23
Tarnee	TT	2001	Wheat	4.5	20.4	Spherical	0.437	0.5	637	637	0.00	1050	0.98	14.3	1.01	637	33.6	4.32
Tarnee	TT	2005	Wheat	3.2	23.2	Stable	0.440	699.4	50000	86842	1.99	1419	1.02	11.1	0.78	1383	72.9	7.54
Glenmore	WA	1999	Canola	2.2	21.6	Spherical	0.054	0.2	459	459	0.00	947	0.21	17.2	1.21	459	24.2	4.07
Glenmore	WA	2000	Wheat	5.4	15.2	Spherical	0.305	0.5	705	705	0.00	946	0.79	11.1	0.78	705	37.2	4.03
Glenmore	WA	2001	Canola	1.9	22.5	Spherical	0.065	8.3	50000	50000	0.00	945	0.30	18.0	1.27	884	46.6	7.71
Glenmore	WA	2002	Wheat	1.5	24.9	Exponential	0.039	0.1	239	717	0.00	941	0.17	21.3	1.50	716	37.7	7.52
Glenmore	WA	2003	Canola	0.9	26.3	Spherical	0.038	0.9	50000	50000	0.00	939	0.06	13.4	0.94	823	43.4	6.41
Glenmore	WA	2004	Wheat	2.5	24.9	Stable	0.072	2.0	50000	1044257	0.36	953	0.49	22.5	1.58	812	42.8	8.25
Glenmore	WC	1999	Canola	2.1	27.2	Spherical	0.141	9.5	50000	50000	0.00	1681	0.62	20.2	1.42	1571	82.8	10.88

Farm	Field ID	Year	Crop	Mean Yield	CV%	Best Fit	C0	C1	A1	Practical Range	Alfa	Maximum Lag	C^*	CV_a	M_v	Cd	S_v	Y_i
Glenmore	WC	2000	Wheat	5.0	22.3	Spherical	0.281	1.1	540	540	0.00	1528	1.35	19.7	1.39	540	28.5	4.74
Glenmore	WC	2001	Canola	2.0	24.5	Stable	0.122	153.2	50000	96418	1.67	1531	0.57	17.2	1.21	1484	78.2	9.77
Glenmore	WC	2002	Wheat	1.5	36.3	Spherical	0.032	0.3	738	738	0.00	1525	0.32	34.1	2.40	738	38.9	7.30
Glenmore	WC	2003	Canola	1.1	30.5	Spherical	0.072	2.8	50000	50000	0.00	1529	0.62	19.6	1.38	1409	74.3	10.14
Glenmore	WC	2004	Wheat	2.3	36.7	Spherical	0.299	0.6	977	977	0.00	1543	0.86	27.8	1.96	977	51.5	7.51
Grandview	10	2004	Wheat	4.1	15.6	Spherical	0.225	0.3	746	746	0.00	702	0.55	10.6	0.75	412	21.7	4.03
Grandview	10	2004	Wheat	4.1	15.6	Spherical	0.225	0.3	746	746	0.00	702	0.55	10.6	0.75	412	21.7	4.03
Grandview	12	2000	Wheat	4.0	36.0	Stable	0.959	2.8	381	661	1.99	612	3.50	26.5	1.87	502	26.4	7.03
Grandview	12	2001	Canola	1.2	20.6	Spherical	0.030	0.0	467	467	0.00	608	0.07	14.1	1.00	467	24.6	3.68
Grandview	12	2002	Wheat	1.5	40.0	Stable	0.000	0.3	18	134	0.55	608	0.35	40.0	2.82	49	2.6	2.70
Grandview	12	2003	Wheat	2.6	40.4	Stable	0.840	12.3	50000	231772	0.72	612	1.36	20.7	1.46	569	30.0	6.62
Grandview	12	2004	Triticale	2.7	24.6	Stable	0.000	0.5	48	1024	0.36	603	0.49	24.6	1.73	221	11.6	4.50
Grandview	13	2000	Canola	1.9	17.8	Spherical	0.074	0.0	185	185	0.00	808	0.12	10.7	0.75	185	9.7	1.96
Grandview	13	2001	Wheat	4.1	13.7	Stable	0.226	98.7	50000	105949	1.46	800	0.46	7.2	0.50	773	40.7	4.56
Grandview	13	2004	Wheat	3.3	13.5	Stable	0.166	51.3	50000	104362	1.49	795	0.27	5.9	0.42	769	40.5	4.13
Grandview	19	2003	Wheat	2.1	15.9	Stable	0.000	0.2	101	11986	0.23	906	0.13	15.9	1.12	528	27.8	5.58
Grandview	20	2004	Wheat	2.9	28.0	Spherical	0.350	0.4	331	331	0.00	1309	0.71	19.4	1.37	331	17.4	3.62
Grandview	21	2000	Wheat	3.8	24.5	Spherical	0.399	0.5	153	153	0.00	832	0.88	20.8	1.47	153	8.0	2.55
Grandview	44	2000	Canola	1.9	24.2	Spherical	0.139	0.1	755	755	0.00	1365	0.22	22.7	1.60	755	39.8	5.80
Grandview	44	2001		2.8	.	Spherical	0.281	0.2	618	618	0.00	1369	0.47	21.1	1.49	329	17.4	5.08
Grandview	44	2002	Triticale	0.2	.	Spherical-cut	0.042	0.7	50000	50000	.	1349	0.07	65.9	4.64	1180	62.2	16.99
Grandview	44	2003	Canola	2.3	12.4	Stable	0.074	0.2	50000	227166	0.73	1355	0.09	12.6	0.89	1259	66.4	7.69
Grandview	44	2004	Wheat	2.6	.	Spherical	0.190	1.2	50000	50000	0.00	1358	0.24	6.0	0.42	1033	54.4	10.03
Grandview	44	2005	Barley	4.4	18.9	Spherical	0.529	0.2	610	610	0.00	1361	0.74	9.5	0.67	610	32.1	3.30
Grandview	46	2004	Wheat	2.1	18.9	Stable	0.073	0.2	416	1712	0.78	826	0.21	18.9	1.33	701	37.0	7.01
Grandview	46	2005	Wheat	4.4	17.0	Spherical	0.255	0.4	465	465	0.00	822	0.62	12.4	0.88	465	24.5	3.45
Grandview	49	2004	Wheat	1.8	15.9	Stable	0.064	23.3	50000	107114	1.44	705	0.11	7.4	0.52	682	35.9	4.32
Grandview	49	2005	Barley	4.6	14.1	Stable	0.305	1.5	50000	449013	0.50	706	0.48	7.4	0.52	633	33.4	4.17
Yaralla	East Ridge	2001	Canola	2.8	26.8	Exponential	0.488	0.1	104	311	0.00	1001	0.58	10.3	0.73	310	16.4	3.46
Yaralla	East Ridge	2002	Lupins	0.7	34.2	Spherical	0.030	0.0	276	276	0.00	848	0.06	23.4	1.65	276	14.5	3.61
Yaralla	East Ridge	2004	Wheat	3.8	17.1	Spherical	0.241	0.2	460	460	0.00	863	0.46	11.4	0.80	460	24.2	3.25
Yaralla	Freeling	2000	Wheat	3.9	30.6	Spherical	0.474	1.1	328	328	0.00	777	1.54	25.1	1.77	328	17.3	4.15

Farm	Field ID	Year	Crop	Mean Yield	CV%	Best Fit	C0	C1	A1	Practical Range	Alfa	Maximum Lag	C^*	CV_a	M_v	Cd	S_v	Y_i
Yaralla	Freeling	2001	Wheat	2.8	19.6	Exponential	0.202	0.3	853	2560	0.00	812	0.38	11.4	0.80	747	39.4	5.61
Yaralla	Freeling	2002	Lupins	0.6	29.7	Exponential	0.009	0.0	112	335	0.00	810	0.03	25.2	1.77	335	17.7	5.61
Yaralla	Freeling	2003	Wheat	4.8	17.4	Exponential	0.358	0.4	119	357	0.00	818	0.74	12.2	0.86	356	18.8	4.02
Yaralla	Freeling	2004	Wheat	4.3	9.3	Spherical	0.106	4.5	50000	50000	0.00	813	0.22	5.3	0.38	733	38.6	3.82
Yaralla	Rhombus	2000	Wheat	5.1	27.2	Stable	1.730	2275.8	50000	86842	1.99	898	2.49	8.1	0.57	875	46.1	5.13
Yaralla	Rhombus	2001	Canola	2.8	20.7	Stable	0.311	393.9	50000	86842	1.99	892	0.44	5.9	0.42	869	45.8	4.39
Yaralla	Rhombus	2002	Lupins	0.8	35.8	Spherical	0.019	0.1	343	343	0.00	883	0.08	30.8	2.17	343	18.1	4.70
Yaralla	Rhombus	2003	Canola	4.6	16.9	Stable	0.554	732.4	50000	86842	1.99	889	0.80	5.0	0.35	866	45.7	4.00
Yaralla	Rhombus	2004	Wheat	1.9	17.5	Stable	0.086	26.3	50000	107455	1.44	900	0.17	8.1	0.57	868	45.7	5.11
Brook Park	Bills	2002	Canola	0.8	50.4	Spherical	0.087	0.1	434	434	0.00	812	0.20	36.5	2.57	434	22.9	5.70
Brook Park	Bills	2003	Wheat	3.2	19.4	Stable	0.192	131.5	50000	112149	1.36	814	0.68	13.7	0.97	784	41.3	6.33
Brook Park	Bills	2004	Barley	2.8	18.6	Exponential	0.054	0.2	120	361	0.00	809	0.29	16.6	1.17	360	19.0	4.71
Brook Park	Bills	2005	Chickpeas	2.2	13.5	Stable	0.040	0.9	43149	265137	0.61	802	0.11	9.9	0.70	735	38.7	5.21
Brook Park	Road	1999		3.4	.	Spherical	0.075	1.2	50000	50000	.	1477	0.13	4.7	0.33	1295	68.2	5.00
Brook Park	Road	2000		3.4	.	Spherical	0.157	0.2	2454	2454	0.00	1466	0.31	8.2	0.58	1090	57.5	5.76
Brook Park	Road	2001		1.7	.	Spherical	0.282	0.1	1689	1689	.	1467	0.39	15.0	1.06	837	44.1	6.83
Brook Park	Road	2002		0.6	.	Spherical	0.316	0.6	2902	2902	.	1472	0.72	68.8	4.85	1164	61.3	17.25
Brook Park	Road	2003	Wheat	2.1	16.7	Spherical	0.099	0.1	2659	2659	0.00	1476	0.15	8.1	0.57	1075	56.7	5.71
Brook Park	Road	2004	Field Peas	1.0	14.8	Exponential	0.012	0.0	158	475	0.00	1470	0.02	10.1	0.71	474	25.0	4.21
Brook Park	Road	2005	Wheat	3.1	10.1	Spherical	0.046	0.1	1276	1276	0.00	1467	0.12	7.3	0.51	1276	67.3	5.86
Clifton Farm	Barn	2000	Wheat	3.3	24.2	Stable	0.554	615.3	30593	53135	1.99	724	0.91	8.9	0.63	706	37.2	4.84
Clifton Farm	Barn	2001	Wheat	6.2	21.0	Stable	1.514	0.6	620	1076	1.99	729	1.99	6.3	0.44	691	36.4	4.05
Clifton Farm	Black Flat	1998	Wheat	4.4	22.6	Stable	0.291	4.1	36065	768678	0.36	773	1.19	18.9	1.34	658	34.7	6.81
Clifton Farm	Black Flat	1999	Faba Beans	3.5	18.8	Spherical	0.386	0.2	2114	2114	0.00	769	0.51	7.0	0.49	570	30.1	3.85
Clifton Farm	Black Flat	2000	Wheat	5.2	15.6	Spherical	0.576	0.2	864	864	0.00	768	0.73	5.8	0.41	404	21.3	2.95
Clifton Farm	Black Flat	2001	Barley	4.8	19.0	Spherical	0.781	3.4	50000	50000	0.00	776	0.86	4.2	0.30	359	18.9	2.37
Clifton Farm	Black Flat	2002	Canola	1.8	25.0	Exponential	0.077	0.1	70	210	0.00	771	0.21	19.6	1.38	209	11.0	3.90
Clifton Farm	Black Flat	2003	Wheat	4.4	12.3	Stable	0.000	0.4	158	12628	0.25	772	0.33	12.3	0.87	493	26.0	4.76
Clifton Farm	Black Flat	2004	Faba Beans	2.0	16.2	Stable	0.092	72.2	29496	51230	1.99	775	0.14	5.7	0.40	755	39.8	4.04
Clifton Farm	Black Flat	2005	Wheat	5.7	12.4	Stable	0.000	0.6	56	3589	0.26	771	0.54	12.4	0.87	448	23.6	4.56
Clifton Farm	Top D	2001	Wheat	4.4	28.2	Stable	1.272	2076.5	26944	46797	1.99	655	2.54	11.4	0.80	638	33.6	5.22
Clifton Farm	Top D	2002	Wheat	4.2	24.0	Stable	0.757	0.9	446	805	1.86	654	1.51	12.3	0.87	599	31.6	5.24

Farm	**Field ID**	**Year**	Crop	**Mean Yield**	**CV%**	**Best Fit**	**C0**	**C1**	**A1**	**Practical Range**	**Alfa**	**Maximum Lag**	**C^***	**CV_a**	**M_v**	**Cd**	**S_v**	**Y_i**
Clifton Farm	Top D	2003	Faba Beans	1.4	55.8	Spherical	0.223	0.4	156	156	0.00	653	0.66	44.9	3.17	156	8.2	3.82
Clifton Farm	Top D	2004	Canola	1.8	27.6	Stable	0.152	0.2	303	594	1.63	651	0.33	16.9	1.19	424	22.4	5.16
Faithfield	Front SW	2004	Wheat	3.1	19.3	Spherical	0.203	0.2	350	350	0.00	1142	0.37	13.0	0.91	350	18.4	3.02
RayvillePark	Field 27	1997	Wheat	3.9	29.0	Stable	1.160	492.9	28723	49887	1.99	906	1.67	9.4	0.67	882	46.5	5.58
RayvillePark	Field 27	1999	Canola	1.3	34.6	Exponential	0.050	0.2	87	260	0.00	902	0.20	29.7	2.09	260	13.7	5.37
RayvillePark	Field 27	2000	Wheat	4.7	17.8	Stable	0.448	0.6	524	909	1.99	904	1.00	10.6	0.75	690	36.4	5.22
RayvillePark	Field 27	2001	Barley	4.4	12.4	Stable	0.262	20.9	50000	108862	1.41	904	0.33	3.9	0.28	872	46.0	3.59
RayvillePark	Field 27	2002	Faba Beans	1.6	37.1	Stable	0.189	112.5	20394	38152	1.75	903	0.66	24.5	1.72	877	46.2	8.94
RayvillePark	Field 27	2003	Wheat	3.8	12.0	Stable	0.166	35.2	50000	105410	1.47	905	0.26	5.1	0.36	874	46.1	4.07
RayvillePark	Field 27	2004	Barley	1.9	17.2	Stable	0.091	135.8	43658	75827	1.99	905	0.15	6.8	0.48	882	46.5	4.72
RayvillePark	Field 27	2005	Wheat	3.4	25.4	Stable	0.652	807.8	50000	86842	1.99	904	0.93	8.4	0.59	881	46.4	5.23
RayvillePark	Field 41	1998	Wheat	2.5	29.2	Spherical	0.269	23.5	50000	50000	0.00	734	0.79	20.2	1.43	678	35.7	7.15
RayvillePark	Field 41	1999	Wheat	1.7	32.5	Stable	0.247	164.2	37964	72230	1.71	734	0.44	14.7	1.04	713	37.6	6.25
RayvillePark	Field 41	2000	Wheat	3.7	21.0	Stable	0.000	2.2	28553	2199137	0.25	738	0.72	21.0	1.48	576	30.4	6.73
RayvillePark	Field 41	2002	Wheat	1.6	39.6	Spherical	0.307	8.8	50000	50000	0.00	735	0.50	19.1	1.35	640	33.7	6.75
RayvillePark	Field 41	2003	Barley	3.8	12.1	Spherical	0.151	5.7	50000	50000	0.00	727	0.28	6.6	0.47	647	34.1	3.99
RayvillePark	Field 41	2004	Faba Beans	0.9	20.3	Spherical	0.013	0.0	478	478	0.00	726	0.04	15.8	1.11	478	25.2	3.97
RayvillePark	Field 41	2005	Wheat	4.0	11.0	Stable	0.018	0.5	7146	348171	0.28	731	0.23	10.5	0.74	577	30.4	4.74
Tingara	Field 146a	1998	Barley	2.3	34.6	Spherical	0.169	0.5	221	221	0.00	784	0.65	29.6	2.09	221	11.7	3.71
Tingara	Field 146a	2001	Barley	2.2	36.1	Spherical	0.028	0.6	199	199	0.00	803	0.62	35.3	2.49	199	10.5	3.86
Tingara	Field 146a	2003	Canola	2.1	20.6	Stable	0.145	0.2	894	1608	1.87	805	0.25	9.3	0.66	772	40.7	5.18
Tingara	Field 146a	2004	Wheat	3.4	23.1	Stable	0.000	0.8	137	1766	0.43	803	0.69	23.1	1.63	492	25.9	6.50
Tingara	Field 146a	2005	Barley	2.5	21.1	Spherical	0.111	0.2	183	183	0.00	807	0.30	16.6	1.17	183	9.7	2.51
Tingara	Field 212c	1999	Barley	2.5	13.5	Stable	0.000	0.2	69	2527	0.31	630	0.13	13.5	0.95	418	22.0	4.60
Tingara	Field 212c	2000	Faba Beans	4.4	13.0	Stable	0.005	0.9	31076	15691400	0.18	631	0.35	12.9	0.91	435	22.9	4.57
Tingara	Field 212c	2001	Barley	4.8	14.8	Exponential	0.345	0.8	1374	4121	0.00	631	0.63	8.5	0.60	591	31.2	4.32
Tingara	Field 212c	2003	Wheat	4.7	15.4	Exponential	0.276	0.2	61	183	0.00	638	0.52	10.5	0.74	183	9.6	2.69
Tingara	Field 212c	2004	Barley	1.8	25.0	Spherical	0.133	8.6	50000	50000	0.00	634	0.30	15.2	1.07	577	30.4	5.72

Table A4.2: Fields per farm with years of adoption and the median of components of the yield variation index (Y_i).

Region	Farm	Field ID	Years of Adoption	Median CV_a	Median M_v	Median Cd	Median S_v	Median Y_i
CFI	Bearbung	Anniies	1	16.8	1.19	342	18.0	4.6
CFI	Bearbung	Camerons	1	18.6	1.31	576	30.3	6.3
CFI	Bearbung	Craig	1	17.0	1.20	321	16.9	4.5
CFI	Bearbung	Creek	4	27.1	1.91	626	33.0	8.2
CFI	Bearbung	Cris	1	16.1	1.13	524	27.6	5.6
CFI	Bearbung	Doolies	5	22.0	1.55	847	44.6	6.7
CFI	Bearbung	Kates	4	15.3	1.08	468	24.7	4.4
CFI	Bearbung	Racecourse	4	20.7	1.46	476	25.1	6.2
CFI	Bearbung	Top Dam	1	8.2	0.58	602	31.7	4.3
CFI	Burrendah	Avenue	1	17.6	1.24	819	43.2	7.3
CFI	Burrendah	Bridge	5	22.6	1.59	765	40.3	6.8
CFI	Burrendah	Glens	6	27.5	1.94	663	34.9	7.6
CFI	Burrendah	House	1	11.5	0.81	630	33.2	3.8
CFI	Burrendah	Woolshed	2	13.1	0.92	691	36.4	5.6
CFI	Connamara	H5	1	9.4	0.66	432	22.8	2.9
CFI	Connamara	H7	1	15.8	1.11	936	49.3	7.4
CFI	Kiewa	Block 3	1	20.4	1.44	827	43.6	6.0
CFI	Kiewa	Bottom L	3	15.1	1.06	568	30.0	5.6
CFI	Kiewa	Brick Kiln	2	7.6	0.54	898	47.3	4.9
CFI	Kiewa	Diamond	2	36.1	2.54	208	10.9	3.3
CFI	Kiewa	Front	2	11.7	0.83	617	32.5	5.0
CFI	Kiewa	Mugs	3	15.3	1.08	929	48.9	7.3
CFI	Kiewa	Ramp	1	14.0	0.99	272	14.3	2.8
CFI	Kiewa	Swamp	3	23.1	1.63	366	19.3	4.2
CFI	Merinda	Airstrip	1	8.1	0.57	506	26.6	3.9
CFI	Merinda	Hoolahan	2	20.7	1.46	837	44.1	7.3
CFI	Merinda	KRS 14_16	2	8.5	0.60	577	30.4	3.7
CFI	Merinda	MRS_A	2	14.8	1.04	861	45.4	6.7

Region	Farm	Field ID	Years of Adoption	Median CV_a	Median M_v	Median Cd	Median S_v	Median Y_i
CFI	Merinda	Ramp	1	11.1	0.79	964	50.8	6.3
CFI	Merinda	Rosewood	2	10.9	0.77	751	39.6	5.5
CFI	PineCliff	Back Paddock	1	13.7	0.97	1235	65.1	7.9
CFI	PineCliff	Btm Glen Erin East	1	4.5	0.32	1267	66.8	4.6
CFI	PineCliff	Duncans	1	9.0	0.63	912	48.1	5.5
CFI	PineCliff	Glen Erin West	1	9.6	0.67	819	43.1	5.4
CFI	PineCliff	Long Shinrone	1	12.7	0.89	1371	72.3	8.1
CFI	PineCliff	Middle Gee	1	20.7	1.46	720	38.0	7.4
CFI	PineCliff	Number 2	1	12.6	0.89	747	39.4	4.4
CFI	PineCliff	Shinrone	1	3.6	0.25	1589	83.7	4.6
CFI	Romaka	Boomerang	1	12.6	0.89	304	16.0	3.8
CFI	Romaka	Bull	1	18.5	1.30	36	1.9	1.6
CFI	Romaka	Lease	2	12.7	0.89	902	47.5	6.0
CFI	Romaka	Pine	2	8.8	0.62	799	42.1	5.0
CFI	Romaka	Skurr	1	10.6	0.75	127	6.7	2.2
CFI	Romaka	South Dam	1	6.5	0.46	429	22.6	3.2
CFI	Romaka	Well	1	26.8	1.89	577	30.4	7.6
CFI	Romaka	West Creek	4	13.1	0.92	570	30.1	4.0
CFI	Tarnee	Bc Sth	1	13.7	0.97	1021	53.8	7.2
CFI	Tarnee	Birdcage	1	14.1	1.00	952	50.2	7.1
CFI	Tarnee	Bt	5	15.2	1.07	1221	64.3	8.6
CFI	Tarnee	Comet A	1	9.4	0.66	1540	81.2	7.4
CFI	Tarnee	Comet B	8	15.2	1.07	964	50.8	7.0
CFI	Tarnee	IXLB	2	12.3	0.87	576	30.4	4.2
CFI	Tarnee	Kerrett	5	18.1	1.28	784	41.3	5.7
CFI	Tarnee	Stock Route	1	21.3	1.50	296	15.6	3.5
CFI	Tarnee	TC	6	14.5	1.02	942	49.7	6.8
CFI	Tarnee	TT	2	12.7	0.89	1010	53.2	5.9
Riverine	Glenmore	WA	6	17.6	1.24	764	40.3	7.0

Region	Farm	Field ID	Years of Adoption	Median CV_a	Median M_v	Median Cd	Median S_v	Median Y_i
Riverine	Glenmore	WC	6	20.0	1.41	1193	62.9	8.6
Riverine	Grandview	10	2	10.6	0.75	412	21.7	4.0
Riverine	Grandview	12	5	24.6	1.73	467	24.6	4.5
Riverine	Grandview	13	3	7.2	0.50	769	40.5	4.1
Riverine	Grandview	19	1	15.9	1.12	528	27.8	5.6
Riverine	Grandview	20	1	19.4	1.37	331	17.4	3.6
Riverine	Grandview	21	1	20.8	1.47	153	8.0	2.6
Riverine	Grandview	44	6	16.9	1.19	894	47.1	6.7
Riverine	Grandview	46	2	15.6	1.10	583	30.7	5.2
Riverine	Grandview	49	2	7.4	0.52	658	34.7	4.2
Riverine	Yaralla	East Ridge	3	11.4	0.80	310	16.4	3.5
Riverine	Yaralla	Freeling	5	12.2	0.86	356	18.8	4.1
Riverine	Yaralla	Rhombus	5	8.1	0.57	868	45.7	4.7
SPAA	Brook Park	Bills	4	15.2	1.07	584	30.8	5.5
SPAA	Brook Park	Road	7	8.2	0.58	1090	57.5	5.8
SPAA	Clifton Farm	Barn	2	7.6	0.54	698	36.8	4.4
SPAA	Clifton Farm	Black Flat	8	9.6	0.68	471	24.8	4.0
SPAA	Clifton Farm	Top D	4	14.6	1.03	512	27.0	5.2
SPAA	Faithfield	Front SW	1	13.0	0.91	350	18.4	3.0
SPAA	RayvillePark	Field 27	8	8.9	0.63	876	46.2	5.2
SPAA	RayvillePark	Field 41	7	15.8	1.11	640	33.7	6.3
SPAA	Tingara	Field 146a	5	23.1	1.63	221	11.7	3.9
SPAA	Tingara	Field 212c	5	12.9	0.91	435	22.9	4.6

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Appendix 5

Different vegetation indices & parameters for other indices (I_i & S_i)

A5.1 - Several vegetation indices used in agriculture

Imagery indices used in **Chapter 5** considered a range of 11 vegetation indices previously used in PA applications (**Table A5.1**), which were calculated using airborne imagery with four wavelengths: blue (450nm), green (550 nm), red (650-670 nm) and infrared (≈ 750 nm).

Table A5.1: Several vegetation indices already applied to PA.

Index	Formula
NDVI - Normalized Difference Vegetation Index (Rouse et al., 1974)	$\frac{IR - red}{IR + red}$
NDVI scaled	$\left(\frac{IR - red}{IR + red} + 1\right) x 100$
VI	$\frac{IR}{red}$
PPR - Plant Pigment Ratio	$\frac{green}{blue}$
PVR - Photosynthetic Vigour Ratio	$\frac{green}{red}$
PCD - Plant Cell Density	$\frac{IR}{red}$
SAVI(0.5) (0.5 = correction of shine of the soil) (Huete, 1988)	$\left(\frac{IR - red}{IR + red + 0.5}\right) x (1 + 0.5)$
GNDVI - Green NDVI	$\frac{IR - green}{IR + green}$
GNDVI scaled	$\left(\frac{IR - green}{IR + green} + 1\right) x 100$
TrVI - Triangular Vegetation Index (Broge & Leblanc, 2000)	$0.5[120(IR - green) - 200(red - green)]$
OSAVI - Optimized Soil Adjusted Vegetation Index (Rondeaux et al., 1996)	$\frac{IR - red}{IR + red + 0.16}(1 + 0.16)$
MSAVI (Modified Soil Adjusted Vegetation Index) (Qi et al., 1994)	$\frac{2IR + 1 - \sqrt{(2IR + 1)^2 - 8(IR - red)}}{2}$
TDVI - Transformed Difference Vegetation Index (Bannari et al., 2002)	$1.5\left(\frac{IR - red}{\sqrt{IR^2 + red + 0.5}}\right)$

These indices have already used to agriculture mostly to consider crop yield predictions of some physiological or physical process modelling. The NDVI formula is far the most popular index for several agronomic applications, while other indices include properties such as: high responses for PPR when leaves are strongly pigmented, high responses for PVR for leaves with strong chlorophyll absorption, and high responses for PCD for leaves with high density of healthy cells.

A5.2 - Best variogram model fit parameters and components of other indices (I_i & S_i)

Table A5.2: Parameters for best fit variogram and NDVI index (I_i).

Farm	Field ID	Year	Mean Yield	CV%	Best Fit	C0	C1	A1	Alfa	Maximum Lag	C^*	CV_a	M_v	Cd	S_v	I_i
Bearbung	Doolies	2003	0.55	11.23	Stable	0.0028	2.6580	25639	1.93	896	0.0069	5.74	0.93	872	46.0	6.5
Bearbung	Doolies	2004	0.35	25.19	Exponential	0.0022	0.0102	463		902	0.0109	19.66	3.17	780	41.1	11.4
Bearbung	Doolies	2005	0.49	18.51	Spherical	0.0059	0.1796	50000		905	0.0108	8.41	1.36	804	42.4	7.6
Bearbung	Front	2003	0.64	9.15	Spherical	0.0023	0.0014	513		873	0.0038	5.07	0.82	513	27.0	3.4
Bearbung	Front	2005	0.60	14.21	Spherical	0.0042	0.0039	496		873	0.0080	9.19	1.48	496	26.1	4.6
Bearbung	Kates	2003	0.58	5.92	Stable	0.0007	0.0057	1508	1.99	779	0.0020	3.84	0.62	756	39.9	5.0
Bearbung	Kates	2005	0.34	34.79	Exponential	0.0023	0.0123	81		779	0.0146	31.78	5.13	243	12.8	8.1
Bearbung	Kates	2006_a	0.10	63.64	Stable	0.0033	2.6000	21859	1.99	779	0.0067	30.30	4.89	759	40.0	14.0
Bearbung	Kates	2006_b	0.40	25.80	Stable	0.0054	1.4370	50000	1.15	776	0.0171	18.11	2.92	742	39.1	10.7
Bearbung	Mugs	2005	0.59	12.12	Stable	0.0038	0.2543	50000	1.14	1172	0.0073	6.07	0.98	1121	59.1	7.6
Bearbung	Racecourse	2003	0.53	12.41	Spherical	0.0013	0.2852	50000	0.02	778	0.0080	9.49	1.53	731	38.5	7.7
Bearbung	Racecourse	2005	0.27	50.28	Spherical	0.0083	0.8835	50000		772	0.0291	22.92	3.70	729	38.4	11.9
Bearbung	Racecourse	2006_a	0.16	54.49	Stable	0.0059	20.1800	47093	1.99	777	0.0116	25.24	4.07	757	39.9	12.7
Bearbung	Racecourse	2006_b	0.43	27.29	Stable	0.0081	1.3380	50000	1.13	741	0.0196	14.46	2.33	709	37.3	9.3
Brook Park	Bills	2003	0.75	2.47	Stable	0.0002	1.1230	44862	1.99	815	0.0006	1.39	0.22	795	41.9	3.1
Brook Park	Bills	2004	0.56	36.37	Spherical	0.0084	0.0426	550		818	0.0510	32.43	5.23	550	29.0	9.3
Brook Park	Road	2003	0.76	6.07	Stable	0.0010	2.0450	50000	1.88	1490	0.0038	4.33	0.70	1441	75.9	7.3
Brook Park	Road	2004	0.63	11.48	Spherical	0.0034	0.0764	50000		1488	0.0068	6.73	1.08	1339	70.6	8.7
Brook Park	Road	2005	0.68	7.74	Stable	0.0018	1.5120	50000	1.81	1491	0.0044	4.60	0.74	1449	76.4	7.5
Burrendah	Bridge	2003	0.69	9.83	Spherical	0.0024	0.1362	0		981	0.0064	6.77	1.09	902	47.5	0.0
Burrendah	Glens	2003	0.68	11.29	Stable	0.0040	0.0024	288	1.99	789	0.0065	6.39	1.03	380	20.0	4.5
Burrendah	Glens	2004	0.68	11.65	Exponential	0.0025	0.0057	357		790	0.0076	9.06	1.46	668	35.2	7.2
Burrendah	Glens	2006_a	0.10	62.28	Spherical	0.0026	0.0055	2331		788	0.0053	35.32	5.70	665	35.0	14.1
Burrendah	Glens	2006_b	0.47	29.61	Exponential	0.0057	0.0150	149		778	0.0206	24.91	4.02	446	23.5	9.7
Burrendah	Woolshed	2006_a	0.54	18.88	Stable	0.0083	1.9980	50000	0.05	841	0.0145	8.00	1.29	811	42.7	7.4
Burrendah	Woolshed	2006_b	0.15	95.10	Spherical	0.0157	0.5089	50000		838	0.0285	40.92	6.60	745	39.3	16.1

Farm	Field ID	Year	Mean Yield	CV%	Best Fit	C0	C1	A1	Alfa	Maximum Lag	C^*	CV_a	M_v	Cd	S_v	I_i
Clifton Farm	Black Flat	2003	0.72	3.66	Stable	0.0005	1.7750	37875	1.99	780	0.0013	1.97	0.32	760	40.1	3.6
Clifton Farm	Black Flat	2004	0.67	18.57	Exponential	0.0121	0.4079	50000		778	0.0184	8.46	1.36	738	38.9	7.3
Clifton Farm	Black Flat	2005	0.59	7.22	Spherical	0.0009	0.0010	271		777	0.0020	5.02	0.81	271	14.3	3.4
Clifton Farm	Top D	2003	0.39	37.58	Spherical	0.0112	0.0176	603		663	0.0287	25.97	4.19	603	31.8	8.6
Clifton Farm	Top D	2004	0.49	15.74	Stable	0.0037	20.8300	29303	1.99	661	0.0147	9.78	1.58	644	34.0	7.3
Connamara	H5	2003	0.59	7.65	Stable	0.0016	1.5300	33206	1.94	1047	0.0034	3.73	0.60	1021	53.8	5.7
Connamara	H7	2003	0.53	9.60	Exponential	0.0015	0.1268	50000		1078	0.0042	6.31	1.02	1023	53.9	7.4
Glenmore	WA	2003	0.50	19.43	Exponential	0.0013	0.0080	47		953	0.0093	18.04	2.91	141	7.4	4.6
Glenmore	WA	2004	0.58	15.00	Stable	0.0057	2.2190	50000	1.55	956	0.0106	7.38	1.19	925	48.8	7.6
Glenmore	WC	2003	0.49	27.93	Stable	0.0133	2.4890	50000	1.42	1525	0.0310	15.32	2.47	1469	77.4	13.8
Glenmore	WC	2004	0.51	27.42	Stable	0.0096	1.7380	50000	1.17	1536	0.0385	19.69	3.18	1468	77.4	15.7
Grandview	12	2004	0.65	10.70	Stable	0.0033	3.3760	15898	1.99	622	0.0086	5.97	0.96	606	32.0	5.5
Grandview	13	2004	0.59	14.71	Stable	0.0047	7.2920	21845	1.99	795	0.0147	9.03	1.46	774	40.8	7.7
GrandView	44	2004	0.78	6.40	Stable	0.0016	3.4400	50000	1.99	1373	0.0043	3.76	0.61	1338	70.5	6.5
Grandview	46	2004	0.67	8.76	Exponential	0.0024	0.1358	50000		827	0.0047	4.71	0.76	785	41.4	5.6
Grandview	49	2004	0.71	8.10	Spherical	0.0021	0.0014	319		714	0.0034	4.92	0.79	319	16.8	2.7
Kiewa	Diamond	2003	0.68	6.51	Stable	0.0017	2.0660	50000	1.99	1227	0.0030	2.51	0.41	1196	63.0	5.1
Kiewa	Swamp	2003	0.29	43.97	Exponential	0.0061	0.0122	304		1514	0.0182	34.47	5.56	911	48.0	16.3
Kiewa	Swamp	2004	0.52	20.58	Exponential	0.0039	0.5524	50000		1513	0.0203	14.74	2.38	1437	75.7	13.4
Kiewa	Swamp	2005	0.41	30.59	Exponential	0.0061	0.0096	129		1506	0.0157	23.77	3.83	386	20.4	8.8
Merinda	Airstrip	2003	0.54	10.65	Spherical	0.0027	0.0305	50000		1807	0.0043	4.66	0.75	1570	82.7	7.9
Merinda	KRS14_16	2003	0.72	12.44	Spherical	0.0025	0.0053	374		2101	0.0078	10.34	1.67	374	19.7	4.3
Merinda	KRS14_16	2004	0.52	20.74	Stable	0.0000	0.0121	123	0.51	2101	0.0119	20.74	3.35	359	18.9	8.0
Merinda	Ramp	2004	0.65	12.72	Stable	0.0043	19.5200	41034	1.99	927	0.0147	7.63	1.23	903	47.6	7.7
Merinda	Rosewood	2003	0.62	15.53	Spherical	0.0033	0.3875	50000		998	0.0149	11.01	1.78	934	49.2	9.3
Merinda	Rosewood	2004	0.53	23.89	Exponential	0.0072	0.0394	1971		1000	0.0229	17.79	2.87	936	49.3	11.9
Pine Cliff	BackPaddock	2006 **a**	0.50	17.40	Stable	0.0061	0.6712	50000	1.39	1383	0.0106	7.88	1.27	1331	70.2	9.4
Pine Cliff	BackPaddock	2006 **b**	0.46	16.21	Stable	0.0039	7.9790	50000	1.99	1388	0.0102	8.78	1.42	1353	71.3	10.0
Pine Cliff	BtmGE East	2005	0.57	11.52	Stable	0.0036	5.3800	50000	1.99	1321	0.0075	4.83	0.78	1287	67.9	7.3
Pine Cliff	Duncans	2006 **a**	0.49	13.12	Stable	0.0034	8.4550	48440	1.99	931	0.0066	5.72	0.92	907	47.8	6.6
Pine Cliff	Duncans	2006 **b**	0.90	3.75	Stable	0.0006	2.4010	50000	1.99	928	0.0014	2.71	0.44	904	47.6	4.6
Pine Cliff	MiddleGee	2004	0.67	9.47	Stable	0.0027	3.6000	50000	1.99	1707	0.0071	5.34	0.86	1663	87.7	8.7

Farm	Field ID	Year	Mean Yield	CV%	Best Fit	C0	C1	A1	Alfa	Maximum Lag	C^*	CV_a	M_v	Cd	S_v	I_i
Pine Cliff	Number 2	2006 [a]	0.27	39.53	Exponential	0.0061	0.0072	465		1557	0.0131	22.84	3.68	1393	73.4	16.4
Pine Cliff	Number 2	2006 [b]	0.82	3.37	Stable	0.0004	1.3390	50000	1.99	1558	0.0017	2.39	0.38	1519	80.0	5.6
Pine Cliff	Shinrone	2005	0.58	12.01	Stable	0.0040	0.0127	2834	1.99	1630	0.0076	4.76	0.77	1581	83.3	8.0
RayvillePark	Field 27	2003	0.68	6.18	Stable	0.0009	0.0056	1143	1.99	917	0.0036	4.34	0.70	903	47.6	5.8
RayvillePark	Field 27	2004	0.72	7.91	Stable	0.0023	0.7623	50000	1.36	921	0.0056	4.34	0.70	887	46.7	5.7
RayvillePark	Field 27	2005	0.68	12.86	Stable	0.0052	0.0038	379	1.42	919	0.0088	3.97	0.64	557	29.3	4.3
RayvillePark	Field 41	2003	0.62	11.59	Stable	0.0030	1.1820	9704	1.97	736	0.0103	7.44	1.20	717	37.8	6.7
RayvillePark	Field 41	2004	0.51	21.03	Spherical	0.0064	0.0084	767		736	0.0148	13.87	2.24	422	22.3	7.1
RayvillePark	Field 41	2005	0.48	22.12	Stable	0.0041	0.0237	621	1.99	734	0.0219	17.57	2.83	695	36.6	10.2
Tarnee	Bc Sth	2006 [a]	0.27	47.73	Stable	0.0139	2.9670	50000	1.54	1207	0.0236	19.14	3.09	1166	61.5	13.8
Tarnee	Bc Sth	2006 [b]	0.23	71.48	Spherical	0.0106	0.0252	1111		1200	0.0358	55.88	9.01	1111	58.6	17.2
Tarnee	Bt	2005	0.52	25.42	Exponential	0.0004	0.0178	138		1295	0.0183	25.09	4.05	414	21.8	9.4
Tarnee	Bt	2006 [a]	0.66	17.19	Stable	0.0092	0.5832	50000	1.20	1296	0.0164	9.04	1.46	1241	65.4	9.8
Tarnee	Bt	2006 [b]	0.49	31.35	Stable	0.0000	0.0371	514	0.42	1273	0.0285	31.35	5.06	976	51.5	16.1
Tarnee	Comet A	2006 [a]	0.46	18.51	Exponential	0.0036	0.0081	926		1801	0.0106	13.19	2.13	1558	82.1	8.7
Tarnee	Comet A	2006 [b]	0.36	41.23	Spherical	0.0079	0.0200	1035		1802	0.0279	32.88	5.30	1035	54.6	12.7
Tarnee	Comet B	2003	0.59	13.00	Stable	0.0035	11.4100	44289	1.99	1188	0.0121	8.17	1.32	1158	61.0	9.0
Tarnee	Comet B	2004	0.48	24.86	Stable	0.0078	42.3200	50000	1.99	1185	0.0325	16.80	2.71	1155	60.9	12.8
Tarnee	IXLB	2006 [a]	0.10	73.26	Stable	0.0044	0.0029	643	1.99	865	0.0068	30.70	4.95	848	44.7	14.9
Tarnee	IXLB	2006 [b]	0.22	61.84	Spherical	0.0086	0.0115	471		865	0.0201	45.40	7.32	471	24.8	10.0
Tarnee	Kerret	2004	0.45	33.71	Spherical	0.0151	0.2822	50000		2184	0.0336	19.46	3.14	1983	104.5	18.1
Tarnee	Stock Route	2005	0.14	96.76	Stable	0.0000	0.0197	108	0.70	1362	0.0197	96.76	15.61	237	12.5	14.0
Tarnee	TC	2005	0.52	11.85	Stable	0.0000	0.0102	50000	0.19	1435	0.0041	11.85	1.91	1004	52.9	10.1
Tingara	Field 146a	2004	0.73	14.84	Spherical	0.0041	0.0078	159		810	0.0119	11.92	1.92	159	8.4	3.0
Tingara	Field 146a	2005	0.56	19.11	Exponential	0.0050	0.0064	56		814	0.0115	14.33	2.31	167	8.8	4.5
Yaralla	Freeling	2003	0.78	6.27	Stable	0.0016	0.4517	50000	1.28	829	0.0040	3.52	0.57	795	41.9	4.9
Yaralla	Freeling	2004	0.63	8.90	Stable	0.0022	0.0032	708	1.89	830	0.0046	4.97	0.80	785	41.4	5.8
Yaralla	Rhombus	2003	0.79	11.46	Stable	0.0058	0.0096	804	1.99	910	0.0127	6.28	1.01	866	45.6	6.8
Yaralla	Rhombus	2004	0.55	15.89	Stable	0.0057	2.1520	50000	1.45	914	0.0123	7.44	1.20	883	46.5	7.5

[a] – First in-season imagery for the month of August.

[b] – Second in-season imagery for the month of September.

Table A5.3: Parameters for best fit variogram and EMI indices (S_i).

Farm	Field ID	EMI	Mean Yield	CV%	Best Fit	C0	C1	A1	Alfa	Maximum Lag	C^*	CV_a	M_v	Cd	S_v	S_i
Bearbung	Doolies	31V	82.4	23.3	Stable	0	528.9	225.7	0.33	894	419.6	23.3	0.88	625	33.0	5.4
Bearbung	Doolies	38V	54.0	29.6	Exponential	31.48	229.7	67.22		894	261.1	27.7	1.05	201	10.6	3.3
Bearbung	Doolies	38H	52.3	24.0	Spherical	30.52	129	160		894	159.5	21.5	0.82	90	4.8	2.0
Kiewa	Swamp	31V	62.1	30.6	Stable	0	1027.6	2631.2	0.59	1507	527.2	30.6	1.16	1330	70.1	9.0
Kiewa	Swamp	38V	34.6	32.8	Spherical	34.53	112.6	764.1		1507	147.2	28.1	1.06	431	22.7	4.9
Kiewa	Swamp	38H	35.2	24.5	Spherical	24.6	55.83	590.6		1507	80.4	20.1	0.76	331	17.4	3.6
Tarnee	Bt	31V	95.9	23.5	Stable	174.1	7814.2	50000	0.72	1294	716.1	19.1	0.72	1202	63.3	6.8
Tarnee	Bt	38V	127.9	23.3	Stable	559.7	36799	50000	1.09	1294	1234.2	14.2	0.54	1235	65.1	5.9
Tarnee	Bt	38H	91.7	21.5	Exponential	243	11236	50000		1294	530.0	13.2	0.50	1228	64.7	5.7
Tarnee	Comet B	31V	105.7	22.2	Stable	100.4	461.2	165.1	1.72	1550	561.6	20.1	0.76	227	12.0	3.0
Tarnee	Comet B	38V	109.5	22.1	Exponential	0	595.3	104.9		1550	595.3	22.1	0.84	314	16.6	3.7
Tarnee	Comet B	38H	83.8	18.0	Stable	92.44	134.1	160.4	1.78	1550	226.5	13.9	0.53	219	11.5	2.5
Glenmore	WA	31V	43.3	21.8	Exponential	0	93.62	96.12		951	93.6	21.8	0.82	288	15.2	3.5
Glenmore	WA	38V	84.3	28.3	Stable	0	612.8	93.48	0.81	951	611.9	28.3	1.07	185	9.7	3.2
Glenmore	WA	38H	64.4	26.2	Stable	0	329.2	126.6	0.60	951	317.4	26.2	0.99	318	16.8	4.1
Glenmore	WC	31V	33.6	38.2	Spherical	37.34	140.6	550.6		1537	178.0	33.6	1.27	311	16.4	4.6
Glenmore	WC	38V	64.2	38.7	Spherical	218.6	425.7	505.7		1537	644.3	31.1	1.18	282	14.9	4.2
Glenmore	WC	38H	35.9	46.4	Spherical	83.38	203	521.3		1537	286.4	38.8	1.47	292	15.4	4.8
Grandview	12	31V	145.9	11.4	Stable	0	361.5	129.7	0.42	629	309.8	11.3	0.43	477	25.2	3.3
Grandview	12	38V	123.4	17.6	Spherical	316.6	15547	50000		629	610.1	10.1	0.38	564	29.7	3.4
Grandview	12	38H	75.1	17.7	Spherical	109	7020.8	50000		629	241.5	10.9	0.41	572	30.1	3.5
Grandview	44	31V	112.4	34.0	Spherical	0	1449.9	395.8		1977	1450.0	34.0	1.29	226	11.9	3.9
Grandview	44	38V	92.7	37.9	Spherical	210.9	1034.2	474.4		1977	1245.1	34.5	1.31	269	14.2	4.3
Grandview	44	38H	57.8	32.5	Spherical	91.5	265.8	547.1		1977	357.3	28.0	1.06	308	16.2	4.1
Brook Park	Bills	31V	57.5	33.1	Stable	11.11	458.8	241.3	1.339	816	467.1	32.6	1.24	364	19.2	4.9
Brook Park	Bills	38V	41.9	23.6	Spherical	1.266	106.2	318.7		816	107.5	23.5	0.89	182	9.6	2.9
Brook Park	Bills	38H	24.6	27.7	Stable	4.278	47.08	153.4	1.84	816	51.4	26.4	1.00	207	10.9	3.3
Brook Park	Road	31V	79.8	16.3	Stable	0	174	69.86	0.535	1477	173.0	16.3	0.62	195	10.3	2.5
Brook Park	Road	38V	50.7	15.6	Stable	0	65.99	33.04	0.3584	1477	64.7	15.6	0.59	153	8.1	2.2
Brook Park	Road	38H	24.3	32.9	Spherical	3.7	62.28	347.7		1477	66.0	31.9	1.21	198	10.4	3.6

Farm	Field ID	EMI	Mean Yield	CV%	Best Fit	C0	C1	A1	Alfa	Maximum Lag	C^*	CV_a	M_v	Cd	S_v	S_i
Clifton Farm	Black Flat	31V	106.4	46.2	Stable	63.21	2385.1	62.03	1.99	777	2448.3	45.6	1.73	82	4.3	2.7
Clifton Farm	Black Flat	38V	75.0	40.9	Spherical	0	948.9	126.2		777	948.9	40.9	1.55	126	6.7	3.2
Clifton Farm	Black Flat	38H	60.5	25.3	Spherical	22.53	213.3	126.3		777	235.8	24.1	0.91	126	6.7	2.5
Clifton Farm	Top D	31V	81.6	56.3	Spherical	0	2781.8	435.2		668	2781.8	56.3	2.13	249	13.1	5.3
Clifton Farm	Top D	38V	67.7	54.2	Spherical	17.98	1589.7	353.9		668	1607.7	53.8	2.04	202	10.6	4.7
Clifton Farm	Top D	38H	64.6	29.9	Spherical	69.61	417.4	459.4		668	487.0	26.9	1.02	260	13.7	3.7
RayvillePark	Field 27	31V	104.8	31.0	Spherical	272.5	1022.7	644.8		911	1295.2	26.7	1.01	364	19.2	4.4
RayvillePark	Field 27	38V	68.6	32.7	Spherical	220.1	359.5	589.1		911	579.5	24.5	0.93	327	17.2	4.0
RayvillePark	Field 27	38H	43.0	31.1	Spherical	60.58	150.6	601.8		911	211.2	25.3	0.96	338	17.8	4.1
RayvillePark	Field 41	31V	78.8	27.1	Spherical	48	424.6	244.3		742	472.6	25.7	0.97	139	7.3	2.7
RayvillePark	Field 41	38V	54.8	26.1	Spherical	44.24	164.3	204.4		742	208.5	23.1	0.88	115	6.1	2.3
RayvillePark	Field 41	38H	38.2	22.4	Exponential	4.431	70.43	63.92		742	74.9	21.8	0.82	192	10.1	2.9
Merinda	Rosewood	38V	93.7	31.4	Spherical	288.7	715.6	651.3		989	1004.3	25.6	0.97	365	19.3	4.3