# Chapter 8 : General discussion, conclusions and future work

## 8.1 General discussion

Some of the discussion points that have already been addressed within the preceding chapters will be reiterated. Importantly, some further discussion will be attempted with the hindsight of seven completed chapters.

### *8.1.1 Spatio-temporal crop-yield variation*

With regards to *approaching quantitative comparisons between spatial and temporal yield variation* a number of interesting discussion points exist. This part of the discussion is premised upon the assertion that understanding the contribution of spatial and temporal variation to total variation of crop yield is necessary to understand the behaviour of crop yield in space and time (Hoosbeek, 1998). The 'null hypothesis of Precision Agriculture' proposed by McBratney and Whelan (1999) asserts the importance of this understanding from a PA management perspective. Further conceptualisation of this idea within the literature has not been extensively addressed.

An essential question is how to quantify spatio-temporal crop yield variation. Explicitly quantitative approaches within the literature are relatively sparse. Examples preceding this work have utilised geostatistics (eg. McBratney *et al.*, 1997) and fractals (eg. Eghball and Varvel, 1997). Several approaches were investigated in this thesis (Chapter 3). These were creation of yield maps for multiple years; creation of temporal semi-variance maps; calculating rank correlations and a principle components analysis; creating spatio-temporal variograms and; creating pseudo cross variograms. Perhaps the most interesting and novel conceptual question arising from this research is, '*for a field, at what spatial and temporal scale are the contributions of spatial and temporal variation to total variation equivalent?*' A practical hindrance recognised in this research and in previous work (eg. Bakhsh *et al.*, 2000; Lamb *et al.*, 1997) is that necessary quantities of data about crop yield in the temporal dimension are currently unavailable.

Following from attaining an adequate ability to quantify spatio-temporal variation of crop yield, the implications of this variation for PA management can be recognised. If one assumes that an answer to the above question is provided, this would allow the optimum scale for potential spatial management to be identified. Whether the optimum spatial unit is smaller, equal or larger than an individual field would depend on the relative magnitude of spatial and temporal variation. In turn, it would be possible to determine the value of SSCM over uniform management. Some results from this research confirm prior research conclusions that the magnitude of temporal crop yield variation usually exceeds the magnitude of spatial variation (e.g. Eghball and Varvel, 1997; McBratney *et al.*, 1997; Schepers *et al.*, 2004). Long-term temporal variograms created in this research also indicate that temporal variation has a large nugget (unpredictable) effect. Subsequently, in the light of McBratney and Whelan's 'null hypothesis', one might consider uniform management to be less risky than variable rate management. However, some further considerations are important. It is important to consider structure of variation as well as magnitude. A relatively simple approach that exists within the literature is to examine the stability of yield patterns between years (Andales *et al.*, 2007). This type of analysis raises an important management question about quantifying acceptable levels of risk based on pattern stability.

### *8.1.2 Crop growth simulation modelling*

The previously mentioned lack of data in the temporal dimension provides a convenient path towards discussion about crop growth simulation modelling. Such modelling can provide a potential wealth of crop yield information within the temporal dimension. Based on the idea that understanding spatio-temporal crop yield information is imperative for effective PA management, it is important to clearly define *expectations about crop growth simulation modelling outcomes for PA*. As a result, three major research questions were addressed during this thesis. First, can APSIM, as a representative of the sophisticated crop growth simulation models, adequately predict spatio-temporal crop yield variability (Chapter 4)?; Second, how can one undertake crop growth simulation modelling at a spatial scale and extent useful for PA (Chapter 5)? and; Third, how important are spatial processes that impact crop yield predictions (Chapter 6)?

These three research challenges are connected by a fundamental theme for discussion. This theme is the conceptual model that underpins point-based crop growth simulation modelling.

Many crop growth simulation models (including APSIM) are described as deterministic at the crop scale. This is the case because all plants in the crop are considered the same in terms of crop characteristics and exposure to environmental conditions (Bouman *et al.*, 1996). As a result, a prediction of the mean behaviour is provided, while on a plant scale, there can be significant departures from the mean. In terms of these models, the genetic, spatial and temporal variation of real crop systems is not accounted for (Loomis *et al.*, 1979). Given that PA grants serious concern to understanding and managing spatial variation, some intrinsic limitations to this type of modelling approach as-is deserve recognition. This shortfall is acknowledged in a review about modelling the growth and water uptake function of plant roots within crop growth simulation models by Wang and Smith (2004). These authors reported that performance of current root-modelling was satisfactory under uniformly distributed dense field crops on homogeneous, non-hostile soils. It is the heterogeneously distributed plants and highly structured soil conditions that require further consideration. This example highlights the importance of recognising that there are many sources and scales of variability in crop yield (Burrough, 1983). An implication of this understanding is the need to be scale specific when describing processes that determine crop yield. Batchelor *et al.* (2002) suggest some model processes that require investigation to determine if they are accurate at scales relevant to PA. Included are macro-pore flow, soil water dynamics in surface depressions and phenological response to stress. One way of acknowledging the inherent uncertainty in soil and management parameters used for yield prediction is stochastic methods such as Monte-Carlo simulation (Bouman, 1994). It appears that actually accounting for this variation within the conceptual model has not been explicitly explored.

This discussion so far raises a general question about the inherent ability of crop growth simulation models to predict spatial variability. Chapter 4 of this thesis addressed whether varying soil available water capacity within APSIM would be adequate to model spatio-temporal variation of crop yield across a field. It was found that some spatial variation of crop yield can be simulated when available water capacity is the only spatially variable input. However, the magnitude of this variation is generally under-estimated. In terms of spatio-temporal variation, the stability of spatial patterns was exaggerated. While this work demonstrated some valuable insight into the ability of APSIM to predict spatial variation, some confounding factors were also pervasive. Within APSIM, there are many complex interactions between available water capacity and other soil parameters and processes which the analysis did not explicitly account for.

The next discussion point associated with the conceptual underpinning of point-based crop growth simulation modelling is the exclusion of lateral processes, particularly water movement across the landscape. This conceptual issue is quite easily comprehended in the light of water-limited cropping systems with landscape features that result in processes such as run-off, run-on and lateral subsurface flow. It is arguable that a one-dimensional modelling exercise is futile if lateral water flow is occurring within the system. This argument is simply that the mechanistic basis for the model is fundamentally flawed as important hydraulic processes are excluded. A significant body of research exists that confirm the significance of lateral water movement impacting crop growth (eg. Jiang and Thelan, 2004; Kaspar *et al.*, 2004; Timlin *et al.*, 1998).

Chapter 6 addresses the idea of enhancing point-based yield predictions with spatial information (topographic, gamma radiometric and electro-magnetic). For most fields included in this research, spatial information offered significant improvements to the yield predictions. This approach successfully demonstrated the importance of spatial processes in determining yield outcomes. An additional point of interest gained from this approach is the ability to attribute relative contributions of point-based and spatial prediction components to total variation of crop yield. This approach implies that spatial processes are physically occurring, however, it does not identify specific processes. A consequence of this modelling approach is that the spatial component of each yield prediction is field specific. Unlike a mechanistic approach to modelling, new models must be applied to new situations. Current research about inter-modular communication is advancing the ability for points within a model such as APSIM to communicate (eg. Huth *et al.*, 2003). This type of research is acknowledging the importance of accounting for spatial processes when simulating crop growth systems.

Finally, within a conceptual context, it is important to consider model complexity. The complexity versus simplicity discussion is partly associated with differences between mechanistic and empirical approaches to modelling. A crop growth simulation model such as APSIM can be largely described as mechanistic; however, the model also contains a degree of empiricism. Generally, the greater degree of mechanism within a model the greater the complexity. An interesting discussion question is: *What degree of complexity is optimum for a model to perform?* This question is akin with Ockham's razor where the cost of information for the addition of model parameters must be equivalent to the value gained from this addition. Reynolds and Acock (1985) made an attempt to identify an answer to this question by separating total error of model predictions into error due to simplification of the system and error due to uncertainty in parameter estimation. This conception of total error potentially allows an optimal level of model simplicity/complexity to be identified. Within the literature there are a number of examples where simple models have proven more reliable than more complex models. For example Bell and Fischer (1994) found that a regression model was superior to CERES for potential wheat yield prediction in Mexico. Sudduth *et al.* (1998) demonstrated that projection pursuit regression and neural networks reproduced yield patterns within a field more closely than a crop growth simulation model. Some further examples are outlined by Sinclair and Seligman (1996). Research within this thesis (Chapter 5) also demonstrates the value of simple regression modelling over complex crop growth simulation modelling for yield prediction when data availability is limited to soil available water capacity and rainfall. However, this research also demonstrates the limitations of over-simplification such as excluding management parameters for crop yield prediction. It is clearly apparent that there is merit in simplifying the modelling process to some extent. For crop growth simulation modelling in a PA context, the ideal degree of complexity/simplicity lies somewhere between models as complex as APSIM and a regression model that simply considers soil available water capacity, monthly rainfall and topography.

Model simplicity versus complexity is also highly relevant to practical modelling issues associated with PA. The major challenge is the computational and human ability to simulate enough points in space so that modelling output is at a resolution useful for PA. As seen in Chapter 5, this is not an issue if simple regression models are used rather than complex crop growth simulation models. However, perhaps novel programming methods to reduce computer memory burden is an important research avenue, particularly if the complexity of spatial variation is incorporated into current models.

Regardless of model simplicity/complexity, some extent of information is essential for input into models. This is another practical modelling issue associated with PA due to the spatial resolution required of modelling outcomes. A popular approach in the literature has been to use modelling techniques that limit the number of necessary simulations such as modelling representative 'homogeneous areas' (eg. Fraisse *et al.*, 2001). However, it is highly desirable to develop ways of obtaining the required information at a high spatial resolution efficiently. Chapter 5 demonstrated an inverse meta-modelling approach to extract soil available water capacity data from crop yield data. Inverse modelling is similar to the use of optimisation to estimate model inputs (eg. Timlin *et al.*, 2001; Braga and Jones, 2003). These approaches take advantage of spatially dense yield monitor data and relationships encompassed within a crop growth simulation model to obtain information about the model inputs of interest. The meta-modelling aspect of this approach is essentially an approximation of APSIM to overcome the computational burden of running the model at a high spatial resolution across large farms. A neural network model to predict soil available water capacity from crop yield was developed. The resultant available water capacity maps proved to be useful for predicting yield using simple regression models; however, this was not the case for simulating crop growth using APSIM. This result is a reflection of some confounding issues that impact the estimates. Estimated available water capacity maps were different depending on the year of yield data. This indicates the presence of climate interactions with the crop, the soil and the landscape. Given that the inverse meta-model excluded a number of processes; it is probable that some other crop, soil and landscape variables manifested themselves within the estimates. It is difficult to determine exactly what information has been included within the available water capacity maps. Perhaps, if APSIM was used in its entirety and all the model variables and parameters other than available water capacity were known accurately then the estimates would have been more near the mark and useful for crop growth simulation modelling. However, this returns to the practical issue of 'accurately knowing' multiple spatially-variable parameters at a high spatial resolution. As well, this is a suitable point to revisit simplicity versus complexity questions.

### *8.1.3 Whole-farm management*

It is apparent that adequate understanding of spatio-temporal variability of crop yield is vital for building appropriate crop growth simulation models. It is also evident that such understanding can be enhanced due to the process of model development. Finally, it is important to discuss another potential benefit that crop growth simulation modelling can provide for PA. *Using crop growth simulation models for integrated whole-farm management* raises some interesting discussion questions about PA for both financial and environmental outcomes. First, the need to evaluate SSCM from a whole-farm and from a long-term perspective is important. Secondly, considering PA beyond SSCM is also highly relevant. Both these questions are addressed in Chapter 7.

Using crop growth simulation models to ask 'what if'-type questions is widely represented in the literature for evaluation of benefits derived from PA (eg. Link *et al.*, 2006; Booltink *et al.*, 2001). However, asking these questions within a long-term and across-farm context is not well represented within PA. Arguably, demonstrating the long-term value of SSCM across whole farms is a necessary and fundamental question for thorough evaluation of PA benefits and for consequent adoption. Considering a number of long-term farm outcomes and comparing across-farm results with field-extent results provide interesting avenues for discussion. Some of the results demonstrated in this thesis are significantly different to those results derived from short-term studies (ie. three to five years) that only consider yield outcomes within individual fields. First, integrating financial and environmental outcomes acknowledges a more holistic approach to farming because the ramifications beyond the individual farmer's finances of management choices are considered. The results in Chapter 7 imply that the scope for SSCM to enhance farming outcomes over the long term is specific to certain fields. At the across-farm extent, the integration of all fields considered does not necessarily result in a net positive outcome. Investigating why certain fields appear to be suitable for SSCM while certain fields are not appropriately returns to the discussion about spatio-temporal variability. It has been previously mentioned in this discussion that temporal variation is large relative to spatial variation. It is possible that over the long term, this temporal variation is compounded and that is why managing spatial variation using SSCM has not proven to be overwhelmingly favourable. Perhaps these results indicate which fields have an optimal combination of spatial and temporal variation with respect to suitability for SSCM. These results certainly demonstrate that at the whole-farm extent, a combination of management approaches including SSCM and uniform management is likely to be optimal.

An extension of the prior-mentioned notion about enhancing the holistic nature of PA and the idea that a combination of management approaches might be optimal provides impetus to discuss alternative manifestations of PA beyond SSCM. Using an in-depth spatial and temporal understanding of resources across a whole-farm to consider alternative land-use options was mentioned in Chapter 7. Further development of this idea is to consider greater intersection between PA and some alternative agricultural systems that would benefit from quantitative spatio-temporal information. For example, within the field of “agro-ecosystem research”, designing systems to perform ecosystem functions (or services) might be enhanced by using spatial and temporal information. PA information might also be useful from a system evaluation perspective.

## 8.2 General conclusions

Certainly, using PA or SSCM to manage whole farms requires a comprehensive understanding about spatio-temporal crop yield variability. Granting consideration to farm outcomes beyond crop yield is also extremely valuable. The work presented in this thesis demonstrates that combining crop growth simulation modelling with spatially dense soil and crop information is a way forward. Some final conclusions are detailed below.

*With regards to spatio-temporal variation of crop yield, some conclusions are:*

- The magnitude of temporal variation of crop yield is often large relative to spatial variation.
- Considering "space-time variation equivalents" is a useful conceptual approach for comparing spatial variation with temporal variation. This is also a useful contribution for the determination of how spatio-temporal crop yield variation impacts suitability for SSCM.

*With regards to crop growth simulation modelling and PA some conclusions are:*

- If landscape conditions are such that lateral flow of water is occurring within a system, valid predictions about spatial variability of crop yield using point-based crop growth simulation models are not possible without consideration of spatial hydraulic processes.
- Simplifications of current crop growth simulation models to include a few essential processes that impact crop yield variation proved better than using a current (complex) crop growth simulation model.
- Inverse meta-modelling is a useful strategy to overcome the practical modelling challenge of efficiently obtaining spatially dense soil information to populate models.
- Spatially dense and temporally vast data resulting from successful simulation modelling is extremely useful for quantification of spatio-temporal crop yield variation and evaluation of SSCM.

*With regard to whole-farm planning some conclusions are:*

- Simultaneous consideration of multiple farm outcomes (eg. crop yield, soil carbon and nitrogen leaching) enhances understanding about management outcomes.
- Over the long term, from an environmental and a financial perspective, the value of SSCM across whole farms is highly field-specific.
- Spatially dense and temporally vast data about environmental and production performance potential is extremely useful for alternative land-use design.

## 8.3 Future work

The possibilities for future work are plentiful. This is an exciting prospect for researchers involved with PA, spatial data analysis and crop growth simulation modelling. Some specific research issues that this thesis has brought to light are outlined below.

First, there is scope to continue developing approaches for *quantification of spatio-temporal variation*. Impetus for continuing this research is multi-faceted. There is the conceptual challenge of how to comprehend comparison between a spatial dimension and a temporal dimension. There is the methodological challenge of how to physically make such comparisons. There is the practical challenge of requiring this type of analysis to optimise the application of SSCM.

Second, striving *towards a modelling framework that is useful for PA* highlights a number of avenues for research. The basis for much of the necessary future work is ensuring that scientists involved with crop growth simulation modelling are asking rigorous questions about the numerous hypotheses that crop growth simulation models are based upon rather than continuing to tweak parameters for calibration and validation.

- From a PA perspective there is scope to challenge the conceptual basis of crop growth simulation models in terms of the scale of applicability. More specifically, to examine and identify processes included within models that might not physically be able to capture spatial variation at a within-field scale. It is important to ascertain which processes within current crop growth simulation models (eg. APSIM) are not designed for the scale of application required for PA; ie. modelling spatial variation within heterogeneous fields.

  Continuing to search for the most useful balance between complexity and simplicity of crop growth simulation models for PA is an important future research pursuit. Identifying vital processes within current models as well as considering excluded processes such as lateral water movement must be featured within this type of research. Relevant also to the simplicity/complexity of models are practical considerations about the cost (computer and human effort) of the modelling exercise in the context of PA. This is particularly pertinent for PA across farms where vast numbers of points in space require modelling. Also, emphasis on greater exchange between crop modelling skills and skills in spatial statistics is important.

  A further practical research issue that requires future work is related to model inputs within the context of PA. As previously mentioned PA across farms involves many points in space. This means that there is scope to continue the development of strategies that efficiently capture information required for modelling exercises.

Third, it is worthwhile to continue the pursuit for *PA across whole farms*. Future work encapsulated by this research goal is related to continued critical evaluation of SSCM and creative evaluation of potential embodiments of PA.

> In the light of achieving some of the above-mentioned future research goals related to crop growth simulation modelling and yield prediction, further evaluation of SSCM across farms and over long time periods (eg. 50 years) could appropriately follow from the research demonstrated in this thesis.
>
> There is scope to continue work in developing an approach to whole-farm evaluation of SSCM. There is potential to enhance the modelling within this thesis through model improvement and adaptation. An interesting aspect of this work would be to incorporate some more environmental outcomes such as deep-drainage and soil biology. This suggests that future work about measuring and modelling multiple farm outcomes at a high spatial resolution would be of great value. It would also be useful to explicitly evaluate economic outcomes over the long term. Integrating the environmental outcomes with the economic outcomes using an economic framework is a possibility that warrants further work. This is one way of integrating financial and environmental outcomes and there is certainly scope to explore other options. Finally, inclusion of social outcomes due to different management approaches to farming should also be considered.
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> With respect to evaluation of SSCM, a point of departure for further investigation is why certain fields across a farm are more suited to SSCM than others. This research question relates back to continuing research questions about spatio-temporal variability as well as how to evaluate SSCM.
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> To ensure that PA develops as a vibrant and relevant part of the agricultural industry it is imperative that research continues to focus on broadening ideas about how PA can contribute. An increasingly dominant theme within agricultural research and society at large is sustainability. There are opportunities for research about alternative embodiments of PA in the context of the search for innovative agricultural systems that are genuinely pursuing a holistic approach to sustainability.

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