

MOVING TO PA MANAGEMENT IN THE GRAINS INDUSTRY

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Abstract

Techniques for gathering data on spatial variability and the presently available options for differential treatment suggest that the technology for Precision Agriculture is developing well. The critical link between these two operations is the agronomic rationale or decision on which to base spatially variable treatments. This is the most conceptually diverse component in the Precision Agriculture management system, and where the greatest information gap resides. Initially causal relationships between soil/crop factors and yield must be established at the within-field scale along with the extent to which these relationships vary across the field. This information should be used to determine whether the observed variability warrants differential treatment and if so, direct the decision methodology to be followed. Delineating management zones with some certainty is a useful method for beginning the process of scientifically evaluating the options and benefits of precision agriculture.

Goals of Precision Agriculture

Precision agriculture (PA) is a scientific endeavour to improve the management of agricultural industries. This improvement must eventually be considered in terms of economic profitability and environmental impact. For site-specific crop management (SSCM), a form of PA that concentrates on managing spatial variability in crop and soil factors, the scale of these impacts will obviously be site-specific. At present the technological tools associated with SSCM are more obvious than the assessment and management of the spatial variation they document. Economic profitability is beginning to be shown internationally (e.g. Brouder & Lowenberg-DeBoer, 2000) but little documented here in Australia. The environmental impact of crop management is considered in very general terms in Australia, but with growing specificity internationally. For SSCM to move into the Australian grain industries, a move must be made in the direction of scientific experimentation and analysis.

To begin this move, an understanding of the conceptual framework in which experimentation could be carried out is required. Figure 1 offers 3 general approaches to managing within-paddock spatial variability in cropping systems. Stage 1 is the traditional uniform method. Stage 2 involves some form of partitioning of the paddock into regions of differing potential/response. Stage 3 is fine scale SSCM, analysing and

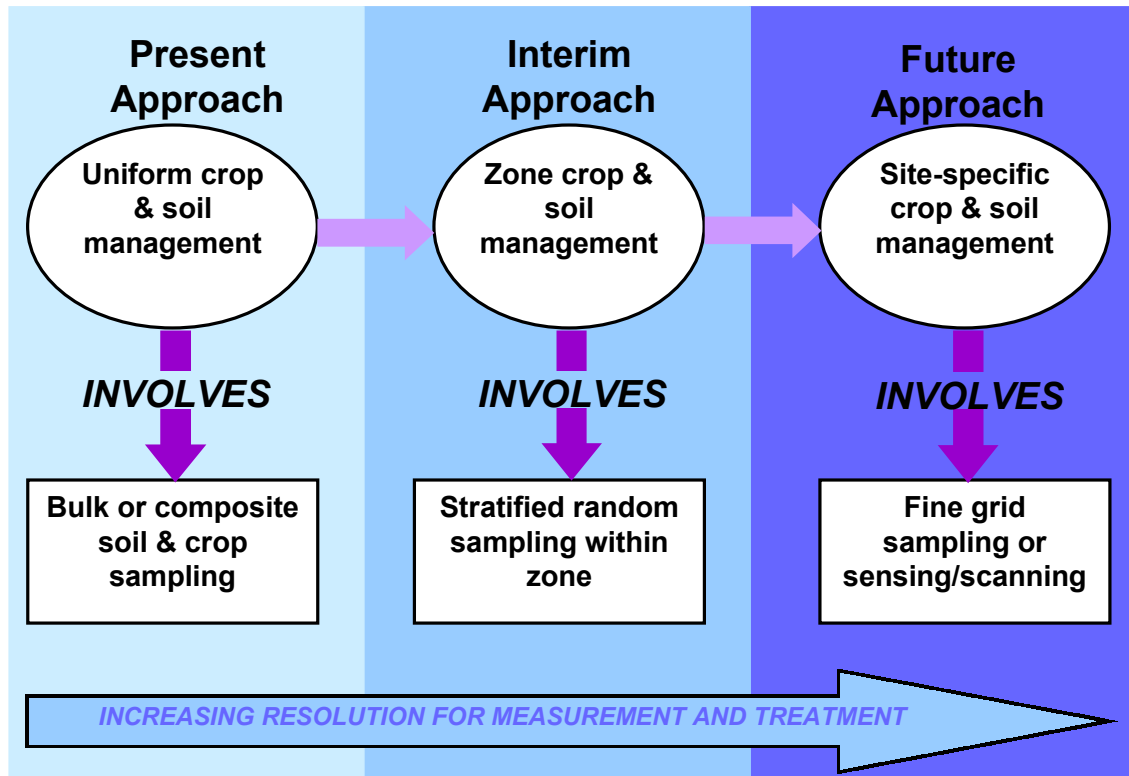


Figure 1. Conceptual framework for the progress in experimentation and management of spatial variability.

treating each point in a paddock as unique. The availability of information on the differing potential/response, and the operational scale of observation and treatment machinery, controls the degree of progress through the stages. At present, the stage 2 option of delineating potential management zones is practically feasible and offers opportunity for PA experimentation.

Delineating Potential Management Zones

Delineation of 'broad' production zones within a paddock has been attempted using soil sampling information, continuous crop yield data and remote sensing (Nolin et. al, 1996; Stein et. al, 1997; Lark, 1997). If significant production differences can be identified between zones and if, through experimentation, the zonal responses to the input/s under consideration for variable-rate application (VRA) can be understood, then PA will be qualified to enter the practical management of cropping.

It would appear sensible to use a number of relevant layers of information to delineate these zones rather than a single factor. Obviously crop yield is the most important as it is the final result that is being targeted. Layers of information that can provide some corroboration to the spatial yield patterns, or better still some explanation, are the next most important. These auxiliary layers include aerial/satellite imagery of crop and soil, soil EM/EC surveys, digital elevation models (DEM) and soil physical/chemical attribute maps.

A Method for Delineating Potential Management Zones with Some Certainty

Yield data for a 75ha field in NSW, Australia was gathered following the 1998, 1999 growing seasons (Figures 2a-2b). Soil electrical conductivity (Figure 2c) and elevation data (Figure 2d) was collected on a similar spatial scale using (respectively) the Veris[®] 3100 conductivity array and an Ashtech[™] single phase rover/base GPS with post-processing. Figure 3 shows soil depth measured with a push-probe and georeferenced.

These attributes were predicted onto a single, 5 metre grid through local block kriging with local variograms using VESPER (Whelan et. al , 2001). With all attributes on a common grid, multivariate k-means clustering was employed to delineate the potential management zones. This is an iterative method that creates disjoint zones by estimating cluster means which will maximise the Euclidean distance between the means and minimise the distances within the cluster groupings.

If PA is to be examined for practical management purposes, it is essential that the delineation of these zones have some agronomic basis. Here, caution must be used because statistically significant differences within individual data layers are easily noted due to spatial correlations within the large datasets generated by PA technology (Whelan & McBratney, 1999). Of the available data layers, crop yield (or the income derived there from) has the greatest bearing on farm management and practices at present. Potential management zones, however they are derived, should therefore display significant differences in yield for VRA to be worthwhile. However, ensuring that the differences displayed in crop yield maps are genuine, let alone significant is difficult. Fortunately, the kriging process provides an estimate of the mean prediction variance (σ^2_{krig}) from which the confidence interval (95% C.I.) surrounding the mean yield estimate within a field (μ) can be calculated (Equation 1).

$$95\%C.I. = \mu \pm \left(\sqrt{\sigma^2_{krig}} \times 1.96 \right) \quad \text{Equation 1}$$

And the absolute difference between mean zone yields ($|\bar{Y}_{zone1} - \bar{Y}_{zone2}|$) should then follow Equation 2 for the zones to be considered representative of regions of significantly different yield ($p < 0.05$).

$$|\bar{Y}_{zone_x} - \bar{Y}_{zone_y}| \geq \left(\sqrt{\sigma^2_{krig}} \times 1.96 \right) \times 2 \quad \text{Equation 2}$$

Two and three potential management zones were delineated as shown in Figures 4 and 5 respectively for the purposes of testing the validity of this procedure through subsequent soil analysis. The delineation of zones using this procedure has provided a C.I. for the two seasons in question. Concentrating on sorghum, a C.I. of +/- 0.2t/ha means that a difference of at least 0.4 t/ha between the mean sorghum yields in the zones should be seen to negate the possibility that the mapping and zoning procedures are incorrectly

depicting the spatial patterns. From Figure 4 this is clearly the case for 2 zones but Figure 5 shows that a split into 3 zones may not be justified based on the yield differences in this paddock.

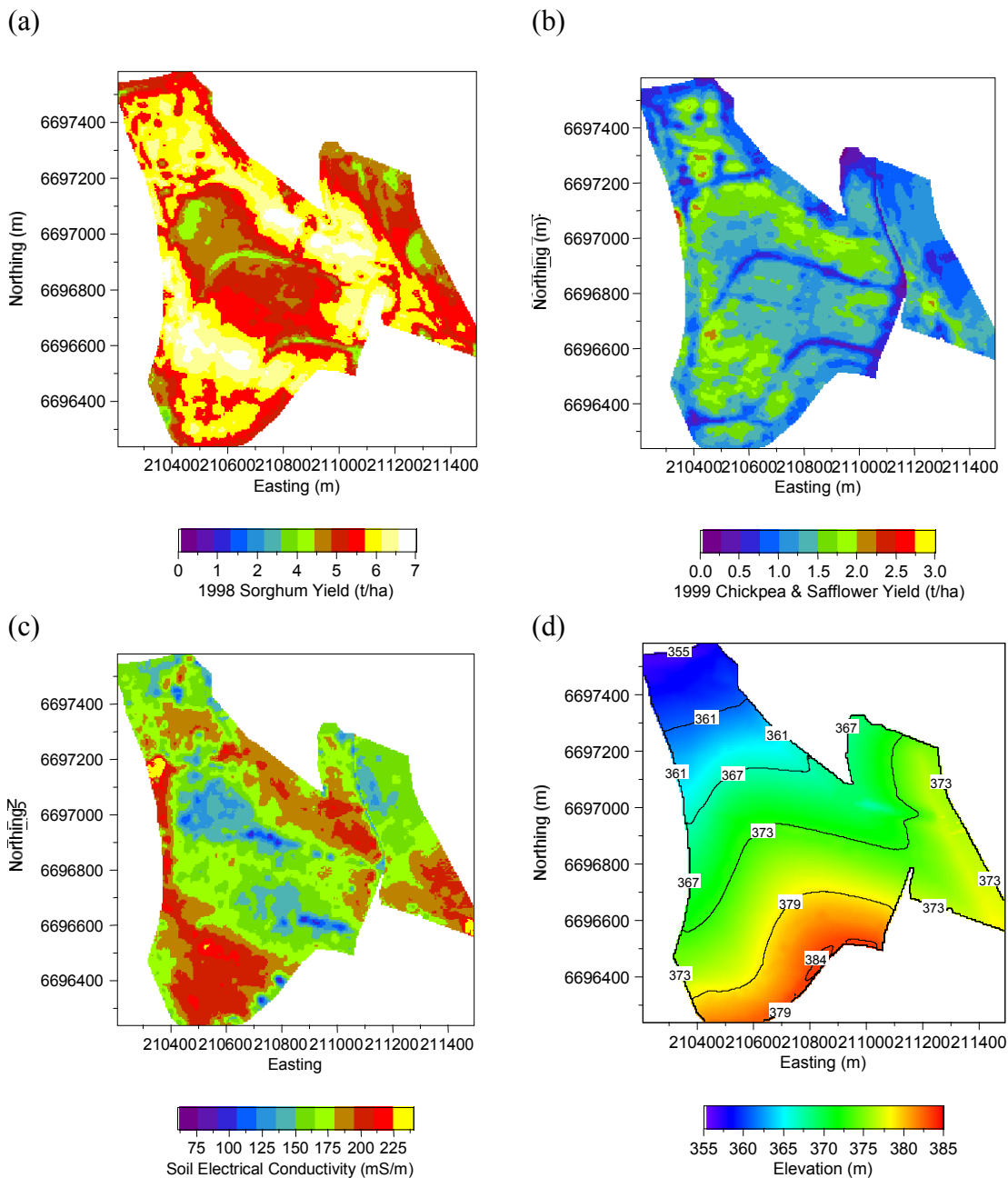


Figure 2. Data layer from a 75 ha paddock – (a) 1998 sorghum yield (b) 1999 chickpea and safflower (c) soil E.C.a (d) elevation.

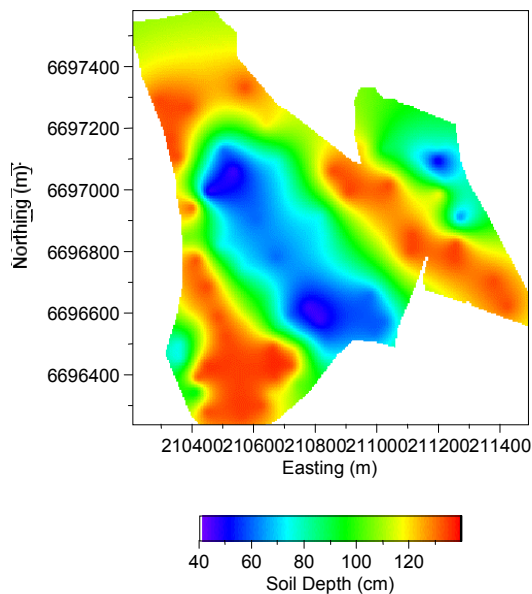


Figure 3. Soil depth measured using push probe and dGPS.

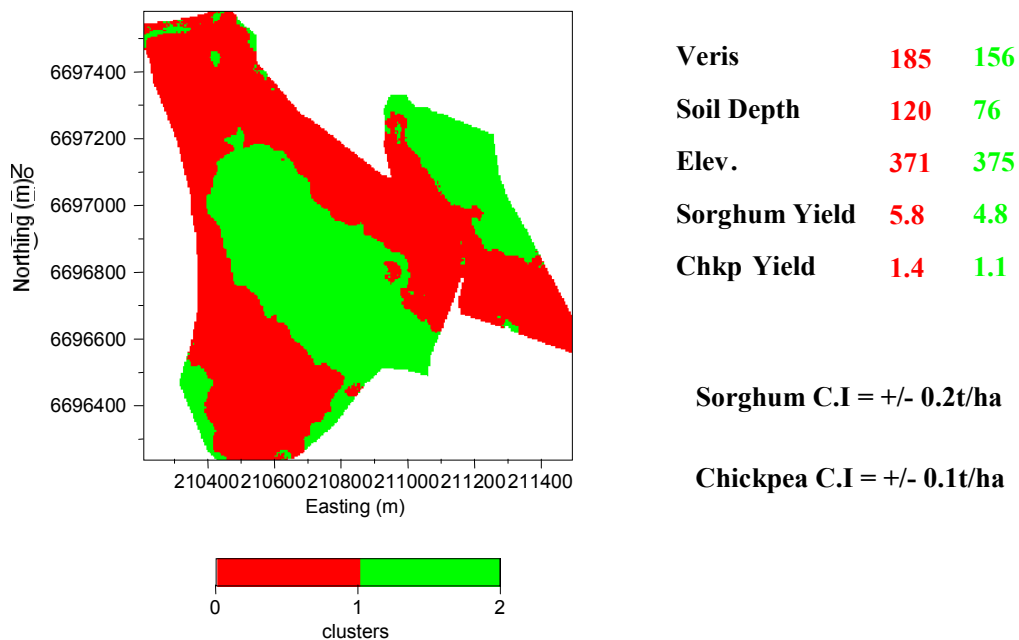


Figure 4. 2 management zones defined by clustering

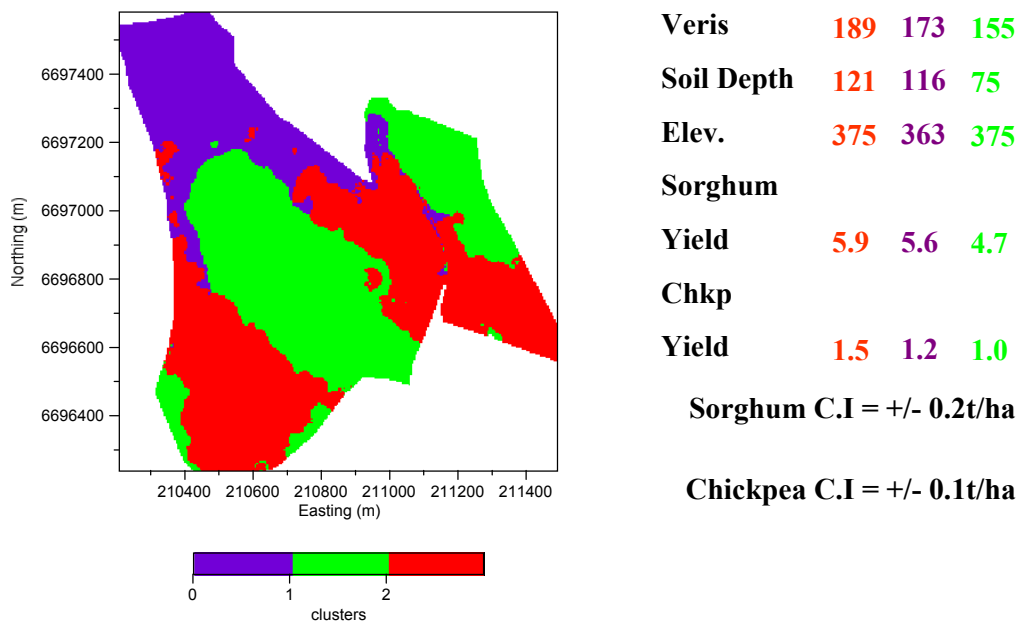


Figure 5. 3 management zones defined by clustering

Directed Zonal Soil Sampling

These zonal delineations may be used to direct subsequent soil sampling. As the zones have been built on production information that has been gathered in great detail, the observed differences should prove very helpful in exploring whether the cause of yield variability can be explained. Figure 6 shows the sampling pattern designed for this paddock. Comprehensive soil analysis and moisture measurement at the sites marked NP was undertaken. The results are shown in Table 1.

Significant differences between the zones in a number of attributes can be seen. Importantly, the differences between the blue and red zones are less than between the green and both the blue and red. This is in accordance with the ambiguity found in the zone delineation process using the prediction uncertainty.

Of the soil analysis results, there is a large difference in profile available moisture that would be driving the crop yield potential differences between the zones. This is not unexpected, but here it has been mapped and quantified at the within-paddock scale.

Experimentation for SSCM

With a zonal pattern determined and an explanation confirmed by soil analysis, experimentation into the best management options for inputs can begin. There are three areas of experimentation that must be considered in exploring and substantiating Precision Agriculture. The first is aimed at uncovering the causes of yield variation observed in crop yield maps, and the second is aimed at defining variability in crop response to applied treatments at the within-field scale. Both of these are inextricably linked in the process of formulating spatial Decision-Support Systems as outlined in Figure 7. Here, the Decision-Support model #1, provides the rationale for delineating

management units within a field. Experimental sampling designs that explore the causal factors of yield variation that has been partitioned using previous years yield maps and other spatial information must be undertaken. Designs for these experiments should maximise soil and crop sampling efficiency.

Decision-Support Model #2 is needed to provide an agronomically and economically suitable response to variation between each management unit. This decision will initially be made on a variable-by-variable basis (ie soil N or soil P). This step in the

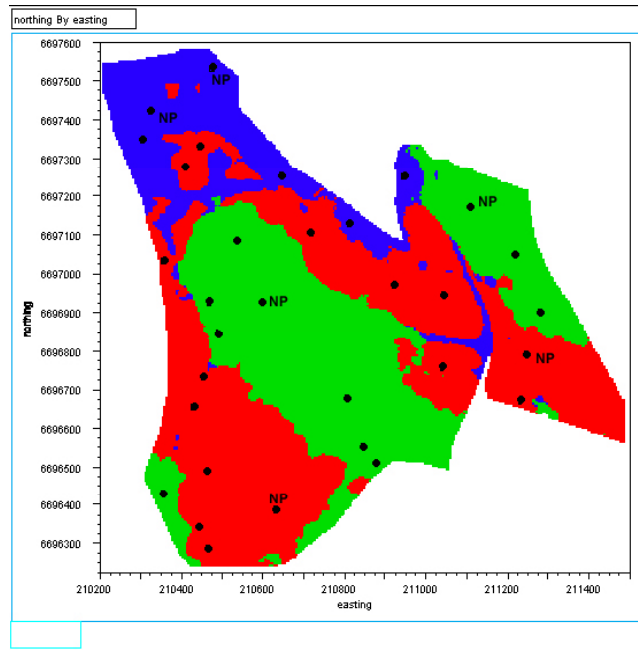


Figure 6. Directed soil sampling sites, randomly allocated within zones and the number weighted by zone size.

Attribute	Zone			Attribute	Zone		
	Green	Blue	Red		Green	Blue	Red
pH	8.2	8.5	8.6	OC	1	0.7	0.7
P	2.7	2.7	2	Na	0.2	1.26	1.5
N03	19.8	13.6	6.7	CEC	41.8	62.9	74.3
Total N	951	770	546	Ca /Mg	6.3	1.9	2.1
K	0.3	0.6	0.5	EC	0.1	0.1	0.1
Ca	34	40	49	profile avail. water	68	108	127
Mg	6.5	20.9	23.3				

Table 1. Soil analysis results from zone directed sampling

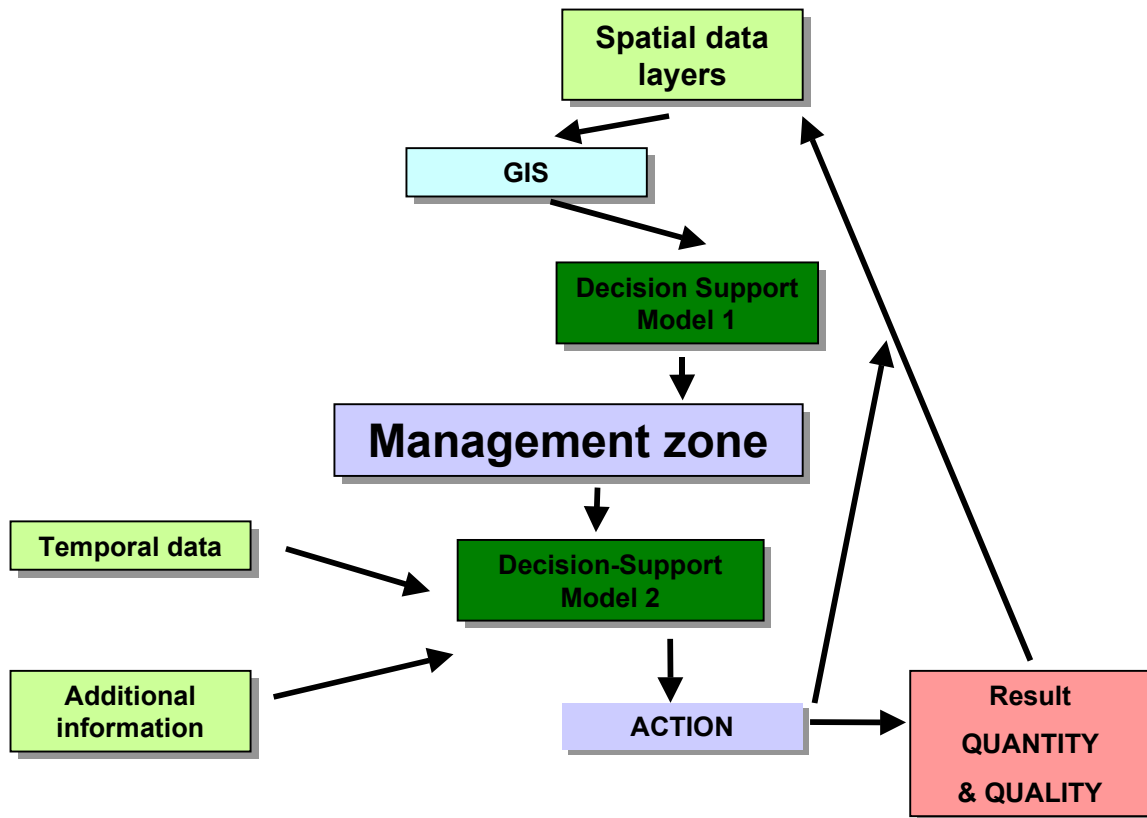


Figure 7. Precision agriculture data and management plan

decision support process will require information on the changing response to application of nutrients within the field. To gather such information, growers will be required to establish response experiments that are designed to illicit this information Bramley et al. (1999) provides an invaluable resource for those embarking on this path. (The unabridged version is especially useful).

Finally, the third area of experimentation is directed at the assessment phase which is required to substantiate any benefits from differential treatment using Variable-Rate Technology (VRT) and the information gained from the previous experiments. In this phase uniform treatments (traditional) will need to be compared with the differential treatments previously calculated.

Experimental design for this must be geared at testing the Null Hypothesis of Precision Agriculture. This may be stated as: 'Given the large temporal variation evident in crop yield relative to the scale of a single field, then the optimal risk aversion strategy is uniform management'.

One alternative hypothesis that can be put forward then is: 'Management of variability at a finer spatial resolution than is currently undertaken would be an improvement on uniform management'.

Framing and testing such hypotheses should be considered vital to PA because the adoption of SSCM practices without reasonable testing may well lead to lower

profitability and poorer environmental outcomes. If this should occur with a number of 'advocated' products or practices then it is easy to imagine that long-term harm may be inflicted on the concept of SSCM.

Testing the hypothesis

As more information becomes available on the variability in space and time of the most influential soil and crop attributes, these hypotheses may be tested under a general range of experimental conditions, that is to say across broad space and time ranges. At present, the testing should be restricted to site-specific conditions, which makes the task simpler but may limit information relevance to the specific field or farm.

A good test will be required to probe the treatment effects of differential management and uniform management over space and time. In the published literature on PA, very few response experiments propose a formal hypothesis and analyse the data in an effective method to test the hypothesis. Most provide only an economic comparison of net returns from uniform versus variable treatment over space. Mostly, the hypothesis as proposed here is probably being informally assumed. The results are predominantly from sites where there is lots of information gathered on variability and also significant control over application timing. Intuitively, under these conditions the null hypothesis as proposed here will often be rejected.

In situations where there is greater natural variation and/or little information (or reduced density of information) on the variability, then the null hypothesis may be accepted. Such conditions may be found when much larger areas are considered (as in Australian farm fields).

A knowledge of response variation is vital for formulating treatment rates. With such knowledge of response to the variable of interest, there are two basic steps that may be considered. Firstly, a management zone approach as previously outlined. Secondly, management based on the assumption that the attribute of interest is continuously variable and will be treated accordingly (the ultimate SSCM from Figure 1).

Figure 8 outlines diagrammatically the necessary treatments required to test the null hypothesis under the two different management schemes. For the uniform treatments, ($U_{s,t}$) is the field mean calculated once and applied in each year of the experiment while (U_s) is the field mean calculated each year taking into account some timely measurement or environmental prediction. ($U_{s,t}$) is spatially and temporally uniform and (U_s) is only spatially uniform. The estimated treatment for ($U_{s,t}$) would require prior information gathered over a number of years.

The differential treatment (V_s) is varied based on the spatial location of observations and applied in each year of the experiment while ($V_{s,t}$) is calculated taking into account some seasonal measurement or environmental prediction. (V_s) is varied in space, ($V_{s,t}$) is varied in space and time. In the management zone approach, the differential treatments (V_s and $V_{s,t}$) would in effect be uniform treatments calculated independently

for each zone. For management of continuous variability, the differential treatments (V_s and $V_{s,t}$) would be individually calculated for the desired space and time co-ordinates.

It is the comparative analysis of the response to these treatments that is required to test the null hypothesis of PA. Ultimately it should be an indicator of the economic and environmental response that should be measured. The response will also need to be observed over time for satisfactory assessment and eventual acceptance or rejection of the Null Hypothesis.

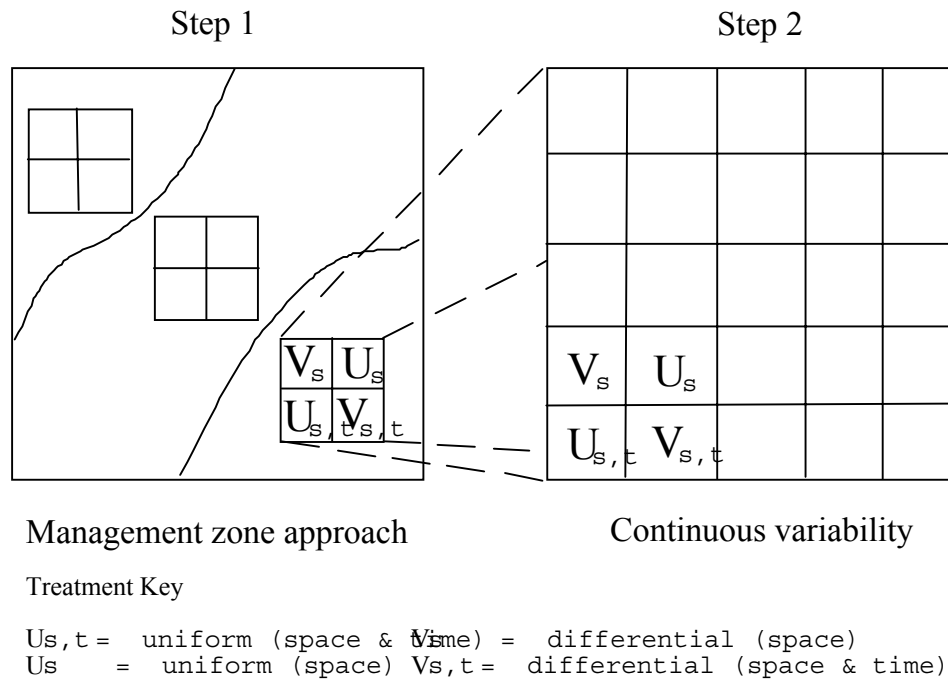


Figure 8. Diagrammatic representation of an experimental design sequence for testing the null hypothesis.

Summary

The move to PA management in the grains industry has begun in Australia. The method of management zone delineation and subsequent experimentation discussed here shows much promise. Soil sampling to determine causal effects on crop yield is more effective when targeted to broad areas that have been defined using production information gathered on a fine scale. Experimentation is now required to ensure management decisions that result from data gathering are agronomically sensible.

Acknowledgements

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