RECONCILING CONTINUOUS SOIL VARIATION AND CROP YIELD

A study of some implications of within-field variability for site-specific crop management

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CHAP. XIX.

Of Differences *between the* Old *and the* New Husbandry.

IN order to make a Compariſon between the ***Hoing Husbandry***, and the ***Old Way***, there are four Things; whereof the Differences ought to be very well conſidered.

I. *The Expence*
II. *The Goodneſs* } of a Crop.
III. *The Certainty*
IV. ***The Condition in which the Land is left after a Crop.***

frontispiece: A facsimilie from **Jethro Tull, (1733).** *The New Horse Hoeing Husbandry: or, an Essay on the Principles of Tillage and Vegetation. Wherin is Shewn, a Method of Introducing a Sort of Vineyard-Culture into the Corn-Fields, in Order to Increase their Product and Diminish the Common Expence, by the Use of Instruments lately Invented.*

CERTIFICATE OF ORIGINALITY

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, or any material published by another person without due reference being made to the material.

Brett Whelan
1998

"Naturam expellas furca tamen usque recurret"

(You may pitchfork nature out but back she will come again)

Quintas Horatius Flaccus (65 B.C. - 8 B.C.)

ABSTRACT

Within-field variability in cropping system attributes is often obvious but difficult to accurately and efficiently quantify. The magnitude of the variation also changes with attribute, location and time. Importantly, variability at this scale of the soil/crop system may give rise to economic, environmental and societal problems on cropping enterprises under traditional 'uniform' management. In general, the problems arise from a decision to use 'mean-of-field' information to guide the amelioration of an area which may result in zones being under- or over- treated. Gathering data on, and extracting useful management information from, within-field variability is the goal of Precision Agriculture.

Assessment of the reported magnitude of variation in the most influential soil/crop attributes is provided as a general, simple guide to that which may be expected at the within-field scale. These may be used as a basic benchmark for variability at this scale. Further study into the structural component of the observed variability provides generalised representations of the form and 'strength' of spatial variability models that may be expected at the within-field scale. These may be used as surrogates for the parameters in unsampled fields, initial estimates in modelling/simulation procedures or as a basis for establishing the sample spacing for initial sampling schemes in unsampled fields. With the exception of soil moisture, the results suggest a 60 metre sample spacing as being the maximum required to accurately capture the spatial variability in most attributes.

The inference from these analysis is that management at the within-field scale may prove useful, with the proviso that attributes that display a moderate to weak spatial structure will prove more difficult to compartmentalise or classify into homogenous management units. In most cropping systems, the field variation in soil type, moisture content, structural integrity and nutrient levels, will contribute to site fluctuations in the potential yield. The progress towards developing such a farm management system that will incorporate a finer scale treatment of variation is reviewed at the end of Section 1.

Section 2 examines the variability at the within field-scale of soil moisture and crop yield. Soil moisture is measured using Time-Domain Reflectometry (TDR) and modelled using a joint space/time technique. The trend in soil moisture content in 3 dimensions is found to be best described by a regression-tree function. The temporal variation component is significantly more influential than the spatial component. Crop yield variability is also studied over a number of seasons and crops using a real-time yield monitoring system.

The results of these experiments confirms the general observation that whole field yield variability decreases with increasing mean crop yield and provides evidence that the spatial component of the yield variability also decreases as mean crop yield rises. It is also clear that annual temporal variation is much larger than the spatial variation within single Australian fields. Temporal variability is shown to be up to ten times the spatial component. Hard-set cluster analysis of crop yield and a number of derived yield attributes is performed to incorporate this temporal variability into the process of identifying strata or management zones. The temporal variance cluster maps appear to offer the best quantitative methodology for the stratification process but one which will require further research to determine the levels at which zoning should occur.

In Section 3, the accuracy and precision of real-time crop yield monitoring is explored by examining the effect of the harvesting mechanics on the grain sensors and the prediction technique on the resultant yield maps. A process is described for determining the flow pattern of sorghum grain through a harvester. Grain movement is shown to be partially influenced by the position of the row in relation to the centre of the cutting platform leading edge. Grain from the outer rows is delayed in comparison with those more centrally located. A more significant impact is made on grain flow by internal mixing during the threshing and auger transport processes. The two effects are combined and modelled using an Inverse Gaussian distribution function to construct a grain transfer function. This transfer function is used to deconvolve the observed grain yield and return an estimate of the true yield quantity and location.

For yield map construction, the form of spatial prediction chosen is shown to impart a significant influence on the final prediction surface. Local kriging using a local semivariogram appears well suited for use as a spatial prediction method for real-time sensed crop yield data. The method makes most use of the dense data files and can be used to provide a statistical estimate of uncertainty as it changes within fields.

Finally, the potential for economic and environmental benefits from precision agriculture is examined under simulated conditions for 'differential' nitrogen application. The uniform yield potential simulations show that such an assumption will be unworkable in most cropping situations. The ideal of promoting a uniform yield across a field is therefore also shown to be unworkable. The simulations based on diverse yield potential have shown, as a reflection of a more realistic natural system, that the potential for site-specific management may be enormous and its impact will increase in crops of higher inputs and greater market value.

ACKNOWLEDGMENTS

The work presented in this thesis is foremost a testimony to the vagaries of the Australian climate, the extraordinary, ever increasing influence of the CPU in society and the overwhelming support of friends and colleagues.

No field-based project in Agriculture is begun without some consideration for the interaction and intervention of climate. Mostly, the negative aspects are optimistically brushed aside. So it was for the original idea and experimental procedures for this thesis. Drought, harvest deluges (combined with mid-season equipment problems) quickly reminded me that optimism doesn't write thesis chapters. At this stage I must thank Frank Ellison and all at the I.A. Watson Research Institute for their expertise and help with establishing the initial experiments. However, my interest in small-scale variability in edaphic factors and their influence on crop yield needed to be re-channelled.

To his great credit, my supervisor Alex McBratney encouraged my diversification into an embryonic field that was attempting to apply small-scale observation of variables in the cropping system to crop management. Precision Agriculture and myself owe a great debt to Alex. He has provided me with access to his immense wealth of knowledge, taught me geostatistical skills that could be gained nowhere else, guided me when my vision faltered and offered friendship and flexibility throughout my work. This thesis would remain unfinished without his input and encouragement.

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My colleagues at the University have also played a significant role. The atmosphere in the labs and offices has always been one of friendliness and co-operation. I must also acknowledge my friends at play. An old man needs humorous and loyal distractions.

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GENERAL INTRODUCTION & AIMS

GENERAL INTRODUCTION

Post-industrialisation farm management practices have tended towards the treatment of individual fields as spatially uniform in respect to yield controlling factors, primarily as a trade-off to economies of scale. However, increasingly critical attention is being focused by both the farming and wider communities on this notion that agriculturally productive land should be managed as a relatively homogeneous unit at the 'within-field' scale. It may be argued that such an assumption could lead to inappropriate resource application and subsequent financial, environmental and social costs. The significance of these imposts (such as input waste, yield reduction and soil, water and air contamination) to whole farming systems has only recently received serious consideration (e.g. Pierce & Lal, 1991; Schueller, 1992).

This concern is encompassed in the philosophy of Precision Agriculture. In general the term refers to the observation, impact assessment and timely, directed response to fine-scale variation in causative components of an agricultural production process. This philosophy may be eventually applied to the spectrum of agricultural industries, for both quantity and quality control.

For field cropping enterprises, a form of Precision Agriculture referred to as Site-Specific Crop Management (SSCM), has been proposed as a remedy to the financial and environmental resource-use inefficiency problems raised above (Robert, 1989; Larson & Robert 1991). The simple rationale that justifies and supports SSCM is founded on both financial and biological levels (Figure 1.).

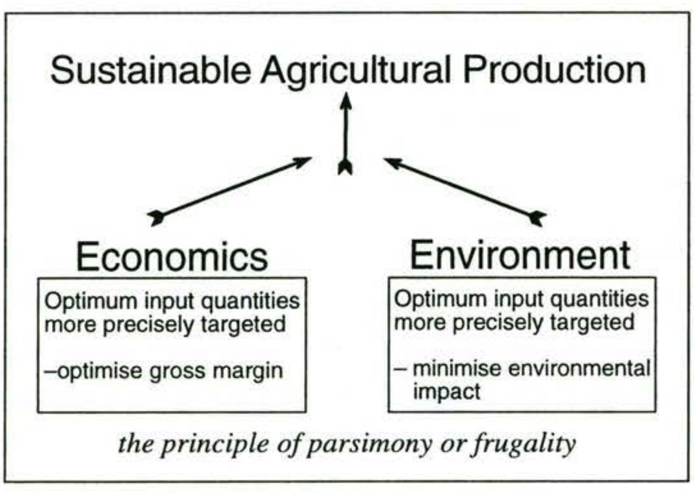


Figure 1. The economic-environmental basis for a site-specific management system.

It relies on matching resource application and agronomic practices with soil attributes and crop requirements as they vary across a site. Collectively, these actions may be referred to as the 'differential' treatment of field variation as opposed to the 'uniform' treatment that underlies the traditional agricultural management systems.

In economic terms, the precise calculation and placement of input resources suggests a more efficient and profitable use of enterprise resources. Figure 2 depicts the generalised gains that may be achieved through targeting resources to the most responsive areas within a field without necessarily increasing resources. If the mean field treatment is aimed at the optimum economic application for response 1, then areas of the field characterised by response 2 will be underachieving. By reallocating enough resources (ΔA) to achieve optimal application in areas characterised by response 2, the yield gain (ΔY_2) is greater than the yield loss (ΔY_1). This is likely to be the most simplistic form of SSCM but serves to demonstrate the basic principle. It is important however, to acknowledge that such gains require a suitably detailed knowledge of the within-field variability in response to an action.

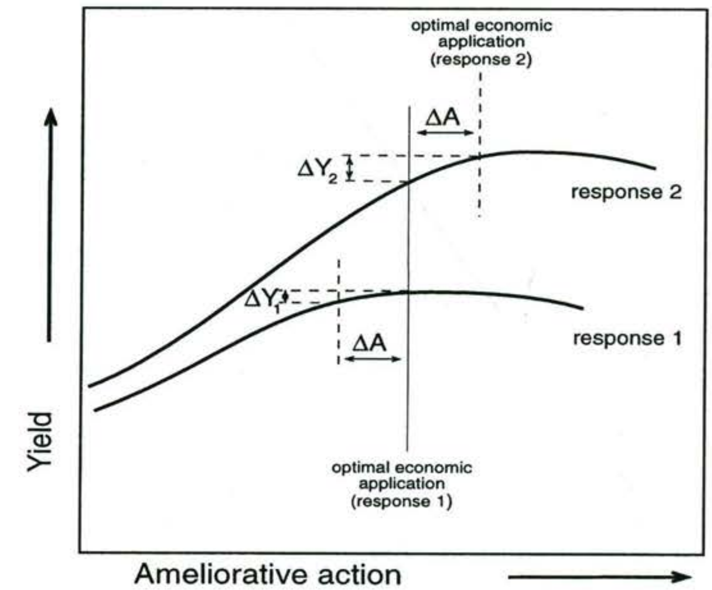


Figure 2. Generalised production impetus for site-specific management.

From an environmental point of view, this precision may offer the prospect of reducing the environmental risk associated with blanket field treatments and provide the ability to work with the natural diversity within each field. By more closely aligning yield goals to the variation in yield potential induced by natural and anthropogenic diversity, it may be possible to improve the sustainability of modern farming systems.

There are 5 components to consider in the development of a Site-Specific Crop Management system (Figure 3). Because the complete process cannot be made in a single pass of the field, the site-specificity is made possible, and indeed relies upon, the ability to accurately resolve ground position during all facets of field operation. The remaining components of the system operate in a cyclical fashion. Influential factors effecting crop yield, along with the crop yield itself, must be monitored at a fine-scale and maps of variation in these factors for an entire field subsequently constructed. The degree of spatial variability found in a field will determine whether unique treatment is warranted in certain parts. Linking the variation in crop yield and the measured factors influencing crop yield using suitable modelling procedures may then be used to formulate agronomically suitable treatment strategies. Finally, if differential management is warranted, operations such as fertiliser, lime and pesticide application, tillage, sowing rate etc. may be varied in real-time across a field.

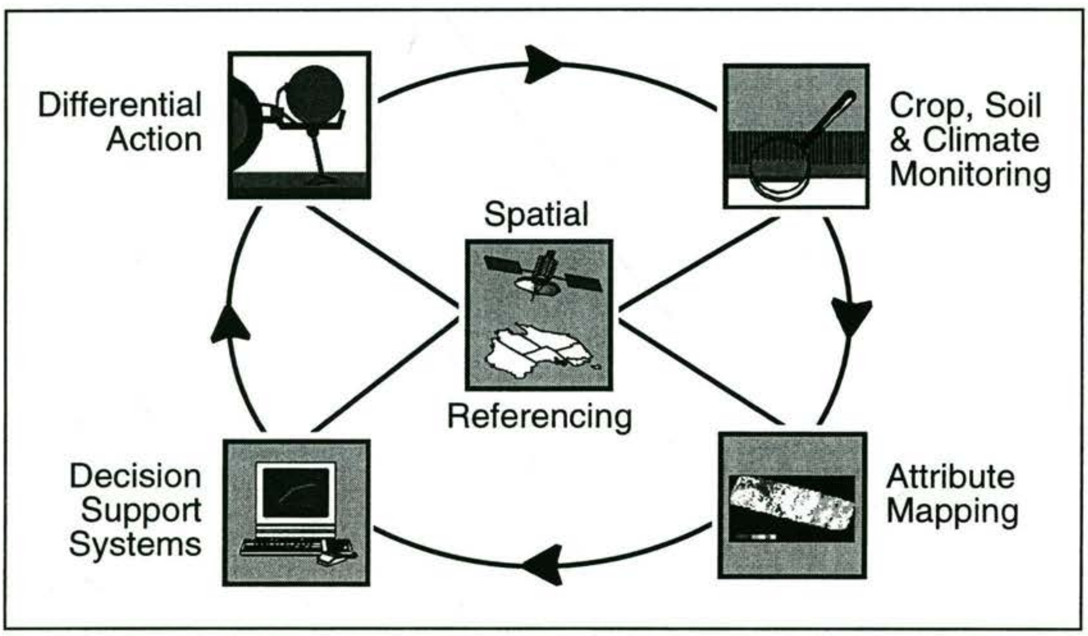


Figure 3. Components of a site-specific crop management (SSCM) system.

These components are at different stages of development and implementation. The technology required to gather detailed data and enact a differential treatment leads the agricultural science of deciphering and formulating responses to the information obtained. Preliminary research provides evidence that yield can vary widely within a field and that the spatial pattern of this variation may change over time. This reflects interactions between influential field attributes and also between these attributes and the environment.

Identifying a significantly yield limiting factor in one year may have limited bearing on the next growing season if its influence is considered singularly.

At present, it is necessary to gather data to characterise the small-scale variability that may be expected over space and time. Research is required to ensure the data gathered is representative of the true variation at this scale, to provide insights into it's implications and use, and to maximise the benefits obtained for agricultural farm management. This thesis will address in particular the issues associated with soil and crop monitoring and mapping at a fine-scale.

AIMS

This thesis has a number of investigative aims. They have the general objective of exploring the methodology, agronomic reasoning and current ability to monitor, record and suitably employ data on variation in soil and crop attributes at the within-field scale.

1. *To examine the literature on variability in soil and crop attributes that impact on crop yield to determine baseline magnitude and spatial structure parameters. Subsequently, to review the literature on methods and opportunities for gathering data on the variability and incorporating the information derived into farming management systems.*

2. *To explore the variability to be found in soil moisture and crop yield during a number of growing seasons and attempt to establish a method for modelling soil moisture over space and time. Observe and correlate the impact of this variability on final yield.*

3. *To establish a real-time yield monitoring system and examine the variability to be found in summer and winter crop yield at the within-field scale under Australian conditions.*

4. *To investigate the mechanics of the mechanical harvesting process to quantify the quality of the yield data.*

5. *To investigate and compare map production methods to determine the most suitable technique for crop yield mapping.*

6. *To model the possible impact of variable rate treatment of N in crop production to ascertain possible financial and environmental benefits and provide a framework for future decision-support models.*

SECTION I

A REVIEW OF THE LITERATURE DEALING WITH SMALL-SCALE VARIABILITY IN AGRICULTURALLY IMPORTANT SOIL AND CROP ATTRIBUTES AND THE DEVELOPING OPTIONS FOR MEASUREMENT AND MANAGEMENT

CHAPTER 1

CHAPTER 1

Variability in Soil Attributes and Crop Yield

1.1 INTRODUCTION

The successful implementation of Precision Agriculture will be dependent on the ability of individual growers to differentially manage their crops to achieve the twin goals of maximising yield or profit whilst simultaneously minimising environmental impact. The major obstacle to this is the lack of, and uncertainty in, local information. That is, information pertaining to the variation (and the component spatial and temporal variance) in crop yield and those factors which determine crop yield and resource losses from the cropping system to the environment.

The importance of such information is not a recent concept. It has been a long held and widely identified notion that field heterogeneity in influential cropping system components will affect crop yield (Harris, 1920). At the regional scale, the observable variation in crop yield can be considered the consequence of variability in the interaction between crop genetics and environmental factors (Bresler et al., 1981; Boyer, 1982). However, at the field scale, site-specific variation in soil type/texture, soil structural integrity, soil moisture content and soil nutrient chemistry will significantly contribute to the spatial variability in crop yield (Russell, 1932).

The variability in these soil attributes (and therefore crop production potential) displayed at a given site, at a given time, is in turn controlled by a number of important processes. The more influential of these are the geological and pedological processes that define the soil type and govern the majority of static soil properties e.g. texture, horizon colour and cation exchange capacity (Jenny, 1941). Additional effects on the variability of soil attributes are contributed by soil management practices and cropping systems. These can greatly manipulate the more dynamic soil properties such as nutrient, water, air and solute regimes (Bouma & Finke, 1993). The magnitude of variability is generally lower in the static compared with the dynamic properties (Wilding, 1985). Variation in crop yield at the within-field scale is also a known to be a function of crop insect pests and diseases (Banyer et al., 1988) and weeds (Cousens, 1985) which may all be important yield limiters.

This chapter will review the literature on the variability of soil attributes and crop yield documented using probability distribution statistics and spatial variance analyses. Crop yield variation will also be reviewed using temporal variance indicators. The impact on crop yield of field variation in the major soil attributes will also be summarised. Together, this will provide information to indicate the need for, and the practicality and appropriate scale of, differential management within fields.

1.2 MEASURING VARIATION

The methods used in the statistical analysis and description of variation in soil/crop system components has evolved substantially. A very basic review of the theories will be presented as background here and the reader is directed to more thorough treatise by Cliff & Ord, 1981; Wilding & Drees, 1983; Webster, 1985; Trangmar et al., 1985; Cressie, 1993.

1.2.1 Classical Statistical Analysis

The variability in field-based attributes such as soil properties or crop yield have been routinely analysed using classical statistical approaches which assume that the expected value for any of these attributes (z) at any location within a field (or sampling area) (x) will be:

$$E\,[z(x)] \quad = \quad \mu \quad + \quad \varepsilon(x) \tag{1-1}$$

where:

μ = the population mean.

$\varepsilon(x)$ = a random, spatially uncorrelated spread of values about the mean which is assumed to be normally distributed with zero mean and variance = σ^2.

In reality, quantifying the probability distribution of a population (Z) is achieved using the central tendency and distribution of a sample population (Z'). The central tendency of a sample (z'_i.....z'_n) may be described by the mean ($\bar{z}'$), and the distribution is commonly characterised by the variance (σ^2) or its square root, the standard deviation (σ) of the sample population, where:

$$\sigma^2 = \frac{\sum_{i=1}^{n}(z'_i - \bar{z}')^2}{n-1} \tag{1-2}$$

In many studies, the variance and standard deviation are often found to be proportional to the mean. It is therefore common practice to compare variability between sample populations using the more stable coefficient of variation (*C.V.*) (Equation 1-3).

$$C.V. = \frac{\sigma}{\bar{z}'} * 100 \qquad (1\text{-}3)$$

These classical procedures are based on the assumption that the variation observed within the sampling area is randomly distributed (i.e. the variable is a random variable with no spatial correlation) and as such they provide only a universal description of the variability for an entire sampling region. Soil and crop attributes are however continuous variables that usually exhibit some component of localised spatial dependence in the observable variation (Wilding & Drees, 1983) as a result of the formative and ameliorative processes discussed earlier. As such, more information on the variability within a sampling area can be obtained by incorporating some form of spatial correlation into the variation analysis.

1.2.2 Theory of Regionalised Variables

The theory of regionalised variables (Matheron, 1963; Journel & Huijbregts, 1978) has been developed to include both spatial and random structure in methods that describe variability within sampling regions. A regionalised variable $z(x)$ is considered a form of random variable in which any value z is a function of its spatial location x within the sampling region and when all values of $z(x)$ are considered at all spatial locations then the regionalised variable may be described by a random function $Z(x)$ (Trangmar et al., 1985).

Two basic assumptions regarding the behaviour of a random function are of relevance to the proceeding discussion of spatial analysis using autocorrelation and semivariograms. Firstly, the random function $Z(x)$ is said to be 'first-order stationary' if the variable Z has the same mean value across the sampling region and therefore follows Equation 1-4.

$$E\,[Z(x) - Z(x+h)] \quad = \quad 0 \qquad (1\text{-}4)$$

where:

h = lag; the separation distance between sample locations.

Stationarity of second order is achieved if the spatial covariance $C(h)$ associated with every sample pair ($Z(x)$ and $Z(x+h)$) is identical across the sampling region (Equation 1-5).

$$C(h) = E\,[[Z(x) - \mu][Z(x+h) - \mu]] \qquad (1\text{-}5)$$

Second-order stationarity implies that the spatial covariance is finite and that it will approach a finite, stationary sample variance as the lag approaches zero (Equation 1-6).

$$C(0) = E[Z^2(x)] - \mu^2 = \sigma^2 \qquad (1\text{-}6)$$

A more relaxed conditional stationarity may be defined when the variance and covariance cannot be regarded as uniform across the sampling region. This is known as the 'intrinsic hypothesis' (Matheron, 1963) and requires that the variance of the difference between points separated by lag h need only be finite for each lag h (Equation 1-7).

$$\mathrm{Var}[Z(x) - Z(x+h)] = 1/2 \times E[Z(x) - Z(x+h)]^2 \qquad (1\text{-}7)$$

1.2.3 Spatial Dependence Analysis

Autocorrelation

Autocorrelation describes the degree of interaction between spatially separated observations of one random variable (Griffith, 1987) based on the assumption of second-order stationarity so that (Equation 1-8):

$$\rho(h) = C(h)/C(0) = C(h)/\sigma^2 \qquad (1\text{-}8)$$

where:

$\rho(h)$ = autocorrelation at lag h.

The plot of $\rho(h)$ against lag h is known as the autocorrelogram, which is a maximum of 1 at $h = 0$ and falls as the lag increases. A random variable is spatially dependent up to the point where $\rho(h)$ ceases to decrease.

If second-order stationarity does not hold, then the autocorrelation function can not be determined without removal of the causative trend. Alternatively, by assuming the less rigid intrinsic hypothesis of stationarity, the semivariogram may be used in the analysis of spatial dependence.

Semivariograms

Under the intrinsic hypothesis, the semivariance $\gamma(h)$ between two observation points separated by lag h is a function of the distance and direction of separation. It is described by Equation 1-9.

$$\gamma(h) \quad = \quad 1/2 * E\,[Z(x) + Z(x+h)]^2 \tag{1-9}$$

And, given the dependence on separation distance and direction only, the mean semivariance can be calculated for each lag h as in Equation 1-10.

$$\gamma(h) = \frac{1}{2N(h)} \sum_{i=1}^{N} [Z(x_i) - Z(x_i + h)]^2 \tag{1-10}$$

where:

N = the number of observation pairs separated by lag h.

The semivariance at each lag h plotted against lag h is known as a the semivariogram and it has been commonly modelled using a number of universal functions. These models, in general, begin from an intercept at lag $h = 0$ of zero (or close to zero) and rise to a plateau semivariance (sill) at some larger lag h (the range of spatial dependence). The models therefore require three parameters for description: 'C0' (intercept or nugget semivariance), 'C' (spatial structure semivariance; (sill-nugget semivariance)) and 'a' (the apparent range of spatial dependence).

These models should also be positive-definite functions for the number of dimensions in which they will be used (Webster, 1985). The most common models that fit these criteria up to 2 and 3 dimensions are presented: linear, spherical and exponential.

Linear:

$$\gamma(h) = \begin{cases} 0, & h = 0 \\ C0 + b(h), & h \neq 0 \end{cases} \tag{1-11}$$

Spherical

$$\gamma(h) = \begin{cases} 0, & h = 0 \\ C0 + C\left[\frac{3}{2}\frac{h}{a} - \frac{1}{2}\left(\frac{h}{a}\right)^3\right], & 0 < h \leq a \\ C0 + C, & h > a \end{cases} \tag{1-12}$$

Exponential

$$\gamma(h) = \begin{cases} 0, & h = 0 \\ C0 + C\left[1 - \exp\left(-\frac{h}{a'}\right)\right], & h > 0 \end{cases} \tag{1-13}$$

Linear and spherical models reach a finite sill value and are described as transitive. The exponential function approaches the sill asymptotically and therefore possesses no absolute range value. However, the semivariance does not effectively increase beyond a certain lag h (termed a' in Equation 1-13), which has been estimated as $1/3\,a$, at which point $\gamma(a')$ is approximately equal to C0 + 0.95C (Webster, 1985).

A model is typically fitted to the semivariogram using some form of nonlinear least squares optimisation. The usual assumptions associated with nonlinear regression do not hold due to the spatial dependence between variogram values at different lags. Cressie (1985) outlines methods for weighted least squares and generalised least squares which deal with this dependence.

In these models, the nugget semivariance *C0* represents the random variation (Wilding & Drees, 1983) or noise (Webster & Cuanalo, 1975) contributed by measurement error or unexplained sources. The structural semivariance *C* represents the component of total variation contributed by systematic sources. A quantification of the contribution of random variation to the data semivariance can be gleaned from the ratio of nugget semivariance to sill semivariance (Trangmar et al., 1985) (Equation 1-14).

$$NR = \frac{C0}{C0 + C} * 100 \qquad (1\text{-}14)$$

This ratio has been used in a qualitative assessment of the strength of the spatial dependence within a field attribute (Cambardella et al., 1994) where:

$NR \leq 0.25$	=	variable with strong spatial dependence
$0.25 < NR < 0.75$	=	variable with moderate spatial dependence
$NR \geq 0.75$	=	variable with weak spatial dependence

1.3 SOIL ATTRIBUTE VARIATION

It is important to understand that a variability study based on an attribute that expresses as a continuous function of numerous, scale-variable influencing factors, will produce results that will be dependent on the scale and frequency of observation. This nested structure of variation (Journel & Huijbregts, 1978) makes it difficult to asses the full spatial structure of an attribute without some form of nested or multi-stages sampling procedure (Trangmar et al., 1985). Burrough (1983) noted that this effect parallelled the self-similarity described by fractal geometry, and surmised that closer examination of the random component of variation would reveal spatial structure. However, the underlying implication is that direct comparison of field study results using various sampling strategies would be misleading. Examination of a range of studies could provide a qualitative assessment of the spectrum of variation that may be observed in the field.

Such variation observed in soil attributes has been documented by numerous individual studies in which sampling strategies are rarely comparable. Beckett & Webster (1971), in a comprehensive review of the literature to that date, attempted to standardise the area of influence applied to CV values for soil physical and chemical attributes. Their results tend to confirm the accepted generalisation that the observed variability in soil attributes increases as the area under study increases. They also suggest that more than half the variation found within an entire field may be observed within any 0.01 ha area.

Gajem et al. (1981) convincingly demonstrate the effect on spatial structure of increasing the sampling area and distance between sampling points. They show that the range of spatial dependence for 9 physical soil parameters increased 10 fold as the sample separation and transect length increased by an order of magnitude (0.2m, 2m, 20m). These relationships are likely to operate in other cropping system variables such as yield and pest infestations.

The degree and structure of variation observed in the more important soil and crop attributes, and the impact of this variability on the cropping system, will be examined individually.

1.3.1 Soil Type/Texture

Variation in soil type may directly influence the yield potential of a site by contributing to the variation in nutrient storage and availability, fluid retention and transport, and soil stability to potentially disruptive processes. While variability in these individual soil attributes will be examined separately, it is the gradual changes between soil type that significantly governs variability.

Variation in soil texture is considered here as a major indicator of soil type variability. Particle size variability will be discussed as it has become the default measurement for soil texture, but it is acknowledged that the nature of the clays present, other inorganic and organic coatings and accretions all combine to create a soil texture (Mott, 1988a). However, quantitative analysis of the sand, silt and clay fractions is important to soil/crop relations in that clay content is positively related to moisture holding capacity (Gregory, 1988) and organic matter decomposition (Sorensen, 1975) and the surface charge effects impact on the behavior of plant nutrients and the reaction of applied fertilisers and pesticides (Mott, 1988b).

The review of Beckett & Webster (1971) concluded that approximately 50% of randomly chosen sample sites within soil mapping units would not match the assigned soil profile definition. In a detailed study of within-map unit variation of soil morphological and physical properties Agbu & Olsen (1990) determined the proportion of total variation attributable to within-map unit variation in twenty-eight properties using a coefficient of non determination (Steel & Torrie, 1980). The results indicated that the majority of the total variation observed resided within the map units and not between them. These two studies imply that substantial variability in soil physical and morphological properties within a field should be expected, even if it is categorised as a single soil type.

While significant variability may be observed within soil units, the magnitude of the variation is likely to be influenced by the soil parent material. Mausbach et al. (1980) examined the variability in 1280 matched pedons representing eight soil orders covering the major cropping regions of the USA. Their study showed that variability of textural properties is least in soil of loess origin (median CV = 18%) followed by glacial drift parent material (24%) and alluvium (33%). The CV for textural classes were highest for C horizons and approximately equal for A and B horizons in all soil.

At a finer scale, Table 1-1 catalogues a number of texture variability studies undertaken over a range of sampling area sizes. Given this variability in sample size and strategy, it is difficult to compare the results, but the median values may provide a rudimentary approximation of the baseline variability to be found at any local sampling scale. The median CV for sand, silt and clay are 37%, 18% and 18% respectively, but it is important to note that the occurrence of high variability in all three particle size fractions may appear at all sampling scales.

The spatial structure component of soil texture variation has not been as well documented. Using autocorrelation analysis, Gajem et al. (1981) sampled intensively at 0.2 m intervals along a 20 m transect and found the spatial dependence to be >5 m for all textural components. At a coarser scale, Webster & Cuanalo (1975) used a 10 m sampling interval over a 3.2 km transect and estimated the spatially dependent range of the texture correlogram to be 230 m. This range, they concluded, was attributable to variation in the underlying lithology which reinforces the impact of parent material on soil type variability.

Author/s	Sampling design	Texture					
		Sand (%)		Silt (%)		Clay (%)	
		μ	C.V.(%)	μ	C.V.(%)	μ	C.V.(%)
Gajem et al. (1981)	20cm lag (20m trsect)	17.3	32	50.9	18	31.8	16
Burden & Selim (1989)	30cm lag (80m trsect)	9.6	29	81.7	4	47.5	31
Miller et al. (1988)	20m lag (5 x 400m trsect)	20.0	29	-	-	37.0	12
Mulla (1988)	20m lag (660m trsect)	13.8	18	-	-	21.2	2
		14.7	14	-	-	18.4	19
Webster & Cuanalo (1975)	10m lag (3200m trsect)	-	-	35.8	22	25.6	16
		-	-	30.0	18	34.5	24
		-	-	18.1	16	39.1	31
Vauclin et al. (1983)	10m lag (0.28 ha)	65.1	8	7.2	44	27.7	18
Kachanoski et al. (1988)	37 comp (1.5 ha)	31.8	66	47.3	22	20.9	58
Williams et al. (1987)	10m grid (1.6 ha)	27.0	18	51.0	6	22.0	10
Hunsaker et al. (1991)	97 rndm (4.2 ha)	61.2	10	20.7	21	18.1	19
Nolin et al. (1996)	30 m grid (10 ha)	16.6	59	39.1	18	44.3	14
Tabor et al. (1985)	49 rndm x 2m grid (13 ha)	41.7	20	26.2	16	32.1	18
Nielsen et al. (1973)	20 rndm x 6.5m^2 plots(150ha)	26.5	60	26.2	38	47.5	25
Chien et al. (1997)	6.25ha grid (1000 ha)	39.2	45	42.5	29	18.2	35
Agbu & Olson (1990)	within soil units	12.3	53	50.8	10	36.9	13
		9.0	49	51.0	14	40.0	16
		11.6	47	58.8	8	29.7	7
		17.0	68	50.0	21	33.0	22
		12.3	65	55.4	11	32.3	13
		19.3	57	42.8	21	37.9	26
		35.8	38	35.1	21	29.1	28
		7.0	12	57.5	64	35.6	47
Wilding et al. (1964)	within soil series	24.7	25	54.7	10	20.6	20
		20.3	37	58.8	11	20.9	17
MEDIAN			37		18		18

Table 1-1. Mean and CV for soil textural properties within increasing sampling area.

Table 1-2 displays the summary statistics of a number of studies employing semivariance analysis of spatial structure. As with the CV data, the median semivariogram descriptors have been presented as a generalisation of the spatial structure model that may apply across all local sampling scales. The nugget ratio (*NR*) of 20% suggests that soil texture is a strongly spatially dependent attribute. The median range of 63 m may approximate the upper limit of the dependence.

The study by Chien et al. (1997) serves as a reminder of the scale dependence of these observations. Operating on a 250m grid within a 1000 ha site, they estimate semivariogram parameters as: sand - C0 = 0.718, C = 0.344, a = 1046m; silt - C0 = 0.736, C = 0.372, a = 1290; clay - C0 = 0.770, C = 0.172, a = 723m. At this scale the particle size fractions have an NR ranging between 67% and 82% suggesting a tendency towards weak spatially dependence.

				Semivariogram Parameters		
Author/s	Sampling design	Attribute	Model	C0 ($\%^2$)	C ($\%^2$)	a (m)
Miller et al. (1988)	20m lag (5 x 400m trsect)	sand	spherical	0.60	33.4	75.0
Mulla (1988)	20m lag (660m transect)	sand	spherical	0.16	5.7	60.1
		sand	spherical	0.99	3.7	71.8
Vauclin et al. (1983)	10m lag (0.28 ha)	sand	spherical	13.37	17.1	33.5
Burden & Selim (1989)	30cm lag (80m transect)	silt	linear+sill	5.30	5.2	19.5
Miller et al. (1988)	20m lag (5 x 400m trsect)	silt	spherical	3.00	12.0	75.0
Vauclin et al. (1983)	10m lag (0.28 ha)	silt	linear+sill	8.06	3.4	50.0
Burden & Selim (1989)	30cm lag (80m transect)	clay	linear+sill	1.80	5.2	13.0
Miller et al. (1988)	20m lag (5 x 400m trsect)	clay	spherical	7.00	14.0	75.0
Mulla (1988)	20m (660m transect)	clay	spherical	0.08	7.3	93.2
		clay	spherical	1.54	11.2	66.1
Vauclin et al. (1983)	10m lag (0.28 ha)	clay	linear+sill	13.37	14.1	35.7
MEDIAN				2.4	9.3	63.0

Table 1-2. Semivariogram model parameters reported for soil textural properties.

1.3.2 Soil Structure

Soil structure may be simply defined as the arrangement of particles that form the soil and the distribution of voids between these solid particles. Such a description, however, fails to project the true dynamism of the soil forming and degrading processes. More comprehensively, Kay (1991) uses the term as an umbrella that encompasses a composite of soil properties namely soil structural form, stability and resilience.

The structure of the soil governs the physical penetration, growth and anchorage of roots along with regulating the air/moisture balance required for plant growth and microbial activity, the soil drainage/water retention characteristic and the erosion potential (Harris et al., 1966). It follows that a decline in soil structural condition may encompass a broad range of deleterious affects on crop growth. A reduction in the availability of oxygen for metabolic processes and adverse effects on soil moisture regimes are the dominant result, however indirect consequences such as a reduction in nutrient availability and perturbations in the soil solution pH and redox potential (Glinski & Stepniewskii, 1985) will ultimately reduce crop yield.

Soil structural condition is inherently unstable when subjected to potentially disruptive forces (Hillel, 1982). These forces may be mechanical, as in the use of cultivation implements or other heavy machinery, or physico-chemical via the frequent saturation of agricultural soil through irrigation and rainfall. Common to both dryland and irrigated cropping is the yield reduction attributed to structural degradation caused by compaction and shearing through tillage and heavy vehicular movements. Hakansson et al. (1987) has shown the yield reduction to extend over a number of growing seasons due to the persistence of the initial degradation. Root distribution and nutrient uptake is reduced and a coarser tilth is produced (Hakansson et al., 1988).

Structural degradation through compaction, and the ensuing increase in soil strength, have also been shown to increase the energy required to overcome tillage draft in subsequent operations. Watts & Dexter (1994) report a reduction in cultivation energy requirements of between 17% and 45% in the absence of machinery traffic. Chamen & Cavalli (1994) observed an average 18% reduction in cultivation draft under similar conditions, while Burt et al. (1994) report a mean 40% reduction in draft under no traffic conditions.

Site variability in field soil structure has been inferred through measurements of soil strength using tillage draft and cone-penetrometer resistance, and pore/solid relationships via air permeametry and bulk density. Following the uniform application of tillage treatments to a 0.36 ha area, Wood et al. (1991) estimate CV's for: cone penetration = 44%; air permeability = 114%; porosity = 37%; bulk density = 9%. Mulla (1988) sampling at a 20m lag (on two 660m transects) reported cone penetrometer resistance =0.22 kPa, CV = 37% and 0.2 kPa, CV = 44%. A similar degree of variability in cone penetrometer resistance was recorded by Hartge et al. (1985) on a 10m transect that reflected compaction patterns resulting from tillage.

Table 1-3 summarises a number of reported investigations into the variability of field bulk density. The median CV value of 5% agrees with the value of 7% compiled from a number of earlier studies by Warrick & Nielsen (1980). This low variability, compared with the other indirect methods, suggests that bulk density may not be a good indicator for the variability in soil structure.

Author/s	Sampling design	bulk density	
		μ (g/cm3)	C.V.(%)
Gajem et al. (1981)	20cm lag (20m trsect)	1.38	14
	2m lag (200m trsect)	1.25	8
Burden & Selim (1989)	30cm lag (80m trsect)	1.35	4
Buchter et al. (1991)	1m lag (400m trsect)	1.39	3
		1.39	3
		1.22	4
		1.21	4
Williams et al. (1987)	10m grid (1.6 ha)	1.40	3
		1.36	4
Hunsaker et al. (1991)	97 rndm (4.2 ha)	1.61	4
		1.65	5
		1.63	3
Cambardella et al. (1994)	25m grid + nest (6.25ha)	1.32	14
	100m grid + nest (10 ha)	1.03	17
		1.24	13
Nielsen et al. (1973)	20 random x 6.5m^2 plots (150ha)	1.47	10
		1.37	6
		1.35	6
		1.31	5
		1.33	5
		1.31	6
MEDIAN			5

Table 1-3. Mean and CV for soil bulk density within increasing sampling area.

The spatial nature of this variability in soil structure has been little considered. Haines & Keene (1925a), in a remarkably prescient study, employed a dynamometer to record the continuous variation in drawbar pull required during parallel transects of a field (Figure 1-1). They showed substantial spatial variability and significant positive correlations between draw-bar pull and clay content, plant establishment and tillering.

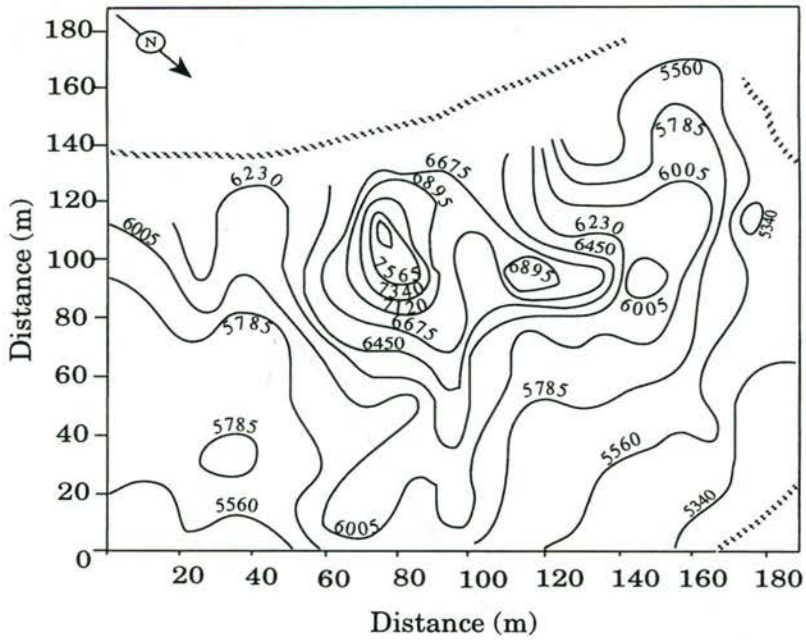


Figure 1-1. Continuous map of draw-bar draught (newtons) **(after Haines & Keen, 1925a).**

Further statistical analysis of the spatial variability has proven inconclusive. Gajem et al. (1981) observed a 3.40 m zone of influence for bulk density when sampling on 20cm lags and hardly any discernible spatial structure at greater lags. On the other hand, Cambardella et al. (1994) using a 25m grid sampling scheme (with closer nested samples) fitted spherical variograms with parameters: C0 = 0.013, C = 0.023, a = 129m. Using a similar strategy but on a 100m grid, they reported variogram parameter values of: C0 = 0.011 C = 0.025 a = 223m and C0 = 0.006, C = 0.019, a = 115m. The NR values ranged from 36% to 24%, suggesting that the bulk density at the site possessed a moderate to strong spatial structure.

Interestingly, Buchter et al. (1991) sampling every 1m on 4 x 100m transects found no spatial structure in the autocorrelation for bulk density in the top 30 cm, but very weak 3m spatial dependence at a depth of 60 cm. Given all these results, it could be hypothesised that vehicle traffic and cultivation may play a role in reducing any inherent spatial structure in soil structure measurements, leaving apparently random or very small-scale structure in most agricultural fields that may only be observed in dense sampling arrays.

1.3.3 Soil Organic Matter (OM)

The amount of soil OM provides an indicator for the inherent soil fertility in most soil types. Specifically, it plays a significant role in maintaining soil physical properties, storing and releasing moisture and plant nutrients and influencing the quality and quantity of soil microbial activity (Lowe, 1978). Of particular interest is the ability of OM to provide mineralisable nitrogen, phosphorus and sulphur (Allison, 1973) as this may influence the requirements for synthetic fertiliser application. The typically slow operation rate of the mineralisation process will limit the release of these nutrients, but this source may provide a significant contribution to dry-land cropping or during the drying cycle on irrigated land. The importance of OM in this storage and release of moisture and plant available nutrients should increase as the percentage clay content decreases.

Author/s	Sampling design	Organic Matter	
		μ (%)	C.V.(%)
Mulla (1993)	15m lag (4 x 650m trsect)	2.04	41
Miller et al. (1988)	20m lag (5 x 400m trsect)	1.26	18
Khakural et al. (1996a)	30m lag (4 x 430m trsect)	5.5	27
Reed & Rigney (1947)	0.015ha grid (0.3 ha)	2.09	22
		0.91	45
Robert et al. (1996)	12m grid (1.6 ha)	2.13	5
	12m grid (1.8 ha)	2.21	5
Mallarino et al. (1996)	15 m grid (3-6 ha)	5.40	9
		3.70	11
		5.60	14
Nolin et al. (1996)	30 m grid (10 ha)	4.84	26
Wang (1982)	one map unit	4.52	60
Cipra et al. (1972)	soil type (7 x 2.4ha)	2.22	5
Wilding et al. (1964)	soil series	2.80	32
		6.40	9
MEDIAN			18

Table 1-4. Mean and CV for soil organic fractions within increasing sampling area.

The amount of OM present will also effect the degree to which inactivation processes act on soil applied pesticides through adsorption and biological and non biological breakdown (Khan, 1978). This is relevant for both ionic and non-ionic active ingredients and its impact should increase as the percentage clay content of the soil decreases. Linear relationships between soil OM and the applied herbicide rate for a designated degree of weed control have been published for atrazine, cyanazine, simazine, alachlor, metolachlor, metribuzin, trifluralin, pendimethalin and diuron (Weber et al., 1987; Blumhorst et al., 1990; Upchurch et al., 1966; Fernandez et al., 1988).

Estimates of the degree of variation to be found in soil organic carbon have been reported by Spain et al. (1983) who describe a coefficient of variation in Australian agricultural soil between 10-20% when measured on a 10m grid and 25-40% on 10's of kilometer separation. These figures agree with the generalisation of Beckett & Webster (1971) who suggest that 10-30% CV within fields is typical for OM. The results of a number of other studies are shown in Table 1-4. The median C.V. value of 18% falls within the scale suggested above.

Studies on the spatial structure of the soil organic fraction have been rare. Miller et al. (1988) sampled organic carbon on 5 x 400m transects using a 20m lag and fitted a spherical semivariogram to the data with parameter values of: C0 = 0.003, C = 0.017, a= 50 m (NR=15%). Mulla (1993) sampled OM at 15m lags along 4 x 650m transects and reported a spherical variogram range of 114m (NR = 39%). Kristensen et al. (1995) fitted exponential variograms for two Danish fields that show ranges for OM from 45m to 99m (135m to 300m equivalent spherical range) with no nugget variance (NR = 0%). While the ranges display a spatial structure varying by up to 250m, the NR values suggests a strong spatial dependence over any range.

As with soil bulk density, agricultural intervention may be detected in the depth of sampling. Wang (1982) shows greater variation in organic carbon content in the A horizon (CV = 42%) as compared with 34% in the B horizon. Kristensen et al. (1995) report a decrease in spatial correlation range to between 22m and 34m (66m to 132m equivalent spherical range).

1.3.4 Soil Moisture

Variability in available soil moisture and soil moisture movement will be controlled by non-uniformity in the physical soil factors previously discussed, along with the supply of moisture (which is likely to be completely random in the case of precipitation).

Soil moisture is crucial to plant growth. Much of the variation in yield response to fertilisers is due to variation in soil moisture and therefore nutrient transport and supply potential across a field. Power et al. (1961) show that 53% of variation in wheat yield can be explained by variability in soil moisture at the time of sowing. They recorded a 29 kg/ha increase in yield for every 1 cm increase in available water. Hunsaker et al. (1991) found that soil water content measured at crop emergence was highly correlated to textural classification, sand especially. Multiple regression estimated that 76% of variation in the infiltration depth at the site was accounted for by antecedent moisture and elevation. Variability in soil moisture content also significantly influences soil biological activity (Harris et al., 1966) and soil temperature variation which inturn effects nutrient uptake kinetics in roots and also root elongation (Fixen & Grove 1990).

Given this importance, quantification of the variability in soil moisture content has been often undertaken and has lead to the general understanding that as soil moisture content increases, the variability decreases (Towner, 1968; Nielsen et al., 1973; Williams et al., 1987; Burden & Selim, 1989; Nash et al., 1989). This maxim forms part of the rationale for crop irrigation.

The results in Table 1-5 support this observation and also suggest that variability increases with sampling distance (Gajem et al., 1981). The median CV's for the two standard measurements are: θg = 11%, θv = 9%. Vauclin et al. (1983) report a CV for available soil water (arguably a more relevant quantity to crop growth) of 19%.

Far more variable at the small-scale are infiltration characteristics of the soil. Nielsen et al. (1973) measured a mean saturated hydraulic conductivity of 20.3 cm/day with an associated CV = 100%. The CV rose to 400% as the soil drained to 78% saturation and hydraulic conductivity declined dramatically. Bresler et al. (1981) reported a lower variability in saturated conductivity in a 0.8 ha field (CV = 64%), while Mulla (1988) calculated CV's of 236% and 355% from two 660m transects and Buchter et al. (1991) record a CV = 200% in the top 30cm which dropped to 100% in the 60cm level in two transects.

Nash et al. (1989) calculated the drainage rate at the 1.35m depth in a soil profile following irrigation. Following irrigation the mean rate was 2.45 cm/day (CV = 45%), after 14 days drainage the mean had declined to 0.15 cm/day (CV = 40%), and 44 days after irrigation the mean rate was 0.04 cm/day (CV = 38%). Large variation remains at low drainage rates which would suggest significant variation in chemical movement and concentrations within the profile.

Along with the effect of non-uniformity in soil physical properties and climate, in an agricultural field the phase of the cropping cycle will influence the spatial dependence of

Author/s	Sampling design	Moisture	
		μ	C.V.(%)
		(θg)	
Gajem et al. (1981)	20cm lag (20m trsect) fc	0.35	8
	20cm lag (20m trsect) pwp	0.18	11
	20cm lag (20m trsect) fc	0.37	4
	20cm lag (20m trsect) pwp	0.21	7
	2 m lag (200m trsect) fc	0.35	8
	2 m lag (200m trsect) pwp	0.19	13
	2 m lag (200m trsect) fc	0.34	11
	2 m lag (200m trsect) pwp	0.19	14
	20 m lag (2000m trsect) fc	0.33	21
	20 m lag (2000m trsect) pwp	0.14	31
Mulla (1988)	20m lag (660m trsect)	0.28	25
		0.35	39
Nielsen et al. (1973)	20 rndm x 6.5m² plots (150ha) sat	0.45	10
	20 rndm x 6.5m² plots (150ha) fc	0.43	11
	20 rndm x 6.5m² plots (150ha) pwp	34	22
MEDIAN			11
		(θv)	
Burden & Selim (1989)	30cm lag (80m trsect) sat	0.54	9
	30cm lag (80m trsect) fc	0.43	8
	30cm lag (80m trsect) pwp	0.14	21
Nash et al. (1989)	1 m lag (90 m trsect)	0.36	7
	1 m lag (90 m trsect)	0.36	13
Buchter et al. (1991)	1 m lag (400 m trsect) sat	0.45	4
	1 m lag (400 m trsect) sat	0.44	4
Or & Hanks (1992)	50 rndm (1.5 ha) sat	0.43	4
	50 rndm (1.5 ha) fc	0.25	4
	50 rndm (1.5 ha) pwp	0.10	9
Kachanoski et al. (1988)	52 rndm (1.5 ha)	0.21	42
Williams et al. (1987)	10m grid (1.6 ha)	0.22	7
		0.21	11
Hunsaker et al. (1991)	97 rndm (4.2 ha)	0.22	12
		0.20	11
MEDIAN			9

Table 1-5. Mean and CV for soil moisture content within increasing sampling area.

the variation in soil water content and available water. Van Wesenbeeck & Kachanoski (1988) show that under a corn crop there is a significant difference between the spatial variation within the plant row and between the rows due to preferential drying and water recharge attributable to the plants. They found the resulting spatial variation was greatest during the middle of the growing season due to significant water use and full canopy closure. Likewise, the spatial structure of moisture content variability in a sloping field is likely to be dominated by down-slope trend (Williams et al., 1987).

The variety of such influences on soil moisture content produces site-specific effects on spatial variability. Gajem et al. (1981) measured an increase from 0.6 m to 160 m in the correlogram zone of dependence for soil moisture content as the sampling lag increased from 0.2 m to 2 km and a general decrease in spatial dependence with drying. Nash et al. (1989), sampling at 1 m intervals also noted a decrease in spatial dependence with drying. Conversely, Or & Hanks (1992) sampling on a 2 m scale found spatial correlation for soil water content to be below 1 m for soil at saturation and field capacity but the range increased to 7 m at permanent wilting point. Burden & Selim (1989) calculated that the spatial range of linear variograms generally increased from 20 to 22 m (refer Table 1-6) and the autocorrelation distance rose from 8 m to 15 m as the moisture content declined from saturated to permanent wilting point.

			Moisture		
Author/s	Sampling design	Model	C0 (%^{2})	C (%^{2})	a (m)
Burden & Selim (1989)	each 30cm (80m transect) sat	linear	0.000793	0.000447	20
	each 30cm (80m transect) fc	linear	0.000793	0.000447	20
	each 30cm (80m transect) pwp	linear	0.000491	0.000242	22
Mulla (1988)	each 20m (660m transect)	spherical	0	0.0062	81
		spherical	0	0.022	52
MEDIAN			0.00049	0.00045	22

Table 1-6. Semivariogram model parameters reported for soil moisture content.

Russo (1986) sampled 130 random locations within a 250ha area and calculated a variogram range of 761 m for soil moisture content. By applying a stochastic approach to modelling the effect of this spatial variability on crop yield (using a very simple crop-response model) he generalised that as irrigation is increased, and the variability of soil moisture decreases, so does the variability in crop yield. These results are significant but the variogram range suggests that the scale of information is quite coarse and inferences could only be applied to similarly broad resolution studies. On a finer sampling scale, the median values in Table 1-6 indicate that soil moisture could only be considered as weakly spatially dependent (NR = 91%).

There appears to be some degree of ambiguity in the published studies on spatial variability in the soil moisture regime. Generally, the soil moisture content is initially controlled by water infiltration and the steady-state infiltration rate is more highly correlated with percentage saturation than moisture content (Nielsen et al., 1973). The percentage saturation is in turn a function of soil physical properties. It would then seem most useful to identify and characterise the dominant physical properties effecting the moisture holding capacity of the soil in an attempt to predict soil moisture spatial variability at a site.

1.3.5 Soil Nutrients

The importance of the availability and supply of macro- and micro- nutrients to growing crop plants is a fundamental pillar of modern agronomy. The spatial variability of these two aspects of soil nutrition is ultimately governed by variability in the physical factors and moisture regimes already discussed, along with the soil pH. These factors influence plant root growth and extension on one hand, and control the supply of nutrients to the roots by controlling the total quantity of diffusible nutrient, the diffusion rate and the convolution of pathways to the roots (Baldwin, 1975). The possibility that as little as 10% of the crop root system is able to absorb nutrients (Burns, 1980) may magnifying the effect of spatial variability in soil nutrient concentrations on crop yield.

The application of fertilisers and the inherent soil organic matter content will also contribute to the total nutrient load and its variability within the soil. The influence on total nutrient content is obvious while the effect on variability may be less known. Trangmar (1982) show an increase in the variability of soil P from a CV of 13% to 21% with a fertiliser application increase from 0 kg P/ha to 45 kg P/ha. Leake & Paulson (1997) sampling on a 36m grid within a 10 ha field found that the CV generally increased from 22% as the concentration of mineral N increased down the profile. Cabrera et al. (1994) show that there is large variability in the amount of N mineralised from organic matter within a field during a season and this contributes significantly to the quantity of soil N required for crop growth.

Author/s	Sampling design	Nitrogen		Phosphorus		Potassium	
		μ (mg/kg)	C.V.(%)	μ (mg/kg)	C.V.(%)	μ (mg/kg)	C.V.(%)
Khakural et al. (1996a)	30m lag (4 x 430m trsect)			25	72	197	26
				30	55	169	21
Reed & Rigney (1947)	0.015ha grid (0.3 ha)			28	16	56	13
				12	58	39	41
Trangmar (1982)	1.5m grid (120 m²)			13	13		
Goovaerts & Chiang (1993)	10m grid (1600m²)	1	51				
		4	15				
Cahn et al. (1994)	0.25 ha grid (3ha)	6	60	74	36	268	43
Mallarino et al. (1996)	15 m grid (3-6 ha)	45	62	88	15	243	13
		26	35	20	25	107	17
		51	55	45	38	213	28
Nolin et al. (1996)	30 m grid (10 ha)	10	36	52	36	347	31
Tabor et al. (1985)	49 rndm smpls on 2m grid (13 ha)	14	31	4	72	0.62	32
Pierce et al. (1995)	0.1ha grid (10-20ha)			31	32	333	25
				85	38	270	20
				124	26		
Wollenhaupt et al. (1994)	0.1ha grid (15-20ha)			24	84	71	61
				18	42	48	31
Everett & Pierce (1996)	30m lag (60 obs in 23 ha)	5	46				
		8	31				
		4	33				
		8	47				
		6	24				
		7	32				
		4	39				
Webster & McBratney. (1987)	0.4ha grid (77 ha)			5	106	26	34
Han et al. (1996)	60m grid (90 ha)	3	45	24	24	183	21
Chien et al. (1997)	6.25ha grid (1000 ha)			217	199		
Carr et al. (1991)	3 soil units	63	12	15	0	330	20
	2 soil units	84	38	15	0	440	9
	4 soil units	17	38	14	54	464	9
	4 soil units	63	64	16	59	385	42
	2 soil units	71	35	12	47	268	17
Nelson & McCracken (1962)	15 soil units	14	32	71	38		
		29	45	52	83		
Cipra et al. (1972)	soil type (7 x 2.4ha)			34	11	847	4
MEDIAN			38		38		23

Table 1-7. Mean and CV for soil N,P,K content within increasing sampling area.

Beckett & Webster (1971) in a summary of knowledge to that date, calculated within-field median CV values from a number of soil studies in cultivated crops and normalised them to represent a 0.01ha area. They summarised the results as: Nitrogen (N) = 10-20%, available phosphorus (P) = 40%, available potassium (K) = 35% and available calcium (Ca) = 10-40%. A more general areal delineation of "within a field" produced CV's of: N = 25-30%, P=45%, K= 70% and Ca = 30%. At a larger scale, the "between field" variance was broken into properties along a management effect line i.e. 10% CV for total P that is little effected by management, 25% CV for total N and 5 -50% for avail P, K, Mg and Ca that are most effected by management. Over a whole soil series they estimate the CV's to be approximately 20, 35, and 60% for the same groupings. Such generalisations for increasing scales are quite useful in demonstrating the influence of sample area on variability, but the implications regarding management are most interesting. They appear to confirm that the intervention of management in the fertility of the soil increases variability.

Nutrient variability within purported 'uniform' soil has been documented by Reed & Rigney (1947). Sampling 0.3 ha areas on a 0.015 ha grid at sites assessed as containing 'non-uniform' or 'uniform' soil series, they observed CV's of 58% for P and 41% for K and 16% for P and 13 % for K at the respective sites. In Table 1-7, the variability displayed in numerous classical variation studies of the major nutrients (N, P, K) for a range of sampling areas and designs is tabulated. The median CV values are 38 % for both N and P, and 23% for K. While the N and P values are somewhat comparable to the "within a field" value suggested by Beckett & Webster (1971), the K value is much smaller than their generalised estimate. A recent comprehensive study by Dampney et al. (1997) closely agrees with the median figures reported herein. They calculated a mean CV of 36% for P and 27% for K based on an experiment that covered 78 English fields between 4-50 ha, sampled on a mean grid of 0.65ha.

This range of variability has been reported for other macro and micro nutrients, e.g. Pierce et al. (1995) show calcium CV ranging from 16% to 44% and magnesium CV ranging from 17% to 51% on 0.1 ha grid over 10-20 ha sampling areas; Khan & Nortcliff (1982) found iron CV at 45%, manganese CV at 49%, copper CV at 20%, zinc CV at 24% on a 7m grid over a 1ha sampling area.

The spatial structure of this variation would be also expected to vary widely. Within the uniform field studied by Reed & Rigney (1947), the variance at different sampling scales show that the contribution from samples in a 15cm radius may dominate P and K variance within the field (this field has greater spatial relationships at higher scales). They find greater spatial variance within the non-uniform field (less spatial pattern).

Author/s	Sampling design	Nutrient	Model	Variogram Parameters		
				C0 (mg/kg²)	C (mg/kg²)	a (m)
Cahn et al. (1994)	200 rndm (0.25 ha)	Nitrogen	spherical	7.24	9.4	5
	50 m grid (3.3 ha)		spherical	5.25	6.5	45
Kristensen et al. (1995)	20m grid (10 ha)	Nitrogen	exponential	0	2.2	*99
				0.8	2.0	*285
				0	9.7	*144
Everett & Pierce (1996)	30m lag (60 obs in 23 ha)	Nitrogen	spherical	1.20	0.3	166
			spherical	0.40	1.7	79
			spherical	0.20	0.3	117
	30m lag (14 obs in1 trsect)		spherical	1.20	0.6	346
			spherical	5.40	10.9	152
			spherical	3.00	2.5	71
			spherical	2.60	0.8	99
Han et al. (1996)	60m grid (90 ha)	Nitrogen	spherical	0.52	0.83	900
MEDIAN				1.2	2.0	117
Mulla (1993)	15m (660m transect)	Phosphorus	spherical	27.6	63.38	145
Cahn et al. (1994)	200 rndm (0.25 ha)	Phosphorus	spherical	404.6	724.33	50
Pierce et al. (1995)	0.1ha grid (10-20ha)	Phosphorus	spherical	233.0	844	172
Kristensen et al. (1995)	20m grid (10 ha)	Phosphorus	exponential	0	4.5	*444
				0	11	*180
Webster & McBratney (1987)	0.4ha grid (77 ha)	Phosphorus	spherical	0.02	0.0847	241
Han et al. (1996)	60m grid (90 ha)	Phosphorus	spherical	26.89	2.5	900
MEDIAN				26.9	11.0	180
Cahn et al. (1994)	200 rndm (0.25 ha)	Potassium	spherical	5265.80	7344.2	40
	50 m grid (3.3 ha)		spherical	4206.60	440.2	45
Pierce et al. (1995)	0.1ha grid (10-20ha)	Potassium	spherical	887.0	391	157
				302	833	174
Kristensen et al. (1995)	20m grid (10 ha)	Potassium	exponential	0	37.7	*75
				0	389	*387
Han et al. (1996)	60m grid (90 ha)	Potassium	spherical	905.18	243.67	284
MEDIAN				887.0	391.0	157

*apparent range equivalent (3 x a': refer Equation 1-13)

Table 1-8. Semivariogram model parameters reported for soil N, P, K content.

Geostatistical analysis of N, P and K variability reported in a number of more recent studies is shown in Table 1-8.

The median values for the range document an increasing spatial dependence for N<K<P with all nutrients showing only moderate spatial structure (NR = N - 38%; K - 69%; P - 71%). Cahn et al. (1994) report the same order of spatial dependence within a single field and suggest that the observed spatial variability may be related to increasing nutrient mobility (N>K>P). At a regional scale, this interrelationship may be further linked to rainfall patterns. Yost et al. (1982) sampling within a 30 m radius at 1-2 km intervals calculated ranges for nutrients between 32 -42 km which they reported as similar to the rainfall range. In the future, a knowledge of localised moisture regime patterns may be used in the prediction of nutrient variability within fields.

This link to the soil moisture parameter is further strengthened by a similar decrease in spatial dependence as fertiliser application rate increases. Trangmar (1982) shows a decrease in the range from 5.6m to 5m when comparing the application of 0 kg P/ha with 45 kg P/ha monitored on a 1.5 m grid within 15 x 8m plots. The mobility of these macro nutrients (especially N) will also affect the spatial variation expected over a profile depth (Everett & Pierce, 1996).

Importantly, Haneklaus et al. (1997) show that the spatially dependent ranges for these nutrients vary widely between farms. In a study of 3 German Farms (total 880ha), the variogram range for the measured soil nutrients were : P - 115m to 153m; K - 67m to 135m; Mg - 70m to 136m. The interaction with management and other soil attributes ensures that the spatial variability in soil nutrient status is significantly site-specific.

1.3.6 Soil pH

The soil pH is a logarithmic index of hydrogen ion (H^+) activity in the soil solution. The level of H^+ activity in the soil solution effects the charge state of both soil organic and inorganic particles (Gregory, 1988). In the routine soil environment, it is this effect that controls the availability of nutrients, with some such as aluminium (Al) and manganese (Mn) becoming highly available and toxic to plants at low pH. Variation in pH across fields will undoubtedly effect the plant availability of nutrients even if applied in uniform quantities.

Table 1-9 documents the variability observed in the much of the literature to date. The median CV value of 5% is equal to the mean value reported by Dampney et al. (1997)

Author/s	Sampling design	pH	
		μ	C.V.(%)
Gajem et al. (1981)	20cm lag (20m trsect)	8.7	3
Miller et al. (1988)	20m lag (5 x 400m trsect)	7.5	6
Khakural et al. (1996a)	30m lag (4 x 430m trsect)	7.5	8
Reed & Rigney (1947)	0.015ha grid (0.3 ha)	5.3	1
Webster & Cuanalo (1975)	10m lag (3200m trsect)	6.1	1
		6.2	1
		6.6	1
Laslett et al. (1987)	0.1ha grid (1 ha)	5.3	4
		4.5	5
Robert et al. (1996)	12m grid (1.6 ha)	8.1	1
	12m grid (1.8 ha)	7.6	3
Mallarino et al. (1996)	15 m grid (3-6 ha)	6.5	3
		6.6	5
		6.2	5
Nolin et al. (1996)	30 m grid (10 ha)	6.0	6
Tabor et al. (1985)	49 rndm x 2m grid (13 ha)	7.3	2
Pierce et al. (1995)	0.1ha grid (10-20ha)	6.5	14
		6.6	14
		6.7	6
Evans et al. (1997)	20m x 40m grid (16 ha)	5.8	7
		6.1	6
Webster & McBratney. (1987)	0.4ha grid (77 ha)	7.7	8
Wang (1982)	one map unit	5.8	17
Cipra et al. (1972)	soil type (7 x 2.4ha)	7.1	3
Wilding et al. (1964)	soil series	6.5	9
		3.0	30
MEDIAN			5

Table 1-9. Mean and CV for soil pH within increasing sampling area.

when sampling 78 English fields between 4-50 ha, on a mean grid of 0.65ha. While this value appears low by comparison with the other soil properties, it is due to the index or ranking nature of the pH scale.

This variation is likely to decrease in horizons further down the profile due to a decreasing variability in soil OM and texture. Wang (1982) shows pH to be more variable in the A horizon ($\mu = 5.7$, CV = 12%) than the B ($\mu = 6.4$, CV = 6%).

The spatial distribution of this variability is highlighted in Table 1-10, which suggests that a strong spatial structure (NR = 12%) over a range of 105m might be expected. Cambardella et al. (1994) suggest that the range may be closely linked to the geology of the sample site as do Webster & Cuanalo (1975) who sampled at a 10m lag over a 3.2km transect and concluded that the 230m spatial range observed in correlogram analysis was caused by underlying lithology.

Any uniform attempt to amend soil acidity or alkalinity will be hampered by such variability in soil pH, however it is possibly more important to know the variability in soil buffering capacity at the within field scale. The buffering capacity is primarily controlled by soil moisture, pH and clay content (van Lierlop, 1990). Spatial variability in all three of these components is likely to interact within a field.

			pH		
Author/s	Sampling design		C0	C	a (m)
Mulla (1993)	15m (660m transect)	spherical	0.17	0.43	132
Laslett et al. (1987)	0.1ha grid (1 ha)	spherical	0.0252	0.0204	53
		spherical	0.0191	0.0321	55
Cambardella et al. (1994)	nested 2-25m grid (6.25ha)	spherical	0.060	0.70	117
Kristensen et al. (1995)	20m grid (10 ha)	exponential	0	0.092	*57
		exponential	0	0.098	*51
Pierce et al. (1995)	0.1ha grid (10-20ha)	spherical	0.089	0.271	105
		spherical	0.06	0.15	190
Webster & McBratney (1987)	0.4ha grid (77 ha)	spherical	0.021	0.33	185
MEDIAN			0.021	0.15	105

*apparent range equivalent (3 X a': refer Equation 1-13)

Table 1-10. Semivariogram model parameters reported for soil pH.

1.4 VARIATION IN CROP PEST INFESTATION

It is widely understood that the distinctly aggregated colonisation mechanisms of most crop pests predominantly results in a clustered spatial distribution (Auld & Tisdell, 1988; Marshall 1988; Mortensen et al., 1993). Yield loss studies by Cousens (1985) and Dorr & Pannell (1992) confirm the benefits to crop yield and enterprise gross margin of efficiently reducing the density of weed infestations, but it is important to note the potential for positive correlation between the absolute yield loss per weed and the potential crop yield. Pannell (1990) noted such a relationship for wheat, implying that the financial loss increases in areas under-treated as the potential yield increases. This emphasises the importance of accurately describing the spatial distribution of weed population densities prior to treatment.

Marshall (1988) reports a negative binomial distribution for weed infestations recorded as counts in quadrants which suggests aggregation at random. The distribution function provides a parameter '*k*' that reflects decreasing population aggregation as its value increases. Johnson et al. (1995) found that the value of *k* was not stable between fields for given weed species but did show significant stability between years in same field for the same species. Such instability between fields would suggest that individual field recommendations for treatment may be required.

Aggregation also infers that parts of a field may remain pest-free. Wilson & Brain (1991) studied a 10 year weed cycle on a 173 ha grazing/cereal farm and found the weed distribution to be irregular but that >60% of the area had no weeds during the cereal crop phases. Rew et al (1996) produced manually scouted weed maps showing between 27 - 97% of 5 cereal fields with *Elymus repens* infestations to be unaffected.

This aggregation may be further defined between the crop row and inter-row space. Mortensen et al. (1995) examined the inter-row areas of 5 corn fields and 5 soybean fields and found a mean 30% of the area with zero broadleaf weeds and 72% with zero grassweeds. The intra-row space showed greater weed-free areas with a mean 71% free of broadleafs and 94% grassweed free. The authors also conclude that the blanket use of herbicides may be increasing aggregation.

It would appear that the spatial distribution of weed plants may be a function of species (weed and crop), environmental conditions and previous/current cultural practices. A meaningful generalisation on variability or spatial dependence other than 'aggregational' would be difficult to prepare. However, in an attempt to quantify the spatial dependence, Nordbo & Christensen (1995) suggest that most weed species display an omnidirectional autocorrelation range greater than 50m and that most fields show a significantly longer autocorrelation range in the direction of tillage and harvest than normal to that direction.

The spatial aggregation highlighted in the previous studies can also be traced through time. Wilson & Brain (1991) reported significant spatial correlations in weed patches between the years of continuous cereals on a 173 ha farm, and also in cereal crops separated by a 3 years grass ley. Gerhards et al. (1996) also report the relative stabilisation of patches of 4 broadleaf weeds in corn and soybean fields over a 4 year study period.

The aggregation pattern of insect pests is often more dynamic than weed pests and is necessarily a function of insect species and possibly insect and crop life-cycle stage (Schotzko & O'Keeffe, 1989; Weisz et al., 1995a). As a generalisation, Fleischer et al. (1997) distinguish the processes of immigration, colonisation, reproduction, emigration and mortality as fundamental to the spatial distribution of insect species.

Schotzko & O'Keeffe (1989) report a spatial dependence range between 15m and 50m for a lentil beetle which depended on life-cycle stage and growing season period. Weisz et al. (1995a) calculated a mean range of 60m to 70m for all life cycle stages in the potato beetle but with the range shorter across rows than down, suggesting migration may be preferential down the rows. Ellsbury et al. (1996) report spatial correlations of between 200m and 550m for corn rootworms in one corn field. More importantly, the authors attribute this spatial variability to the effect spatial variation in soil and host plant conditions has on insect mortality.

Given the variability in these results it could be argued that external influences on the insect population dynamics processes described above, and their inherent spatial and temporal variability, may be ultimately governing distribution. Therefore, knowledge of the soil/crop variability before pest infection may aid prediction of the spatial distribution of subsequent pest infestations.

1.5 CROP YIELD VARIATION

The variability of individual crop system components described above contributes to spatial variation in yield potential within fields, with the interaction between the components undoubtedly adding complexity to the patterns of variability. Variability in soil components has been linked to differential germination and growth rates causing variation in yield production potentials between 5% and 51% within English fields (Evans & Catt, 1987). The Cation Exchange Capacity (CEC), which reflects the ability of soil to store and release essential cationic nutrients and is a function of many of the soil attributes discussed, may provide an integrating indicator of overall soil contribution to yield potential. A CV of 45% in A horizon CEC between different delineations of one soil unit within a County has been demonstrated by Wang (1982). The variation decreased in the B horizon (CV = 17%). Mausbach et al (1980) examined the CEC of 1280 matched pedons representing 8 soil orders from the major regions of the USA and reported CV's ranging from 14% for Entisols to 51% for Ertisols. This degree of variation is likely to manifest as spatial variability in crop yield.

1.5.1 Spatial variability

Much of the early work on spatial variability of crop yields using uniformity trials was reported in a remarkable paper by Fairfield Smith (1938). In fact, he presented one of the earliest yield maps derived from data collected in Australia during December 1934 and it is reproduced here as Figure 1-2. It shows approximately 100% variation in yield from lowest to highest across the area. Using this data, and data from other authors that had been reported earlier, Smith attempted to negate the influence of sample area and normalise the CV for each study to represent a 0.01 ha area. Some of the results are listed in Table 1-11, but this process is crucially dependent on assumptions regarding individual sample size and method of collection (i.e. bulking etc.).

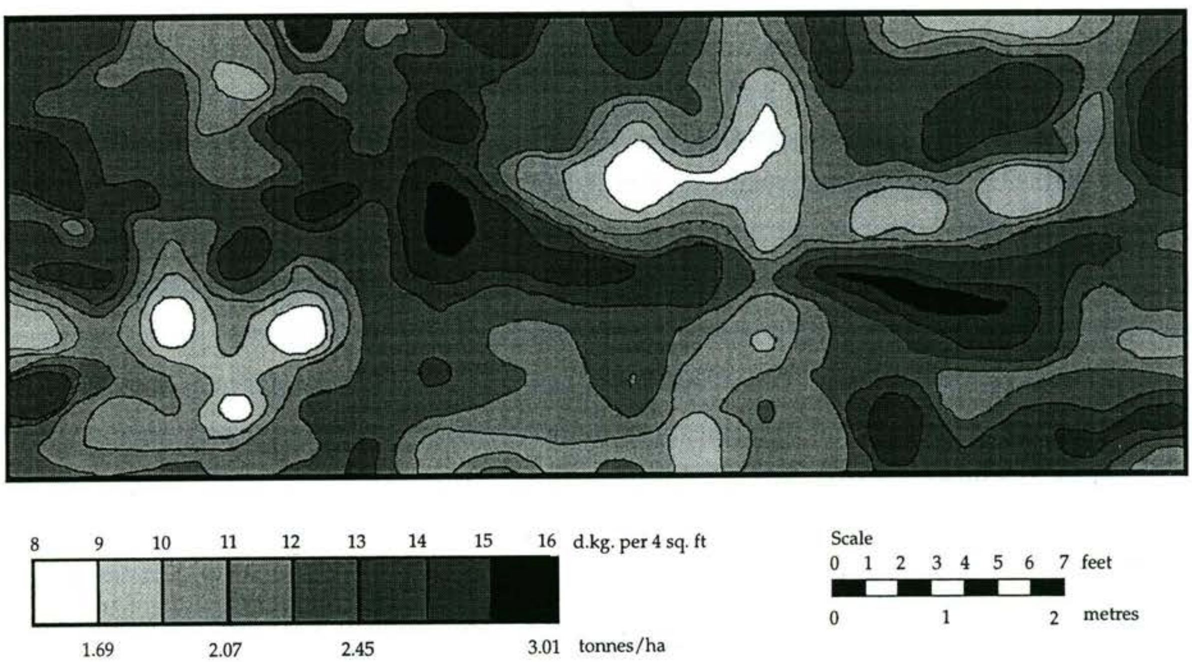


Figure 1-2. 1934 Wheat yield map - Australia (after Fairfield Smith, 1938).

Crop	Year	Location	Plot Size (m^2)	Number of Plots	Mean Yield (t/ha)	CV for 0.01 ha (%)	b'
wheat	1911	Rothamsted	8.10	500	2.2	6.3	0.46
	1932	Rothamsted	0.08	1092	2.5	4.4	0.54
	1913	Nebraska	2.80	224	2.4	4.9	0.54
	1920	Missouri	0.30	3100	1.4	3.7	0.80
	1920	Missouri	0.30	3100	1.4	6.9	0.58
	1938	Australia	0.05	1080	3.2	1.7	0.74
	1938	Australia	0.20	54	2.7	3.1	0.54
irrigated wheat	1935	Idaho	1.40	1440	4.2	10.5	0.22
potatoes	1924	West Virginia	3.30	186	14.6	10.5	0.45
		West Virginia	3.30	290	10.5	18.9	0.29
		West Virginia	3.30	3309	7.1	25.1	0.32

Table 1-11. CV estimates for crop yield within 0.01 ha area and associated heterogeneity index '*b*' (adapted from Fairfield Smith, 1938).

More significantly Fairfield Smith (1938) showed that the variance of crop yield per unit area could be described by an empirical law (Equation 1-15)

$$\log V_x = \log V_1 - b' \log x \qquad (1\text{-}15)$$

where:

V_x	=	Yield variance per unit area
V_1	=	constant
b'	=	uniformity index
x	=	area of plots

The model incorporates a uniformity parameter '*b*' (a coefficient of yield uniformity where the crop yield uniformity increases with increasing b) which is listed for the various experiments in Table 1-11. The index b' may prove useful in the development of field heterogeneity thresholds as an aid to site-specific crop management.

Author/s	Crop	Sampling design	grain yield μ (t/ha)	grain yield C.V. (%)
Taylor et al. (1997)	Barley	29 samples (0.026 ha)	8.1	21
	Barley	"	6.7	17
	Barley	"	7.3	21
	Barley	"	6.8	18
Long et al. (1995)	Wheat	5.4m² plots (864 samples in 0.5 ha)	1.5	16
Guitjens (1992)	Wheat 1985	1m lag (500m trsect)	3.6	36
	Wheat 1985	"	4.6	27
	Wheat 1985	1m lag (171m trsect)	3.6	25
	Wheat 1985	1m lag (154m trsect)	4.2	27
	Wheat 1986	1m lag (500m trsect)	2.9	40
	Wheat 1986	"	5.1	15
	Wheat 1986	1m lag (171m trsect)	2.9	34
	Wheat 1986	1m lag (154m trsect)	4.8	19
Cassel et al. (1988)	Corn	39 samples (3 x 198m trsect)	7.4	12
	Corn	"	8.5	11
	Corn	"	7.9	13
	Corn	"	7.7	19
Mulla (1993)	Wheat	15m lag (4 x 650m trsect)	4.1	29
Khakural et al. (1996a)	Corn	30m lag (4 x 430m trsect)	10.7	7
	Soyabean	"	3.8	7
Mallarino et al. (1996)	Corn	15 m grid (3-6 ha)	11.2	15
	Corn	"	10.1	16
	Corn	"	12.5	11
Nolin et al. (1996)	Corn	30 m grid (10 ha)	7.9	4
Miller et al. (1988)	Wheat	20 x 50m grid (10 ha)	3.4	27
Pierce et al. (1995)	Corn	30m lag (8 trsect)	6.8	9
		30m lag (7 trsect)	7.6	7
		30m lag (13 trsect)	10.5	5
Everett & Pierce (1996)	Corn 1992	30m lag (60 obs in 23 ha)	9.9	13
	1993	"	9.4	9
	1994	"	12.9	4
Karlen et al. (1997)	Corn 1992	45 m² random (36 ha)	11.4	12
	Corn 1994	"	10.6	12
	Soybean 1993	"	1.8	45
	Soybean 1995	"	3.3	9
	Corn 1992 (no till)	"	11.6	7
	Corn 1993 (no till)	"	4.9	27
	Corn 1994 (no till)	"	11.4	7
	Corn 1995 (no till)	"	9.6	6
	Soybean 1992 (no till)	"	3.2	6
	Soybean 1993 (no till)	"	1.9	43
	Soybean 1994 (no till)	"	3.8	8
	Soybean 1995 (no till)	"	3.4	6
Burrough & Swindell (1997)	Rapeseed 1993	continuous (1.2s)	2.0	22
	Wheat 1994	"	6.4	17
	Barley 1995	"	5.5	14
Shiel et al. (1997)	Wheat	continuous (16m)	11.4	16
	Wheat	"	9.2	6
	Rapeseed	"	3.6	12
	Rapeseed	"	4.7	10
MEDIAN				14

Table 1-12. Mean and CV for crop yield within increasing sampling area.

A number of more recent classical statistical studies on yield variability are recorded in Table 1-12. Over a wide range of sample areas and sizes, the median CV value of 14% falls within the range of estimates reported by Fairfield Smith (1938). For the crops examined, the median yield variability increases as: soybean (8%) < corn (11%) < rapeseed (12%) < barley (18%) < wheat (27%). For other crops, Schneider et al. (1996) report a median CV value of 33% for potatoes under centre-pivot irrigation. These values are reflected in the study of Bresler et al. (1982) where CV values for corn under various irrigation and tillage treatments ranges from 11 - 20% and 12 - 26% for irrigated winter wheat.

Gales (1983) in a substantial review of wheat and barley variation and factors affecting it in Britain also found a CV = 26% for one wheat variety grown at 11 sites over 8 yrs and a CV = 22% for a second variety grown at 7 sites over 10 years. By analysing the CV of the fundamental crop physiological components that make-up yield (i.e. mean grain mass and number of grains per area) Gales (1983) reported that the number of grains per area was between 2 and 3 times more variable than the grain mass. The conclusion appears to be that environmental factors that effect grain per unit area, such as climatic and soil conditions prior to anthesis, are very important.

This significant effect of soil type has been demonstrated by Carr et al. (1991) where the within-field yield CV for wheat (10 m^2 samples within 0.25 ha), harvested according to soil type, ranged between 7% and 37% in one year. It is also noted that as yield increases towards the potential crop yield, the variability within a field tends to decrease. This is most noticeable in irrigated crops where moisture deficit can be controlled. Guitjens (1992) sampled irrigated winter wheat in 1.6 m^2 continuous plots along two transect lengths and concluded that as water deficit increased and yield correspondingly declined, the CV increased linearly. Hunsaker (1992) sampled sixteen 12.2 m^2 plots of irrigated cotton within each of twelve 0.35 ha basins under three irrigation treatments. In two successive seasons, CV's for high to low irrigation treatments ranged from 7 - 17% and 12 - 26% displaying a significant decrease in CV as irrigation (and yield) increased.

The spatial structure of this variation has been less well studied. Guitjens (1992) who reported that greater uniformity in wheat yields along transects associated strongly with higher yields also found the autocorrelation distance to vary from 5m to 27m. Unexpectedly, the autocorrelation distance showed no significant correlation with yield or CV. It could be reasonably expected that greater autocorrelation distances would be associated with more uniform crops.

Table 1-13 shows the variogram parameters for a number of recent yield studies with a median range value of 88m. The median nugget ratio of 37% suggests that crop yield may

Author/s	Crop		Sampling design	Model	Yield		
					C0 (t/ha²)	C (t/ha²)	a (m)
Mulla (1993)	wheat		15m lag (4 x 660m transect)	spherical	0.84	1.14	70
Nolin et al. (1996)	corn		30m grid (10 ha)	exponential	11.15	13.67	*51
Pierce et al. (1995)	corn		30m lag (7 trsect)	spherical	0.68	0.424	231
Everett & Pierce (1996)	corn	1992	30m lag (60 obs in 23 ha)	spherical	0.54	1.29	85
		1993	"	spherical	1.32	0	8
		1994	"	spherical	0.33	1.15	20
Kristensen et al. (1995)	wheat	1993	continuous (2-3 seconds)	exponential	0.90	1.02	*150
		1994	"	"	0.18	0.50	*102
	barley	1993	"	"	1.19	1.13	*183
		1994	"	"	0.30	0.48	*123
Lutticken et al. (1997)	wheat	1993	continuous (time unknown)	spherical	0.20	0.60	85
	barley	1994	"	"	0.30	0.60	80
	wheat	1993	"	"	0.20	0.50	85
	barley	1994	"	"	0.24	0.43	75
	wheat	1993	"	"	0.40	1.05	75
	barley	1994	"	"	0.18	0.65	70
MEDIAN					0.37	0.63	83

*apparent range equivalent (3 x a': refer Equation 1-13)

Table 1-13. Semivariogram model parameters reported for crop yield.

be expected to display moderate to strong spatial structure in the field. The median range value is comparable to the 80m range of influence for dryland wheat reported in an earlier study by Miller et al. (1988). Haneklaus et al. (1997) continuously sampled wheat, rapeseed, barley, oats and beans over an area of 880ha on three farms and recorded a mean and median range value of 90m.

1.5.2 Temporal variability

While the above studies confirm that spatial variability in crop yield occurs within fields and that its magnitude varies between fields, it should also be important for farm management to quantify the extent to which crop yield varies with time. Sadler et al. (1995) and Karlen et al. (1997) show that annual changes in yield CV values for whole fields can be quite significant and the effect can be different for different crops and different soil units within the field. Significant temporal variability would increase the difficulty of yield goal determination and operations planning.

To quantify this variation, Porter et al. (1996) studied corn and soybean yields for 10 years in small plots within 1 ha areas at 3 locations. Their results show that the seasonal (temporal) variability in continuous soybeans was 3 times greater, and in continuous corn 4 times greater, than the variability between plots in any year (i.e. spatial variability). On an even finer sampling scale, Thylen (1997) continuously sampled within a 12 ha field the yield of four crops in a four year rotation (oats/barley/oats/barley). The yield CV values (in chronological order) ranged from 10% to 21% for oats and 17% to 14% for barley.

In a more innovative, yet coarser -scale study, Eghball & Power (1995) employed a fractal analysis to the annual average yield of barley, maize, oats, peanuts, rice, rye, sorghum, soybeans, wheat and cotton fibre in the USA over the 61 year period from 1930 to 1990. The fractal dimension (*D*) (Mandelbrot, 1977) was calculated using the semivariance estimated for different year intervals, with a value of *D* close to 1 suggesting that long-term variation dominated (genetic and cultural practice improvements) whereas a value approaching 2 suggests the dominance of short-term variation (climatic).

While improvements in plant breeding and increased fertiliser, pesticide and herbicide use contributed to a strong increase in yields during the study period, the results showed that there were significant differences between the ten crops. The values of *D* ranged from 1.20 for rice to 1.47 for oats. Rice displaying the least effect of short-term variation while oats and soybeans showed a more pronounced effect, suggesting that the later two crops may be particularly sensitive to annual variation in some environmental growth factors. It is not unexpected that rice growing techniques may reduce the yield sensitivity to annual climatic variability.

At the field scale, grain yield data for maize (1953 to 1993) under different fertiliser management regimes was used in a similar temporal yield variability study by Eghball et al. (1995). While no significant differences in *D* values were found between the treatments, the values ranged between 1.958 and 1.996 indicating the dominance of short-term temporal variation. The authors conclude that for this study location (western Nebraska) management practices cannot override the strong influence of variable environmental conditions. This may well be the case at the field scale in most modern field cropping regions.

Where long-term variability can be demonstrated it may be possible to predict crop yields over time and model temporal plant growth. However, high values of *D* which may indicate that environmental factors rather than management practices affect the year-to-year variability of crop yields, would prove more complex to manage. Values of D also indicate the uncertainty or risk involved in growing a particular crop in a particular location. Increased yield variability in the short-term (higher D) indicates greater risk in crop production.

It should also be noted that the fractal dimension D is scale independent and the values of D depend on variability rather than yield so values of D may be compared (Eghball and Power, 1995). It is therefore a useful device for comparing the magnitude of temporal variation between fields and may also be useful in establishing temporal variability thresholds in the same manner as suggested for b and D in spatial variability.

1.5.3 Joint Space-Time Models

The development of space-time models remains in its infancy although several have been suggested (e.g. Stein, 1986; Posa, 1993; Stein et al., 1997). Buxton & Pate (1994) have used a joint temporal/spatial variogram in a 3-dimensional kriging process to estimate pollutant concentrations in time and space. The validity of their method being confirmed by Dimitrakopoulos & Luo (1994). Heuvelink et al. (1996) applied a more flexible model to the prediction of soil moisture under a pine forest.

McBratney et al. (1997) have also documented a number of simple, general models for the analysis of stationary, non-stationary and intermediate data sets and examined wheat dry matter and grain yield from the Rothamsted Classical Experiments (Johnston, 1994). The results show that the temporal variance between locations in the field may be up to 4 times the spatial variance in drymatter production and 6 times the spatial variance in grain yield.

1.6 SUMMARY

Within-field variability of soil attributes, crop pest infestations and the resultant crop yield is obvious. The magnitude varies with attribute, location and time. Table 1-14 lists median CV values for the variables examined in this chapter which may be taken as a general, simple guide to the magnitude of variation that may be expected at the within-field scale. These may possibly be used as a basic benchmark for variability at this scale.

Offering a more comprehensive view of variability in a number of these attributes are the figures in Table 1-15. These values agree with the median values calculated by Haneklaus

Attribute		Median CV (%)
Soil Texture	Sand	37
	Silt	18
	Clay	18
Soil Structure	Bulk density	5
Soil O.M.		18
Soil Moisture	θg	11
	θv	9
Soil Nutrients	N	38
	P	38
	K	23
Soil pH		5
Crop Yield		14

Table 1-14. Median CV values for important soil /crop system attributes.

et al. (1997) for attributes studied on 18 fields. They may also be considered as generalised representations of expected variability at the within-field scale and could be used as surrogates for the parameters in unsampled fields or initial estimates in modelling procedures. The provision of a spatially dependent range (*a*) may also prove useful in establishing the sample spacing for initial sampling schemes in unsampled fields. With the exception of soil moisture, these figures tend to suggest a 60m sample spacing as being a maximum required to accurately capture the spatial variability in most soil attributes. Franzen & Peck (1995) compared the abilities of a 100m and a 66m sampling grid to delineate the spatial features in soil pH, P and K observed on a finer 25m grid. They concluded that the 66m grid provided sufficient detail but that the 100m grid delivered an unacceptable loss of information. Similarly, Haneklaus et al. (1997) suggest a soil sampling grid of between 50m and 100m for reasonable spatial delineation.

The values in Table 1-15 are similar in magnitude to the average variogram parameters calculated by McBratney & Pringle (1997) in a recent variability review of a number of soil attributes. They concluded that the degree of variability (variation doubling as area increases from 0.1 ha to 1 ha) and structural ranges suggested that management at the 1m to 100m unit scale was potentially useful. These results tend to support such a hypothesis,

Attribute	Median Variogram Parameters				
	C0	C	C0 + C	a (m)	spatial structure
Soil Texture (%^{2})	2.4	9.3	11.7	63	strong
Soil Moisture (%^{2})	0.00049	0.00045	0.00094	22	moderate
Soil Nitrogen (mg/kg^2)	1.2	2.0	3.2	117	moderate/strong
Soil Phosphorus (mg/kg^2)	26.9	11.0	37.9	180	moderate/weak
Soil Potassium (mg/kg^2)	887	391	1278	157	moderate/weak
Soil pH (units^2)	0.021	0.15	0.171	105	strong
Crop Yield (t/ha^2)	0.37	0.63	1.0	83	moderate/strong

Table 1-15. Median semivariogram model parameters for important soil /crop system attributes.

with the proviso that attributes that display a moderate to weak spatial structure will prove more difficult to compartmentalise or classify into homogenous management units.

Importantly, the variation in attributes of the soil–crop system highlighted by this review may give rise to economic, environmental and societal problems on cropping enterprises under traditional 'uniform' management (Lowenberg-DeBoer & Swinton, 1995; Wollenhaupt & Buchholz, 1993). In general, the problems as summarised in Table 1-16, arise from a decision to use 'mean-of-field' information to guide the amelioration of an area which may result in zones being under- or over- treated.

For the majority of impacts listed in Table 1-16, the implications are obvious and require no further elaboration. The significance of excess denitrification products provides an exception. In areas with soil nitrogen levels above crop requirements, there is a greater opportunity for the excess nitrogen to result in increased production of nitrous oxide (N_2O) through the denitrification process. N_2O release is believed to contribute to the global greenhouse effect and is instrumental in the breakdown of stratospheric ozone (Hauck, 1984).

At present, the problems of input resource waste and failure to attain optimum yield remain economic dilemmas of the individual producer. Escaped fertiliser and pesticide, along

Attribute	Economically Significant Yield Loss	Excess Fertiliser Cost	Excess Fertilisers in Tailwater or Groundwater	Excess Denitrification Products	Excess Pesticide Cost	Excess Pesticide in Tailwater or Groundwater	Pesticide Residues in Soil
Soil Type / Texture	✓	✓	✓	✓	✓	✓	✓
Soil Structure	✓	✓	✓	✓		✓	
% Soil OM	✓	✓	✓	✓	✓	✓	✓
Soil Moisture	✓	✓	✓	✓		✓	
Soil Nutrients	✓	✓	✓	✓			
Soil pH	✓	✓	✓	✓			
Pest Infestations	✓				✓	✓	✓

Table 1-16. Problems associated with not treating spatial variation in influential soil/crop system components.

with contamination of follow-on enterprises with residual pesticides, has entered the public domain. Legislation has been foreshadowed on the right to use and apply chemicals, and on containment strategies to reduce the contamination of waterways and food chains. Failure to comply will undoubtedly bring another economic dilemma for the individual producer.

Technology is now becoming available to tackle the operational difficulties inherent in the problems raised by spatial variability. Providing further impetus is the now greater general awareness of the natural boundaries limiting resource requirements, availability and application. Given that this review points to the conclusion that a much finer delineation of homogeneity in management units is required than presently utilised, it may therefore be efficacious to attempt to account for, and operate with, spatial variation as the solution to the potential problems of soil spatial variability.

Chapter 2 will review the progress towards developing a farm management system that will incorporate a finer scale treatment of variation.

CHAPTER 2

CHAPTER 2

Site-Specific Measurement and Management of Attributes

2.1 INTRODUCTION

The preceding review highlights the variability that has been observed in the major components of crop production systems. It also raises the concept that the scale of spatial variation in crop yield is critically dependent on the scale of spatial variation in significant field-based factors that contribute to crop yield. This interrelationship has tended to be overlooked by farm managers as operational logistics enticed them towards larger field sizes. Given the spatial relationships presented in Chapter 1 it is entirely feasible that the incorporation of more variability within each field may have followed.

With the advent of tools such as the differential Global Positioning System (dGPS), Geographical Information Systems (GIS), and miniaturised computer components there is now an increasing interest in, and quantification of, the variability in soil attributes, crop yields, pest infestations and climatic factors. These tools allow agricultural enterprises to gather more comprehensive data on this production variability in both space and time and has fostered a new attempt to understand and manage the variation at the within-field scale.

The desire, and ability, to monitor and respond to variation on a fine-scale is the goal of Precision Agriculture. This desire has both an economical and environmental basis. Matching inputs to crop and soil requirements as they vary within a field should improve the efficiency of resource use and minimise adverse environmental impact.

At present, monitoring and mapping the spatial variation in small-grain crop yields is receiving much publicity in Australia. Yield mapping is only one component of a Precision Agriculture system (refer Figure 3) and small-grains is not the only enterprise to embrace the ideas. Crop yield monitors are also available for potato, peanut and forage harvesters and are under development for cotton, sugarcane and a range of horticultural crops.

Achieving the operational harmony called for in a site-specific crop management system will require a holistic approach to describing, and delineating suitable responses to, the spatial variation found in the influential components of a cropping system. A union of data acquisition operations, information processing and decision formulation procedures would be necessary to successfully complete this process. Ideally, for many ameliorative operations the whole process would be undertaken in 'real-time' as depicted in Figure 2-1, however many technological and agronomic barriers remain. This Chapter will review the progress towards constructing such a management system.

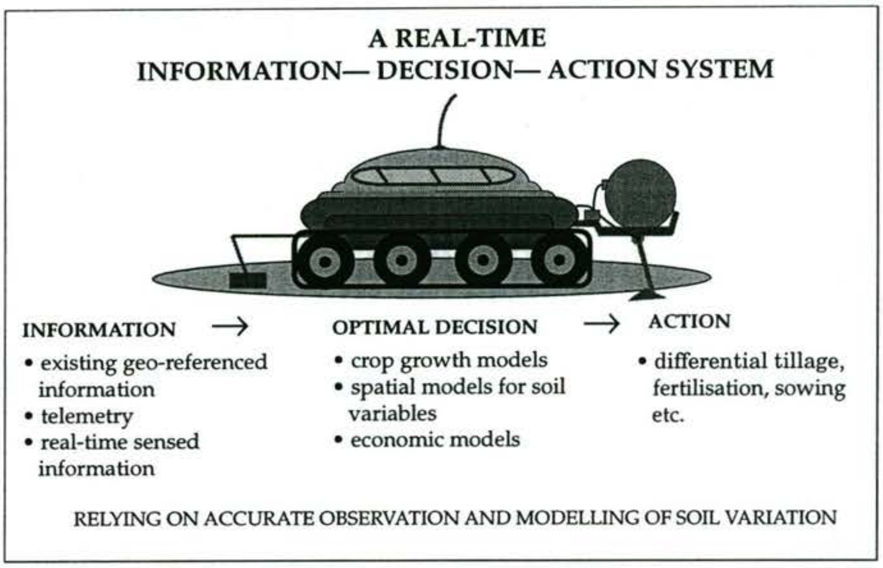


Figure 2-1. A proposed real-time system linking information acquisition, decision making and action operations (McBratney & Whelan, 1995b).

2.2 COLLECTING DATA ON SPATIAL VARIABILITY

A critical requirement for collecting data on the spatial variation in any land-based attribute is an ability to accurately resolve ground positions in the field. All data must be geo-referenced to facilitate the production of a representative field map and for the purpose of correlating the information on various attributes obtained from a field. The technology is available to determine the position of a stationary/moving vehicle with increased accuracy using satellite-based navigation systems or land-based triangulation telemetry systems.

Local triangulation systems rely on calculating a position relative to a configuration of ground based beacons. A number of radio-frequency, time-multiplexing positioning networks that allows radial distance real-time positions to be calculated and converted to x,y data have been explored (e.g. Hiel et al., 1986; Palmer, 1990). The beacons may be permanently fixed in position or moved to allow coverage of new areas, however the position must always be initially surveyed. These systems are generally low-powered and currently have operating radii of 5-25 kilometres (km). Satellite navigation systems will be discussed here because they are now becoming ubiquitous within agriculture and the wider community.

2.2.1 Satellite Navigation Systems

Two satellite systems have been developed. The NAVSTAR Global Positioning System (GPS) is owned by the government of the United States of America, and the Global Navigation Satellite System (GLONASS) is controlled by a consortium headed by the Russian Government. Both systems are built using a space segment comprising a constellation of dedicated satellites, a control segment that monitors, manoeuvres and updates information to the satellites, and a user segment trying to determine accurate ground position. The systems are basically similar (see Kruger et al., 1994 for comparisons) however far more receivers have been developed by commercial enterprises to utilise the information from the GPS satellites so its operation will form the basis of the following review.

Methods of position calculation are beyond this general review and readers are referred to Hofmann-Wellenhof et al. (1994) for a thorough explanation of theory and practice or the NAVSTAR technical characteristics reference (USA Government, 1993). In basic terms a user's position is determined by resection using the distances measured to the satellites. These distances are most commonly estimated using satellite orbit, current position and time information uniquely coded into a transmission signal from each satellite. The distance to four satellites must be instantaneously determined by a remote receiver in order to obtain a point position in three dimensions. One satellite each for resolving latitude, longitude and elevation and the fourth is required to determine nonsynchronisity between the satellite and receiver time pieces.

The GPS satellites are currently controlled by the U.S. Department of Defense who regulate the quality of information available to civilian users. This regulation, known as 'selective availability' (SA), is initiated by dithering the satellite clock and position information that is included in the coded signals available to non-military users. A reduction in the accuracy of satellite distance determination and therefore remote receiver position results. This is especially the case in the 'stand-alone' mode of operation whereby a ground position is calculated using a single receiver that tracks and obtains data from the satellites. The specified accuracy with SA has a 95% confidence interval of ±100 metres (m) and a ±300 m 99% confidence interval. Without SA the 95% confidence intervals are 3-35 m (Kruger et al., 1994). Georgiadou & Doucet (1990) have demonstrated that SA can increase positioning errors from 15m to 100m.

The errors introduced by SA can be reduced with the introduction of a second receiver installed at a fixed, surveyed position. The position data collected by the fixed receiver can be used to calculate a correction factor that may be applied to the data gathered by a mobile receiver. Using a GPS in this operational configuration is known as differential GPS (DGPS). This correction may be stored and applied to the mobile receiver's data following a reconnaissance or survey operation (post-processing) or used as individual positions are calculated by the mobile receiver (real-time) using a radio frequency communication link.

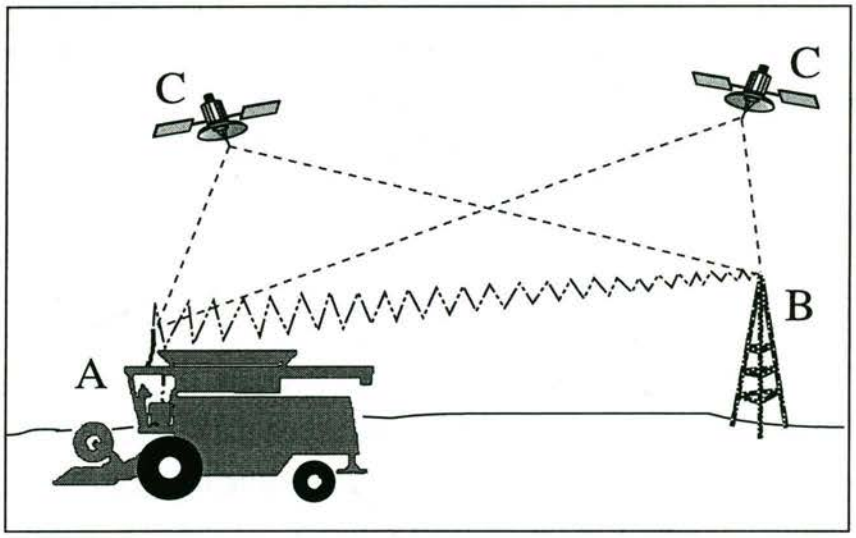


Figure 2-2. Operational configuration of a real-time Differential GPS (DGPS).

Figure 2-2 depicts the basic set-up of a real-time DGPS. The mobile receiver (A) and the fixed position base unit (B) interrogate the navigation satellites (C). (B) continually compares its surveyed position with that calculated using the data from the satellites (C). A correction (differential) is computed to truth the incoming data and the differential is relayed by radio frequency to the mobile unit (A). The mobile unit is thus able to more accurately calculate its position from the satellite data (C) and the differential supplied by the base station (B).

Real-time DGPS allows instantaneous position reckoning and the associated ability to store position information with other observations while they are being observed. Initial studies on civilian use of DGPS with user controlled base stations suggested an accuracy between 2-4m was attainable if the two receivers were positioned close together (Beser & Parkinson, 1982; Kalafus et al., 1983). This accuracy would degrade at approximately 1cm per km (Ashjaee, 1985) until the separation distance reached 100 - 200km (Brown, 1989; Kee et al., 1991). Further separation would subject the user to position error up to approximately 15m at 500km (Kruger et al., 1994). Such degradation would limit the usefulness of operating DGPS with a single base station to short-range operation.

If the differential signal is broadcast on a FM frequency sideband the system can accommodate multiple users within the effective range. Such differential correction signal coverage is available for many of the major cropping regions in Australia through Ausnav Services Pty Ltd.¶ who lease a proprietary programmed receiver to the user.

The differential calculated using one fixed receiver reduces/removes the GPS system errors produced by SA, the internal position and time monitoring errors associated with the satellites and the time monitoring errors associated with the receivers. The range restrictions that are still incurred are a result of variation within the atmospheric layers through which the satellite signals are propagated as well as internal receiver noise and multi-path signal reception.

An ionospheric delay, imposed on the transmissions as a function of signal frequency and the number of free electrons along the path, will therefore vary with satellite elevation. GPS satellites transmit a basic model of this delay that reduces the ionospheric error to a mean of 50% of the true effect and using one base-station DGPS can only improve this within 185 km separation (Brown, 1989). A tropospheric delay is induced as a function of local elevation, humidity and temperature and this is not corrected in single base-station DGPS (Brown, 1989).

In general, using a single fixed base-station assumes that all errors applying at this reference station should apply exactly to the mobile but as separation distance increases the two receivers may be observing different satellite information errors and receiving the satellite signals via different atmospheric travel paths (Ackroyd & Lorimer,1994). However, these effects are spatially correlated between separated receivers (Loomis et al., 1991; Clark, 1992) so they may be overcome by the use of two base stations as proposed by Tang et al. (1989) or multiple base stations (Brown, 1989; Loomis et al., 1991; Mueller et al., 1994) that allow the spatial pattern of these "line of sight " errors to be modelled. The proposed methods weight the differential corrections computed at various ground stations and combine them to obtain an improved estimate of errors at a users location. The weightings are a function of the correlation distance of the GPS errors and the distance between user and the reference stations. Tang et al. (1989) concluded that the error reduction with two base stations appeared as a function of separation geometry. The multiple base station systems, with a wide spread of fixed reference points is less susceptible to this problem (Loomis et al., 1991).

¶Ausnav Services Pty Ltd., PO Box 7396, Canberra Mail Centre, ACT 2601

A solution has been designed that incorporates a wide network of fixed position receivers (D) that communicate with the GPS satellites (E) and calculate a correction algorithm which is then passed to a master station (F). The master station computes a vector correction from all the individual stations and relays this to a general communications satellite (G) that increases the broadcast range to remote users (H). The correction transmission is supplied in a standard format (RTCM-104) defined by the Radio Technical Commission for Maritime Services (Kalafus et al., 1986). This operational configuration is known as Wide Area Differential GPS (WADGPS) and is capable of providing sub-metre accuracy that is spatially independent of mobile receiver location within the network (Figure 2-3).

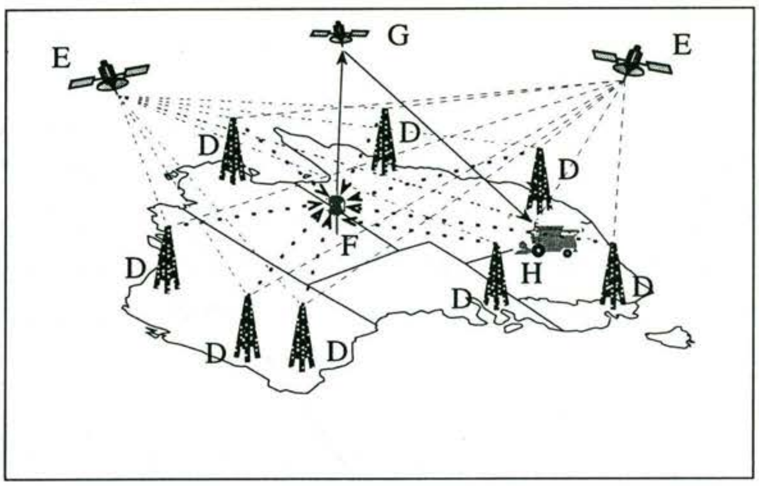


Figure 2-3. Operational configuration of a Wide-Area Differential GPS (WADGPS).

This form of correction is available in many countries (including Australia) through the competing commercial operations of Fugro Starfix§ and Racal Survey‡ The remaining spatially uncorrelated errors in the user segment are receiver noise, which should be reduced as electronic technology continues to advance, and multi-path signal reception that can be significantly reduced using antennas that will not accept signals from below the local horizon.

More accurate modes of operation are available whereby the distance to satellites is determined in a codeless manner using the phase change of the information carrier signal between propagation and reception (Larsen et al., 1994). This method offers potentially greater accuracy but requires more expensive receivers and user provided base stations with radio links. The range of these systems and the cost will restrict their use to very detailed survey, terrain modelling or vehicle guidance at present.

§ Fugro Starfix 18 Prowse St, West Perth, WA 6005. ‡ Racal Survey Australia Ltd. 4 Ledgar Rd., Balcatta, WA 6021.

In an agricultural context, the required location accuracy and precision will depend on the operation being undertaken. Stafford & Ambler (1994) suggest and accuracy of ± 1m for the operation of a boom spray with controllable 2m boom sections; <10cm for controlling spray overlap between adjacent passes; and for monitoring crop yield the resolution may only be required to be below the width of the cutter-bar (i.e. ± 3m for a 5m cutter). In precision tests they show that prior to S/A operation an accuracy of 1.9m was obtainable in 95% of measurements (root mean squared error (RMSE) × 2) using stand-alone GPS receiver and a correction signal transmitted for a broad area. This extended to 5-15m with S/A, but prior to the 1993 completion of the GPS satellite constellation. After the full constellation was airborne, a tram-line test using an in-field base-station found improvement to 2.7m (easting) and 1.9m (northing).

Delcourt & De Baerdemaeker (1994) calculate a 1m error in 95% of measurements as a requirement for soil sampling to delineate spatial units. This accuracy should also be the aim for crop yield monitoring as any error will be incorporated into the final map. The belief that the cutter-bar width can dictate the GPS resolution is erroneous.

There are now numerous DGPS receivers commercially available with manufacturer reported accuracy of 1.0m (2 × RMSE). Saunders et al. (1996) proposed static and dynamic tests to verify the suitability of receivers for Precision Agriculture which highlighted the variability in performance attributable to receiver specification. Performance will also be location and time dependent.

In general, the pseudorange GPS method of position determination would appear to adequately fulfil the requirements for monitoring crop yield and possibly boom spray operation. It is not yet suitable for accurate spray overlap control, vehicular guidance or digital terrain modelling. The more expensive operations such as Real-Time Kinematic (RTK) DGPS carrier phase systems and the synchronous use of DGPS and dead-reckoning instruments have been shown to produce centimetre level accuracy and precision (Van Zuydam et al., 1997; Le Bars et al., 1997) and should be employed for these tasks.

In the future, it may be possible to combine the GPS and GLONASS systems to increase the number of satellites visible at one time and improve reliability and accuracy. GLONASS may bring a number of benefits such as a constant and more easily modelled bias because S/A is not imposed and a higher satellite inclination (65 deg compared to 55 deg) which improves satellite visibility.

2.2.2 Attribute Observation Strategies

Some data on soil and crop variability may already be available. Regional soil maps are compiled from coarse-scale survey information but may be useful as an initial indication of the soil variation to be expected on a farm level. Soil sampling and testing that may have been carried out in previous years would also provide useful data on temporal variation and soil response to treatment strategies.

Discrete Sampling

Field observation has been traditionally based on discrete sampling procedures using either a grid-based or statistically based random sampling strategy. Sampling by grid is at present a laborious procedure if large areas are to be tested. For the production of accurate maps, the appropriate sampling scheme and minimum lag must be determined, and as highlighted in Chapter 1, the inherent variability expected in most attributes would suggest the principal sampling lag should be as small as possible. This inevitably leads to a conflict between accuracy and sampling cost.

To increase the speed and efficiency of such sampling (and eventually reduce the per-sample cost) a small low ground-pressure utility vehicle such as a 4 wheel motorbike, equipped with positioning technology and an industrial grade personal computer may be employed. Such a unit may be used to collect soil samples for *ex situ* chemical analysis or perform *in situ* measurements of attributes such as nutrients (Wild et al., 1997), moisture content by TDR (Zeglin et al., 1989), structural interpretations using air permeability (Fish & Koppi, 1995) and salinity by electromagnetic induction (EMI) (Rhoades, 1992). The position of the sample site being logged simultaneously using the on-board positioning technology. A further step towards greater automation in sampling has been made by McGrath & Skotnikov (1997) who present a traillable sampling, packaging and labelling machine for field soil sampling.

Much of the soil and crop attribute sampling for Precision Agriculture has been conducted manually on grids of 100m or larger. Birrell et al. (1996) graphically depict an observed increase in the confidence range for the spatial representation of soil pH, K and P associated with an increase in sampling grid from 25m to 100m. The common choice of grid size appears to indicate that reducing sampling cost has triumphed over accurate spatial resolution. Such economic rationality will always restrict the detail in information obtainable from discrete sampling procedures. While the procedure will continue to be employed, it is imperative that more intensive methods of data gathering are developed.

Remote Sensing

Remote sensing encompasses techniques for collecting data on the spatial variation of both soil and crop parameters using aerial or satellite observation platforms. Most techniques rely on the fact that different landcovers have often characteristic ambient reflectance signatures in the visible and/or non-visible electromagnetic (EM) spectrum. Images of this reflectance covering various spatial resolutions may be captured using photographic film, video or digital media. Satellite observed images that are available to civilians have a typical resolution of 20 m^2 to 30 m^2. The resolution of images captured by aerial platforms is generally a function of observation altitude and media composition.

Harrison & Jupp (1989) list the soil attributes most influential on reflectance as moisture > OM > texture > structure > iron content. Unfortunately, the influence is exerted by the characteristics of the top few millimetres of soil, which (with the possible exception of OM and texture) may not be representative of the condition of the underlying topsoil. However, reflectance measurements from bare soil using the visible and near infrared (NIR) wavelengths have proven useful in assessing variability in soil texture (e.g. Stoner & Baumgardner, 1981) and OM content (e.g. Krishnan et al., 1980; Bhatti et al., 1991) and in turn may be applied to inferring variation in yield potential in the future.

Airborne radar imaging units are able to penetrate further into the soil. The information gained represents the top 5 cm of soil and can be analysed to retrieve accurate determinations of soil moisture content (Engman, 1990). The American National Aeronautic and Space Administration (NASA) operates one such system known as Airborne Synthetic Aperture Radar (AIRSAR), has tested a system in 1994 from the spaceshuttle called Spaceborne Imaging Radar-C/ X-Synthetic Aperture Radar (SIR-C/X-SAR), and has plans for a dedicated satellite based system (LITESAR) to be launched in 2001.

The emission of gamma radiation, particularly from a radioactive potassium isotope (^{40}K) has been remotely sensed and used to distinguish soil parent materials and has been suggested for use in conjunction with terrain models and aerial photographs in estimating the spatial variability in soil materials (Cook et al., 1996).

The reflectance response of vegetation displays more potential. Reflectance in the red (0.6 - 0.7 µm) and NIR (0.8 - 1.1 µm) wavelengths is known to be influenced by agronomic practices that effect the crop leaf area index (LAI), biomass and percent soil coverage (Daughtry et al., 1980). Variation in reflectance response across a field may then be used to estimate variation in yield potential or target areas for amelioration. Bausch et al. (1997) assessed plant N status using a Nitrogen Reflectance Index (a ratio of NIR/green reflectance across a crop is compared to the ratio expected from a crop with no deficiency) and suggest the index provides a rapid assessment of N sufficiency. Plant photosynthetic activity and thus potential crop yield has also been related to a normalised difference vegetation index (NDVI) based on the ratio of NIR minus red reflectance, divided by NIR plus red reflectance measurements (Taylor et al., 1997). A modified version of NDVI (mNDVI) has been presented by Jurgens (1997) and is calculated as the ratio of NIR minus medium infrared (MIR), divided by NIR plus MIR reflectance measurements. The author reports that such an index can be useful in determining the reduced cellular moisture content of plants damaged by frost. Data from AIRSAR and SIR-C/X-SAR imagery has also been used to calculate variation in leaf area index within agricultural fields (Paloscia, 1998).

Reflectance measurements in the thermal infrared range (10.5µm to 12.5µm) may be used to monitor variation in crop canopy air temperature in a transpiring crop. This is believed to provide an integrating indicator of the underlying spatial variability in plant-available soil profile moisture status (Yates et al., 1988). This variability has been further correlated with soil texture and structure variation (Jackson, 1982; Smith et al., 1989) which affect soil moisture content and availability. Gauthier & Tabbagh (1994) directly measured the thermal response of soil from an aerial platform and successfully detected spatial variability in soil moisture content and could delineate textural changes as soil units.

Aerial video imagery has also been used to calculate percentage land affected by saline soil areas using red narrow band and colour infrared reflectance (Everitt et al., 1988). Brown et al. (1994) utilised aerial still-video camera images captured using four discrete spectral windows to discriminate between seven weed species in a corn field. The spectral regions were chosen to allow separation of the different plant species based on their individual spectral signatures. Hanson et al. (1995) used aerial colour and NIR imaging to classify 8.3 m^2 cells within two young wheat fields as either infested or not with wild oats. They achieved a minimum 80 % correct classification and suggested that the resolution of digitised film images was superior to that obtained from a digital camera. Colour infrared and panchromatic NIR in conjunction with GPS and GIS tools proved useful for Everitt et al. (1994) in the detection and mapping of blackfly infestations in citrus orchards.

Table 2-1 summarises the remote sensing techniques and the relevant attributes that can be estimated. In general, employing these techniques prior to sowing a fallow field may provide data on soil moisture and texture variability and during the cropping phase vegetative growth may be monitored for variation resulting from nutrient deficiencies, water stress or pest infestation. This form of data appears suitable for quantifying more coarse-scale variation but as the resolution of the technology increases, and ground-truthing is improved, this may become a more useful tool for assessing small-scale variation.

Observation technique	Platform	Attribute estimated	
		soil	crop
Visible/ NIR reflectance	Aircraft/Satellite	Moisture	Leaf area index
		Organic matter	Biomass
		Texture	N status
		Salinity	Photosynthetic activity
			Species identification
			Physical damage
Thermal infrared	Aircraft/Satellite	Moisture	Canopy temperature
			Moisture stress
			Vigour
Radar	Aircraft/Satellite	Moisture	Leaf area index
		Surface roughness	Biomass
			Surface roughness
Gamma emmission	Aircraft	Mineralogy	
		Clay content	

Table 2-1. Relevant remote sensing techniques and the attributes estimated.

Continuous Sampling

This refers to the practice of collecting samples for, or directly measuring, variables 'on the go'. Collecting samples or direct data on the variable/s during a pass over the field produces a more fluent data set and obviously enhances the observation resolution. In the case of direct or 'real-time' data collection, there are no sample transport/storage concerns, no laboratory variation to contend with and no delay in accessing the results. Ultimately, the results would also be available in real-time so that farming operations dependent on analysis outcomes may be accomplished in the same pass of the field.

The development of such sensing technology in the area of crop yield measurement has progressed rapidly. The more complex chemical and physical attributes of soil and other crop quality parameters is proving more difficult.

Crop Yield Monitoring

The continuous measurement of crop yield has received much attention in the grain industry. Borgelt (1993) briefly summarises the various approaches under review at the time and a number have progressed to commercialisation (Figure 2-4). These sensors are all harvester mounted and measure the flow of clean grain at some point in the harvest process either directly by using flow impact force or volume, or indirectly through flow density observation using attenuation of signals in the gamma ray, visible, NIR, and radiowave regions of the electromagnetic spectrum.

Murphy et al. (1995) and Pierce et al. (1997) give a more detailed account of the operation of these commercialised sensors and it is apparent that these emerging technologies have driven the development of real-time yield monitoring. Constructing spatial yield maps from the data generated by these sensors requires that a calibration be determined for the conversion of signal to grain mass/volume and that a harvest area be assigned to the grain quantity at each measurement. Most systems discussed here assume a fixed crop cutting width (commensurate with comb width) or allow some manual adjustment during operation, and monitor ground speed for the purpose of area calculation. These matters will get brief discussion here but will be further considered in later Chapters.

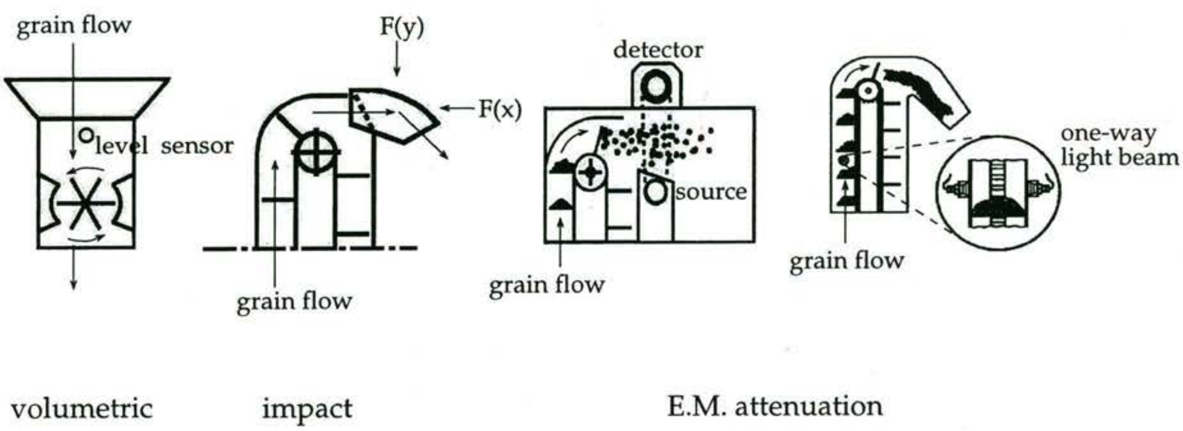


Figure 2-4. Diagrammatic representation of the commercial methods of grain yield monitoring.

In a pioneering study, Schueller and Bae (1987) monitored sorghum 'yield' using engine speed (rpm) as a surrogate for the harvested crop while attempting to hold ground speed and throttle control constant. Using a microwave ranging system to gather positioning information (with a maximum position error of 8m during mobile operation) they mapped average engine speed over 10m cells in the field. Peterson et al. (1989) noted that harvester engine speed would be difficult to utilise where slopes or surface roughness effected machine ground speed and decided that the most suitable location for yield estimation was in the clean grain flow. An isolated motor was installed to drive the grain-bin auger and the amperage used was correlated to yield flow rate during harvest ($R^2 = 0.96$). The Loran C positioning system was employed but produced highly inaccurate positioning of the header paths which made mapping the yield fruitless.

In a further progression of yield monitoring techniques Searcy et al. (1989) directly monitored grain flow volume by recording paddle wheel rotations required to meter out grain sorghum from the end of the bubble-up auger into the grain bin. Harvester position was determined using a microwave ranging system. Yield maps were constructed on mean yield within 6m square cells (determined by the cutting width) and cells were classified using ± set percentages of the yield as the categories.

Using dead reckoning to determine harvester position, Stafford et al. (1991) monitored the grain flow density at the exit of the clean-grain elevator by correlating the attenuation of gamma-ray radiation directed across the grain flow to grain yield. Assessment of the system accuracy was qualitative but positive. They also reported the development of a capacitance-based sensor for mounting at the exit of the bubble-up auger which operated at a maximum 2% error in yield determination during calibration checks. However, the capacitance sensor appears more sensitive to grain temperature and moisture fluctuations, and to the cross-sectional flow dimension in the delivery system.

Vansichen & De Baerdemaeker (1991) also used dead reckoning to establish harvester position but employed a direct mass flow sensor based on monitoring the change of momentum in the grain flow when obstructed by a curved plate. The plate is attached to a force transducer and the component of the recorded force attributable to mass flow rate can be calculated. This yield sensor had a quoted calibration check accuracy between -2.7% and +3.5%, but the authors believed that in operation an absolute maximum error of 6% should be assumed. Like all the mapping efforts discussed above a cell-based system was used, and in this instance the yields allocated within 10 m square blocks were averaged.

In 1992, Reitz & Kutzbach (as reported in Aunhammer et al. 1994) utilised a mass-balance approach using weighing scales to produce a discrete yield/time observation. In another approach, Klemme et al. (1992) used an ultrasonic level sensor mounted over the grain bin to measure the volume of grain in the bin every 12m. Positioning was determined by dead reckoning. The results displayed a maximum of 40% error in small volume measurements which decreased to 25% for larger volumes. This method encountered difficulties in the measurement of grain height due to machinery vibration and pitching, and irregular bin shape.

With the GPS network partially operational in December 1990, position determination of agricultural vehicles via this system began in 1991. Selective Availability (S/A) was initiated in December 1991 prior to constellation completion in December 1993. Schnug et al. (1993) reported one of the first uses of the GPS for harvester positioning during the 1991 European summer harvest. They operated with both the paddle-wheel volume yield sensor and with the gamma-ray sensor, and while not commenting on the accuracies or operational differences, quote a position error of less than 20m using the initial non-S/A version of the GPS. Stott et al. (1993) also used the paddle-wheel volume yield sensor and achieved an average error in the yield estimates of 1% and with DGPS attained a location accuracy of ± 2m.

Pringle et al. (1993) trialled another method for yield monitoring using a load cell mounted under an active section of the clean-grain transport system to determine grain weight as it was delivered to the grain bin. The yield estimates displayed a mean error of ± 2% and in DGPS mode, the position accuracy was also determined to be ± 2m. Such a method will obviously be susceptible to terrain influence and vibrational interference.

In an attempt to further evaluate the volume versus mass flow sensing systems, Auernhamer et al. (1994) compared a paddle-wheel sensor with the gamma detection system and also tested the DGPS as a positioning prospect. They reported a reduction in position error from 12-15m in 1991 prior to S/A to 2.5m in 1992 that they attributed to technology improvements and correction techniques (carrier phase correction determination). The mean accuracy of yield measurements with both sensors was less than 2%, but the volume based sensor was found to be susceptible to variation in grain density, the effect of which could be reduced with individual tank recalibration. The mass flow system proved far less sensitive to this problem.

More recent studies have enabled some evaluation of newer versions of these yield monitoring systems. Murphy et al. (1995) suggest that the volumetric measuring system can achieve ± 1% accuracy when calibrated and offer anecdotal evidence for an accuracy of < 2% for the light attenuation system. Hummel et al. (1995) reported a field accuracy of ~ 3% for the light attenuation system. Birrell et al. (1995) found less noise apparent in an impact-based as compared with a volumetric type system, possibly due to the more continuous sampling technique of the former system.

These quoted errors are all based on a mass balance monitored over a reasonably large area or grain tonnage. The accuracy over small areas or weights has received less scrutiny. Missotten et al. (1996) describe an overall error of 5% for the measurements from a curved plate impact sensor on 20m by 20m sampling grid, which decreased to 1.6% over a 6ha sampling area. Unlike the previous studies, they fitted an ultrasonic range detection system to the harvester comb to measure changes in crop width entering the harvester. When investigating the yield calculation process applied to whole field operations they still report errors from the cutting width sensor of 5% and 2.5% for the speed sensor. Their results infer that the system under evaluation is subject to a 12.5% error at the 20m by 20m mapping resolution.

Vansichen & De Baerdemaeker (1991) report a 7% error in the area calculation introduced by assuming a full cutting width when harvesting a 5 ha field as compared with the mean cutting width determined using an ultrasonic ranging system. The accuracy of the range estimation is quoted as 2% of the measured distance. Stafford et al. (1997) also evaluated two ultrasonic ranging systems and concluded that a broad beam and long range detection were desirable attributes. They estimate that the error in assuming a fixed width in the area calculation to be in the order of 10%. There appears to be a high probability that systems operating without such width sensors are subject to a yield calculation error greater than the 12.5% estimated by Missotten et al. (1996) at a 20m x 20m resolution.

This increase in error for the 'instantaneous ' measurements appears to be primarily due to errors associated with allocating a harvest area to the quantity of grain measured at the sensor and errors introduced by the grain flow dynamics within the harvester. Pierce et al. (1997) provide a comprehensive discussion of these errors and grain flow dynamics will be considered in more detail in Chapter 5. However, it is important to note that there have been novel attempts to negate some of these errors by relocating the grain measurement point closer to the harvester front.

Pang & Zoerb (1990) investigated the novel use of impact sensitive film installed below the separating sieves. A piezoelectric material (high polar Poly-Vinylidene Film (PVDF) which could register an approximate maximum of 2000 equally spaced impacts per second was assessed for the sensor. At a flow rate of 16.2 t/hr they calculated a piece of film 4x5cm would receive 575 impacts/sec. When installed under the sieve an average 4.5% error in yield determination for 5 short flow runs (max = 7.5%) was recorded. Problems in field operation resulted from variation in the location on the sieve where the main grain flow occurred due to fluctuating internal air speed and active separator width. Under optimum operating conditions the authors suggest grain should fall through the front section of the sieve. While these changing conditions make the system difficult to use for yield measurement, it may be useful in the future as a monitoring system for separator operation and guide adjustments for increasing harvester operation efficiency.

Klassen et al. (1994) trialled a capacitance sensor for crop feed rate that used one plate inserted into the cutting-table and the table auger as the other plate. The capacitance between the 'plates' was affected by the thickness of the crop matt on the table, the density of the crop matt and the moisture content. With compensation for moisture content variation, a reasonable linear relationship existed between feed rate and capacitance. Klassen et al. (1994) also measured the table auger drive shaft torque using a torque sensor and the linear displacement of the feeder-house conveyor using linear potentiometers and attempted to correlate observations with crop feed-rate . Both were found to be less linear than the capacitance method.

Feed-rate will always be difficult to convert to crop grain yield because a fixed relationship between dry matter and grain yield must be assumed. A straw mass sensor at the cutting-table or in the feeder house may however prove useful to cross check with data from a grain yield sensor and help explain why grain yield is varying (a ratio of the two would provide information on crop density).

Grain moisture may also be monitored in the grain flow to improve the estimation of grain mass at a single grain moisture content. Using the correlation between electrical properties of grain and moisture content, capacitance-type measurement systems are more common but alternatives such as microwave attenuation that requires no grain contact (Kraszewski & Nelson, 1991) have been examined.

While grain crop yield has received the most research, other crops have had yield measurement systems investigated or developed. Rawlins et al. (1995) used commercially available conveyor weighing technology to monitor the yield of potatoes during harvest with a reported accuracy of ~ 5%. Schneider et al. (1996) provide further detail on the operation of this commercialised system.

A similar conveyor weighing process has been employed to monitor sugarbeet yield (Walter et al., 1996). This technology could be applied to any other harvester that relies on a conveyor system for harvested crop transport e.g. grape harvesters. Boydell et al. (1996) used load cells beneath the basket of a peanut harvester to monitor crop yield by direct weighing. Cox et al. (1996) reported the preliminary development of a system for sugarcane yield mapping that utilises a correlation between monitored power required to drive the cane elevator and mass cane flow. An absolute error in calibration of 1.4% was recorded. Silage crop harvesting has also seen the use of power or torque surrogates for mass flow

(Vansichen & De Baerdemaker, 1993), and impact based flow sensors (Missotten et al., 1997). A load-cell instrumented trailer has been investigated for monitoring the increasing crop weight of non-combinable crops such as sugarbeets as they are loaded in the field (Wheeler et al, 1997). This simple system may also be applied to numerous other agricultural and horticultural crops.

The opportunity for use of Precision Agriculture within the high input/high output cotton industry has been mooted for some time (McBratney & Whelan, 1995) but has been restricted by the slow development of a lint yield sensor. A prototype sensor based on the principle of light transmission and absorption was developed by Wilkerson et al. (1994). The technique used a plane of light propagated orthogonally to the cotton flow and a light receptive array that responds to the light attenuation caused by the passage of cotton. The transmitter and sensor are mounted in the pneumatic conveyors and the output of the sensor correlates with the volumetric flow rate of cotton.

Installation of such a sensor is non-intrusive of the cotton flow but must be responsive to flow rates of 50m/sec in the chutes. In laboratory tests the regression of instrument response on cotton mass produced an R^2 of 93%. The prototype sensor was however sensitive to cotton feed-rate, with higher and faster mass flow reducing the accuracy. More recently Boydell et al. (1997) reported the assessment of a similar flow sensor and published a yield map. Schoenfisch (1997) also reported the development of a comparable system but offered only qualitative assessment.

Table 2-2 summarises the available yield monitoring techniques for combinable and non-combinable crops.

Soil Organic Matter

Correlation of soil OM with externally measurable soil attributes has focused on the reflectance properties of soil. Many early studies have been efficiently reviewed by Sudduth & Hummel (1991) suggesting that the visual to near infrared (NIR) range of the spectrum offered most promise. Shonk & Gaultney (1988) chose the red waveband (660nm) for the first reported real-time OM sensor. The sensor array comprises 6 x 660nm LED's and a photodetector mounted within a purpose-built tine. The base of the tine operates below the soil surface with the leading edge providing a level surface for the reflectance measurement. Such a system is in effect measuring the colour of the soil. Shonk et al. (1991) report a linear relationship for fine to medium textured soil in the 1%-6% OM range and a curvilinear relationship for more coarsely textured soil and field test results with regression R^2 ranging from 0.83 to 0.95. Because only one waveband is employed, the

	Yield measurement	
Crop type	Technique	Sensor location
Combinable crops	Mass flow by impact force	Clean-grain elevator exit
	Volume flow by light attenuation	Across clean-grain elevator
	Volume flow by mechanical metering	Grain-bin auger exit
	Mass flow by gamma attenuation	Clean-grain elevator exit
	Mass flow by radio freq. attenuation	Clean-grain elevator exit
	Mass flow by mechanical weighing	Cross-auger floor
Potatoes, Beets & Tubers	Mass flow by mechanical weighing	Active conveyor idler wheels
Cotton	Mass flow by light attenuation	Across basket delivery shute
Peanuts	Mass flow by mechanical weighing	Peanut basket
Grapes	Mass flow by mechanical weighing	Active conveyor idler wheels
	Mass flow by mechanical weighing	External weigh-wagon
Sugarcane	Mass flow by power requirement	Chopper drive
	Mass flow by power requirement	Elevator drive
Forage crops	Mass flow by impact force	Delivery spout
	Mass flow by mechanical weighing	External weigh-wagon
	Mass flow by power requirement	Chopper drive
Tomatoes & other horticultural	Mass flow by mechanical weighing	Active conveyor idler wheels
	Mass flow by mechanical weighing	External weigh-wagon

Table 2-2. Commercial or well researched crop yield monitoring systems - operational technique and sensor location.

system is deemed to be landscape-dependent (Sudduth et al., 1991) requiring calibration for changes in soil texture and moisture content. Shonk et al. (1991) also report reduced accuracy with low quantities of OM.

A more complex system utilising light in multiple narrow-band wavelengths (1630 - 2650nm in 52nm bandwidths) has been developed to prototype stage (Sudduth et al, 1991). The authors results suggest that the additional spectral information gained will ensure the sensor is landscape independent (insensitive to variation in soil moisture and texture). Although more costly and less robust, they believe it should provide a more versatile measurement tool.

For heavy textured, dark soil low in organic matter (e.g. Vertisols), the single wavelength instrument may be limited by the characteristic dark colour that is dominantly a function of ferromagnesian mineral contents. Krishnan et al. (1980) report that this reduction in effect on soil spectral properties may be expected below 2% OM. The multiple wavelength device may prove more suitable in these cases.

Soil Nitrogen

For soil nitrate sampling, a number of ion selective probes have been produced and involved in a limited release (Borgelt 1993). Continuing work is focusing on the use of Ion Selective Field Effect Transistors (ISFET) which use ion-selective sensors mounted on computer chips, in conjunction with specific membranes, to measure soil solution ion concentrations. Birrell & Hummel (1997) report successful analysis of nitrate samples within a 1.25s timeframe using flow injection analysis. The samples were manually extracted for the experiments and the authors concede that maintenance of constant flow parameters and precise injection times is important to maintain measurement accuracy. Development of a rapid, automated sampling and extraction system remains as the major limitation to the employment of these devices as real-time soil nutrient sensors.

The development of electrochemical nitrate measurements using a nitrate selective electrode in an electrochemical cell to monitor nitrate levels in a extraction obtained from an 'on-the-go' sample is also progressing. Adsett and Zoerb (1991) designed and tested a mechanised sampling and monitoring station that operated at a forward speed of 3 km/hr and sampled every 30 seconds. While the sampling operation, using a modified chainsaw bar, performed adequately, the inconsistency in nitrate extraction has proven a major limitation.

Soil nitrate measurement using electrical conductivity has been examined using a coulter-based implement (Borgelt, 1993) and is commercially available[¶]. The scientific basis for such an instrument appears fragile. Calibration of conductivity to soil nitrate concentrations would only be of use in a medium that was dominated by the nitrate ion (e.g. a sandy soil used for intensive production).

Other Soil Attributes

The ISFET sensing systems previously mentioned would appear suitable for all ionic nutrients, but there is no published literature on their development. Clearly, the eventual completion of a nitrate ISFET sampling and sensing system will lead to similar real-time sensors for a variety of soil nutrients. However, the ISFET technology is being employed in preliminary experiments for sensing soil pH in real-time. Viscarra Rossel & McBratney (1997) concluded that the ISFET provided the necessary ruggedness and speed of response for development as areal-time pH sensor and proved superior to more common electrode systems.

Electromagnetic induction (EM) instruments measure the apparent electrical conductivity of a material by generating electromagnetic fields and monitoring attenuation. Changes in the electromagnetic response are caused by variation in ionic concentration. In soil, the volumetric moisture content, quantity and identity of ions present and the texture effect the observed ionic concentration. EM instrumentation has been mobilised using towable PVC sleds suitable for pre-sowing use or dedicated all-season field vehicles to provide a contiguous assessment of salinity levels in the crop root zone (Henkes & Dietz, 1994; Rhoades, 1992). The technique has also been successfully employed to monitor variability in topsoil depth in claypan soil (Sudduth et al., 1995), soil moisture content in soil with low electrolyte concentration (Kachanoski et al., 1988) and soil clay content (Williams & Hoey, 1987). With these numerous influences on the EM field, it is important to be able to isolate the effect of the attribute of interest. Jaynes et al. (1996) discovered this complexity when unsuccessfully attempting to correlate basic EM readings with crop yield over 3 years.

The soil reflectance sensor, previously discussed as a means of determining organic matter content, may also prove useful in recognising gradual changes in soil type and texture that would be valuable in the accurate classification of field variation in crop yield potential. This technique, as with EM, appears particularly promising for use in areas where heavier textured, clay dominant soil intergrades with lighter textured, more sandy soil.

[¶] Soil Doctor ™- Crop Technology, Inc. USA

The continuous monitoring of soil moisture content may also offer a means of identifying areas susceptible to waterlogging and aid in the determination of soil textural variation. The requirements and development of a number of contact and non-contacting sensing techniques, including electrical resistance, microwave attenuation, capacitance probes, nuclear magnetic resonance (NMR), near-infrared reflectance, microwave reflectance and ground-penetrating radar (GPR) are examined by Whalley & Stafford (1992). The contact sensing techniques, with the inclusion of the Time Domain Reflectometry (TDR) measurement technique, appear most suitable for incorporation in a cultivation tine. Lui et al. (1996) report the continuous measurement of soil moisture content using a resonance frequency and phase lock technique to monitor changes in soil dielectric properties from a tine mounted sensor. GPR appears to offer the greatest depth of penetration of the non-contacting sensors.

GPR has also already been used 'on-the-go' to map textural discontinuities and thickness of soil horizons (Collins et al., 1986; Truman et al., 1988), depth to spodic and argillic horizons (Collins & Doolittle, 1987), depth to soil water tables (Truman et al., 1988) and improve the determination of soil map unit boundaries (Schellentrager et al., 1988). The GPR technique does appear to function best in soils with abrupt textural changes at horizon boundaries.

Liu et al., (1993) showed preliminary results of a novel acoustic method for determining soil texture in real-time. A tine mounted microphone measured acoustic emissions generated by the release of energy during the dynamic process of tillage. They showed promising differentiation of soil types based on texture but more work is required to determine which frequencies are best for delineating soil types.

Information on the variation in soil compaction may be obtained via a moisture calibrated correlation with soil strength. Alihamsyah and Humphries (1991) tested and recommended a shank-mounted, horizontally operating penetrometer with a 30° prismatic tip leading-edge to measure the mechanical impedance of the soil 'on-the-go'. This technique could be employed in conjunction with a moisture probe to quantify soil strength.

Young et al. (1986) modelled the instantaneous draft of tillage tools using time series analysis and found that the parameters relevant to soil analysis were the mean draft, residual draft and the auto regressive coefficients of the model. The mean draft equated to the average dynamic soil strength, changes in soil strength as the soil is tilled was evident in the residual draft, and the auto-regressive coefficients reflect the soil/tool interaction. Such analysis could be used to asses soil physical condition. They suggest using a trailling tool in the tilled soil following a cultivation gang to act as a transducer to measure the physical state of the soil. This method is reactionary rather than predictive and the soil condition agronomically suited to a variety of crops has not been accurately characterised.

Plough draft has also been monitored and correlated to clay content in an effort to map spatial variation in soil type (Van Bergeijk & Goense, 1996) and a soil texture/compaction index to be used in modifying liquid application rates (Lui et al., 1996).

Other Agronomic Attributes

Most other 'on the go' sensing has concentrated on weed mapping and management. The systems developed and studied have usually involved detection of living weeds in fallow fields using optical sensors (Felton et al., 1991) although Green et al. (1997) report the use of height selective spraying equipment employing infrared light beams to detect Texas panicum in peanuts. These are integrated detection and treatment systems and will be further discussed in a later section.

Alternatively, many grain yield monitoring systems allow manual operator flagging of weed patch positions observed from the harvester cabin during harvest. While this method is time efficient compared with traditional scouting, Colliver et al. (1996) show it may potentially overestimate weed infestations and is less spatially accurate than perimeter patch scouting with a GPS prior to harvest. Stafford et al. (1996) also report only a general agreement between the two methods as increasing subjectivity and required recognition speed appear to be affecting the accuracy of the cabin-based system.

Measurement of plant spacing to infer plant population density has been investigated by Plattner & Hummel (1996) using a photoelectric emitter and receiver pair to measure the in-row distance between corn plants. An estimate of plant population density at harvest time would be very useful for the subsequent process of determining the cause of crop yield variation detected by yield monitoring.

Plant tissue nitrogen status has also been monitored using tractor mounted continuous remote sensors. Wollring & Reusch (1997) report success in monitoring experimental variations of 50 kg N/ha in applied N fertiliser at 2 weeks post application using measurements in the red and infrared wavelengths. The system showed significant variability in N nutrition status in fields supposedly uniformly fertilised. The authors believe that this continuous monitoring can be used to direct differential split fertiliser applications

Soil Attribute	Measurement technique
Texture	Visible and NIR reflectance
	Electromagnetic induction (EMI)
	Ground penetrating radar (GPR)
	Acoustic sensors
	Tillage draft
Moisture	Electromagnetic induction (EMI)
	Ground penetrating radar (GPR)
	Electrical resistance
	Electrical capacitance
	Time-domain reflectivity (TDR)
	NIR reflectance
	Nuclear magnetic resonance (NMR)
Organic matter	Visible and NIR reflectance
Nitrogen	Ion selective electrode
	Ion selective field effect transistor (ISFET)
	Electrical conductivity
pH	Ion selective electrode
	Ion selective field effect transistor (ISFET)
Salinity	Electromagnetic induction (EMI)
Compaction	Penetrometer
Topsoil depth	Electromagnetic induction (EMI)
	Ground penetrating radar (GPR)
Horizon boundaries/ claypans	Electromagnetic induction (EMI)
	Ground penetrating radar (GPR)

Table 2-3. Options for continuous sensing of soil attribute variation.

2.3 MANAGEMENT OPTIONS FOR SITE-SPECIFIC MANAGEMENT

In implementing this type of management, rate-based operations that influence crop yield can be targeted to achieve desired yield goals with the minimum input of resources. Such governing operations occur at nearly all phases of the crop growth cycle. Schueller (1992) describes the array of variable-rate control designs available or proposed at the time, ranging from simple control of flow rate to more complex management of rate, chemical mix and application pattern. The author emphasises that the control segment of any variable rate application should optimise both the economic and environmental product of the field and must ensure that estimates of operational accuracy and dynamics are included in the application process. This is an important point, as incorrect spatial application may be economically and environmentally detrimental.

In all the operations that will be discussed here, the control commands may be instigated by combining input data with the real-time use of a response algorithm or a by accessing a two-dimensional array of set points which in effect is a raster display of application rates and positions (Schueller, 1992). For the majority of cropping industries the important areas of managerial intervention would include:

2.3.1 Soil Tillage

Generally, the current tillage systems in use attempt to apply a uniform treatment to the soil at a site irrespective of the spatial variation in soil tilth/structural condition that may occur. Tillage operations modify the soil propensity for plant growth and erosion by imparting compaction/disintegration forces on the soil while endeavouring to achieve a desired level of soil disturbance or crop residue/ameliorant incorporation. Readers are referred to Voorhees (1991) for a review of the criteria for assessing the impact, and economics of, ameliorating soil compaction using tillage.

In general, variation in soil texture, structure and strength within a field may combine to produce significant spatial variability in the tillage required to achieve a suitable or optimum result. Soil moisture content and soil texture at the time of an operation also influence the effect of a tillage implement (Allmaras et al., 1967). Schafer et al. (1985) discuss the concept of 'prescription tillage' as involving the combination of soil characteristics, the interaction of soil/machine operations and the eventual crop requirements into a suitable tillage operation.

Therefore, prescribed tillage or differential tillage operations for a specific crop may be achieved by controlling the type of tillage implement and the depth of operation. The type of implement employed and depth of operation will directly influence the resulting surface roughness, porosity and degree of organic matter incorporation (Voorhees et al., 1993). They report that incorporation increases as tillage is changed from chiselling to disking to mouldboard ploughing.

The potential impact of this concept on soil structural change is shown in a study by Cassel et al. (1988). Their experiments reveal appreciably different interpolated yield patterns between disked, chiselled, subsoiled and bedded treatments in a field with a tillage clay pan. In this example the chisel treatment provided the highest mean yield and the most uniform influence as assessed by a low semivariogram variance and almost random model. The authors hypothesise that the chisel treatment resulted in the most unifom soil mechanical impedance within the field thereby giving better access for plants to subsoil moisture. It does appear that the chisel treatment homogenised the field in terms of mechanical impedance as evidenced by the random nature of the variogram model. The bedding and sub soiling treatments retained a spatial structure in the yield data which aside from greater heterogeneity, may also be reflecting variability in the quantity of organic matter incorporated. A degree of heterogeneity in soil physical parameters and greater organic matter incorporation may be more economically and ecologically beneficial than homogenisation in some fields in the long term.

For a differential tillage operation, both the original and desired soil condition should be quantified on the same scale, e.g. soil strength and ductility by mechanical impedance (Chandler & Stafford, 1987). The most suitable tillage implement and operational depth to achieve this goal could then be chosen based on the moisture content and texture of the soil.

A sensor such as a shank-mounted cone penetrometer (Alihamsyah & Humphries (1991) or draught transducer (Young et al., 1986) mounted in front of an implement could monitor the initial soil condition while the resulting condition of the tilled soil is gauged by a similar trailling sensor. Chandler & Stafford (1987) and Stafford & Ambler (1990) have proposed image analysis techniques to monitor clod or aggregate size distribution as an alternate method of monitoring tillage results. The information obtained from such sensors could be used in a control loop to vary implement action.

A hydraulically controlled tool frame supporting a variety of implements with real-time engaging and depth control could perform the desired tillage operation. Voorhees et al. (1993) suggest including a front disk gang for residue incorporation backed up by a chisel gang for deeper or more vertical disturbance. Roytburg & Chaplin (1995) have proposed a stochastic random-walk model based on soil resistance force to predict tillage outcome from the initial soil condition. This would enable real-time decisions to be made regarding implement and/or operating depth required for the desired final soil condition.

Such systems are now being developed. Scarlett et al. (1997) have successfully employed ultrasonic depth sensors to control and vary the operation depth of a power harrow and also trialled the ultrasonic sensors to measure surface roughness in real-time as a guide to resultant seed bed quality. They report a good regression response when comparing the sensor to sieve analysis under laboratory conditions ($R^2 = 0.92$) and found that the sensor underestimated aggregate size in the field. The authors suggest this may be due to a fine aggregate surface artifact created by the powerharrow. Further research with less destructive implements may prove more successful.

2.3.2 Fertiliser Application (both in quantity and mix)

The application of fertilisers to provide sufficient nutrients to maximise crop growth and yield is broadly viewed as essential in intensive cropping systems. Since the seminal response studies of von Leibig (1847) and subsequent modelling by Mitscherlich (1913), numerous fertility trials have quantified the yield response to application of the various macro and micro nutrients (applied in isolation and with interactions) for the majority of economically significant crops (see Cooke, 1982). This response to individual nutrient addition has continued to be modelled with varying success using exponential, quadratic, square root or paired linear functions in their full, modified or inverse forms (e.g. Bock & Sikora, 1990; Boyd et al., 1976; Danke & Olson, 1990). Determination of the most suitable model seems reliant on the initial soil nutrient conditions, the boundary nutrient levels (fertiliser levels applied) and climatic and landscape parameters (Cooke, 1982). Many authors have also explored the role of nutrient interactions through response surface analysis (e.g. Colwell, 1978; Dillon & Anderson, 1990).

However, given this acknowledgement of the complexity of nutrient dynamics in the field, and the difficulty in assessing the optimum response model, it remains a common practice to use regional average nutrient–yield relationships in conjunction with soil analysis (e.g. Peck & Soltanpour, 1990; Daniells & Larsen, 1991) or crop leaf testing (e.g. Baethgen & Alley 1989; Roth et al., 1989; Scharf et al., 1993), to construct singular fertiliser rate and formulation regimes for whole fields.

While the ability and/or legitimacy of available techniques for delineating soil nutrient management units at the within-field scale remains to be comprehensively tested, the ability to control the composition and rates of chemical application in real-time has significantly progressed. Scheuller & Wang (1994) discuss the requirements and available variable-rate technology (VRT) for the purpose of co-ordinating of this task. Differential fertiliser application usually combines some or all of the following technologies: dGPS, GIS, automated map reading and controlling electronics, fertiliser mixing and precision application apparatus. These components are commercially available individually from a number of manufacturers allowing VRT systems to be constructed and customised by individual operators to suit standard dry or liquid applicators.

As an example, Robert et al. (1991) reported the development and evaluation of a variable rate anhydrous ammonia application system utilising common farm implements. A predetermined application map (based on discrete soil sampling and subsequent yield goal determination) was used to direct the quantity of fertiliser applied. The map was loaded and read through a cab-mounted lap-top computer which is connected to a ground speed monitor, a flow rate indicator and a rate control valve. Gaseous anhydrous ammonia is converted to the liquid phase in an expansion chamber and then applied through the applicator knives at rates varying between 60kg N/ha – 260kg N/ha.

Further, Macy (1993) successfully developed a automated spatially variable system for dry and liquid fertiliser application using in-house controlling software and rate prescriptions based on soil test results, yield goal estimation and expert (farmer) recommendations. A multiple channel master controller is used to broadcast target rates to additional slave controllers governing the product flow rates in conventional fertiliser applicators. Having a component based system allows the master controller to be used in the control of other rate-driven machine operations such as sowing, pesticide application, and lime spreading. Incorporating automatic rate adjustment removes the need for cabin operators to monitor and change rates, allowing equipment performance to be more closely observed.

At the other end of the scale, dedicated vehicles for the spatially variable application of either dry or liquid fertilisers have been designed and marketed by a number of enterprises, principally in the USA. Ag-Chem®[†] has employed flotation-tyred vehicles with individually controlled nutrient bins allowing a variable dry chemical mix to be applied in variable quantities. The initial technology was developed for fertiliser spreaders and basically operated as a real-time custom blending and spreading vehicle (Luellen, 1985). The technology has been refined to a four bin plus pesticide impregnation system for pneumatic delivery of variable mixes and rates (Schueller & Wang, 1994). For liquid application, two autonomously metred tanks using separate flow and nozzle systems are

[†] Ag-Chem Equipment Co., Inc. *Minnetonka, Minnesota, USA.*

combined in a single boom array that enables up to 7 different rates for each flow system (Schueller & Wang, 1994).

For each of these systems a predetermined fertiliser requirement map is constructed from soil sampling results and yield goal estimates to control the rate of application. On-board computer software determines the vehicle position and reads fertiliser requirements from a screen-based field map comprising colour coded polygons representing differential fertilisation zones. Chemical mix and application rates are calculated as a function of DGPS determined vehicle position in the field and fed via a central controller to slave valves or pump actuators.

Tyler®[§] have also marketed a computerised, self-propelled fertiliser applicator with VRT capability that utilises the OM sensor developed by Shonk & Gaultney (1988) to determine the level of soil OM preceding the applicator and, via on-board calibration and decision software, then calculates the fertiliser application rate required. The correct amount is subsequently applied as the rear mounted applicator bar passes over the designated observation point. This system has been commercialised and employed in herbicide and fertiliser application operations (McGrath et al., 1990; Alsip & Ellingson, 1991) but appears to be under re-evaluation at present due to limitations of the sensor discussed in Section 2.2.2.

Any VRT system, whether component-based or dedicated applicator vehicle, must maintain accuracy in controlling the application rates. Weber et al. (1993) after a substantial test of standard anhydrous ammonia applicator accuracy report that 59% of controllers and 27% of regulators performed within acceptable application rates. The most significant influences on accuracy appeared to be variation in implement speed information and incorrect initial setup. Uneven application of fertiliser may greatly increase the probability of reducing the mean yield through under- and over- fertilisation (Lutz et al., 1975; Dilz & van Brakel, 1985) however, the impact of inaccurate fertiliser spreading appears to be predominately random. Van Miervenne et al. (1990) found no spatial dependence in soil N within a 1ha area studied on a 2.5m sample separation after supposed uniform fertiliser application. The results did suggest some periodicity across the direction of machine pass corresponding to machinery overlap which was implicated in a loss of 71kg/ha in yield compared to application of the correct amount. This is not significant when compared to the total yield of 7.5 tonne (~ 1%) but may be of greater significance in the lower Australian wheat yields (~4%).

[§] Tyler, *Benson, Minnesota, USA.*

Ensuring application accuracy is therefore imperative for VRT management. Persson & Moller (1997) provide an evaluation of fertiliser spreader accuracy using computer controlled actuators. The systems were considered to operate accurately with regard to the desired outputs being dispensed at varying speeds, with different spreading widths and with varying rates. However, the authors suggest that even though the expected quantity of fertiliser is released, the distribution may be poor as the spreading pattern is often influenced by the flow rate.

Olieslagers et al. (1997) have attempted to stabilise the spreading pattern when flow rates are changed by developing flow calibrations based on varying the disc height from the ground and from the drop point of the spreader hopper above the discs. This produces a fertiliser application pattern with a CV less than 11%. To ensure accurate flow rates are delivered to the hopper drop point, Van Bergeijk et al. (1997) have implemented a dynamic weighing system that allows real-time re-calibration of spreader fertiliser flow rates to match desired rates. They believe the hygroscopic qualities of dry fertilisers may mean the flow calibration changes with time and are able to maintain a calibration accuracy of 1% mass between desired and actual rates. These advances should increase the accuracy of variable -rate spreader programs.

A further impediment to application accuracy in all systems is the response dynamics of controllers and regulators to commands changing the required fertiliser level. Schueller (1992) and Schueller & Wang (1994) discuss this 'feed-forward' problem and the solutions devised to model and compensate for the effects on application quantities at the boundaries between rate changes. Indicative of the degree of this effect, Cahn and Hummel (1995) using a modified a anhydrous applicator for variable rate N sidedressing of corn, found a 2 second response lag between control signal and actual rate change with a 5% application error at the boundary caused by the response of the control valve in this transient phase.

While these mechanical controls for variable rate application continue to be refined, it may be just as important to consider varying fertiliser placement depth and/or plant relative position. Eghball et al. (1990) note that P applied in bands may move very slowly through the soil and influence the variability of soil P within a field. The banded P may also remain available for many years. It may also be feasible to control the temporal application of fertilisers by varying blends of slow or controlled release fertilisers with different activation properties for different soil conditions or different plant developmental stages. A step in this direction has been achieved by Shoji et al. (1996) whereby a granulated urea formula coated in a resin with defined water absorption properties controlled by temperature (Meister N) is used to manage the temporal supply of N fertiliser.

2.3.3 Nitrification Inhibitor

The loss of applied nitrogen through the gaseous products of the denitrification process is a limiting factor in the efficient utilisation of artificial N fertilisers. Greater rates of denitrification are likely to occur in wetter regions of dryland fields (i.e. hollows and lower slopes) and closer to the head ditch in flood irrigated fields. In a simple study applying uniform nitrification inhibitor and N fertiliser down a toposequence Malzer et al. (1995) found only a weak correlation between corn yield at a landscape position and soil N levels. However, the yield at the lower elevation appeared to benefit most from the nitrification inhibitor as would be expected

In irrigated cotton, Freney et al. (1992) reported a 57% recovery rate for ^{15}N labelled fertiliser applied one month prior to sowing in the absence of nitrification inhibitors. Significant increases in the recovery rate were achieved using the nitrification inhibitors N-Serve (74% recovery) and wax-coated calcium carbide (78% recovery). For a mean field application of 190kg N/ha the inhibitors allow access by the crop to approximately 33 kg/ha – 40 kg/ha more N. The results also indicated a greater increase in the recovery rate (92%) could be achieved using 2-ethynylpyridine, however the cost for commercial field use appeared prohibitive. Identifying the spatial variation in denitrification potential at a site may allow differential application of these inhibitors and reduce the cost of treatment.

A combination of moisture monitoring in conjunction with soil textural or OM measurement could provide the required data on zones in a field more susceptible to denitrification. The variable rate application technology developed for fertiliser application would require only minor adaptions to control a differential treatment with nitrification inhibitor.

2.3.4 Gypsum/Lime Application

The dispersion of clay and the decline in soil structure associated with sodic and highly sodic soil may be alleviated through the application of calcium in the form of gypsum ($CaSO_4$) or lime ($CaCO_3$). Sodic soil is identified as containing sodium concentrations that contribute >6% to the total cation exchange capacity. The addition of calcium acts to flocculate dispersed clay by increasing the total content of soluble salts in the soil solution and helps maintain aggregation by replacing sodium ions on the clay surfaces.

The application of $CaCO_3$ is also widely used to increase the soil solution pH in acidic soils (generally pH <6) by reacting with and removing H^+ ions in the form of water. The importance of soil pH on crop production has been discussed in section 1.3.6.

Mapping the spatial variability in soil lime requirements or regions of a field that exceed the 6% Na threshold would provide information for the differential application of the appropriate calcium-based product. Evans et al. (1997) calculated the spatial lime requirement for 2 fields with spatially variable pH and OM and concluded that uniform application may leave up to 58% of a field incorrectly treated. Lime and gypsum are traditional applied using the same broadcasting mechanism as a fertiliser spreader. Control of the spreader is exactly as discussed in Section 2.4.2 and even though the spreading operations may lack the accuracy of pneumatic delivery systems, the large range indicated by Evans et al. (1997) should enable substantial management units to treated uniformly.

A liquid application system described by Anderson & Hendrick (1983) used a modified sub-soiling tine and slurry feeding mechanism to inject a lime mixture into the soil. This operation could be quite accurately rate-controlled and has the benefit of simultaneously performing multiple tasks. As the price of lime increases such operations may become more widely accepted.

2.3.5 Seeding Rates

Matching the rate of sowing to a predetermined yield potential also offers an opportunity to apply site-specific management. All soil types do not possess an identical ability to germinate and support a given plant population to reach its full potential. It is also arguable that areas considered to be of uniform yield potential will achieve their potential given a range of emergence rates. Ellis (1997) highlights this adaptability of crop plants by modelling the effect on yield of spatial variation in emergence using yield/plant population density equations. The results show a negligible direct effect on yield and sowing rates. The conclusion appears to be that varying sowing rates to achieve an even population in a field that displays variable emergence characteristics may be unnecessary (and not cost effective). However, varying sowing rates between areas of different yield potential may offer some agronomic advantages.

Control of seeding rates may be achieved by replacing the ground drives on conventional seeders with speed independent, rate-variable motors. Neuhaus & Searcy (1993) controlled the seeding density from flat-plate planter boxes using a hydraulic motor with an electric solenoid and controller. Under field conditions they managed to get seed spacing to within $\pm$ 5% of desired set points at speeds up to 7 km/hr. Using an electric motor and actuator on a conventional seed drill, Bahri et al. (1996) found under experimental conditions that incremental changes of 10kg seed/ha were less easily controlled than 20 kg seed/ha and took longer to reach a steady flow rate following the step. Importantly, the results from a comparison of 6 different sowing implements showed that in the direction of operation, the CV at a rate of 80kg seed/ha was between 10% and 20%. This would explain the greater control with larger increments and suggests that attempting to control small incremental changes in seeding rates (< 15 kg seed/ha) may be fruitless.

Other aspects of sowing may also be targeted for variable control. Carter & Chesson (1993) discuss varying depth of seed placement according to optimum soil moisture conditions. The method requires electrical conductivity sensors calibrated to moisture content and a model of the relationship between soil moisture and depth. As sowing progresses, moisture readings deemed to be outside desired limits trigger actuators that raise or lower the implement gang. This is an effective method of ensuring optimum germination conditions given the degree of variability in within-field soil moisture conditions documented in Section 1.3.4.

The opportunity could be taken to optimise the seed row spacing for different soil types or yield potentials. As a beginning, Solie et al. (1991) have calculated the optimum row spacing for maximising wheat yield based on Oklahoma State sowing rates. In any case, accurately recording the sowing rates and spacing that occur during the planting operation would appear relatively simple and useful. Using a modified planter monitor (Saraiva et al., 1997) recorded seeding rates and speed which were linked with GPS determined position to produce seed population maps. These maps may be invaluable in the processes of determining causal effects of yield variation observed in crop yield maps.

2.3.6 Crop Variety

Little research or discussion is recorded in the literature on variation in crop variety within fields. For most crop species, varietal characteristics could be used to advantage in fields where significant soil type/textural change or variation in the degree of compaction may be identified. As an example, the more waterlogging tolerant cotton variety Siokra L22 may be considered for heavier textured or compacted areas and the less well adapted Siokra 1–4 planted on lighter textured, non-compacted zones, to optimise the quantity of lint from a field.

At present, varietal combinations may raise apprehensions over possible non-synchronisation of maturity dates, mixture of quality attributes and variation in harvesting characteristics. Certainly such concerns would seem to restrict this option to reasonably large management units so that harvest operations could be successfully segregated if necessary. As restrictions are imposed on other aspects of crop management these concerns may reduce in importance.

2.3.7 Pesticide Application

In general, the traditional 'timetable treatment' regime for preventative crop pest management has been replaced, where practicable, by an economic threshold trigger. However, this economic threshold is routinely based on an assumption of homogenous distribution of pest infestation. This may be reasonable for very mobile insect pests and mobile insect life-cycle stages where population dynamics are often greatly influenced by environmental factors on a larger scale than those considered here (Crossley et al., 1984), but may be inappropriate for more sedentary insect pests and life-cycle stages as discussed in Section 1.4.

In principle, site-specific crop management could be applied to the control of insect pests. Aerial photographic and ground-truthing techniques may be applied to detect crop stress or damage inflicted by initial insect infestations (e.g. Everitt et al., 1994). Mapping these areas within a field may be useful in identifying zones suitable for initial treatment to prevent further spread or for directing the differential application of insecticide over the entire field. In this second case, the whole field may receive a minimum application rate with higher rates being applied to the outbreak zones.

Weisz et al. (1995b) used crop scouting of potato beetle within potato fields to establish a suitable sample support size (20 plants per sample) for successfully estimating the spatial structure of pest variability. Maps of the field colonisation, when compared with threshold values, showed significant areas of the fields would require no treatment even though the field mean exceeded the critical value. The authors contend that differential treatment would reduce the chemical load on the environment, decrease pressure on resistance selection and offer possible economic benefits. In a further study, Weisz et al. (1996) compared uniform pesticide treatment with differential application and found that over two seasons a cumulative pesticide saving of between 30% and 40% was achievable across a broad range of colonisation pressures. As pest pressures begin to overwhelm a field the saving would be negated and the results should be considered as species specific, but they suggest that differential management of insect pests is viable.

The assumption of homogenous population distribution would definitely appear unsupportable in weed management programs given the clustered spatial distribution highlighted in Section 1.4. And, if agricultural industries move towards more controlled traffic/reduced tillage systems, the spread of weed propagules is likely to be further reduced. This may result in even more stationary individual weed populations and a more clustered overall weed pattern in a field. Greater clustering implies an increase in weed-free areas. A more irregular pattern also presents the opportunity for differential treatment as opposed to blanket field applications of herbicide.

Inappropriately assuming a uniform pest population distribution may then result in whole-field applications of pesticides that are overestimated or unwarranted. Conversely, portions of the crop where colonisation is high may be inadequately protected using 'mean of field' applications.

Two approaches to spatial identification and treatment of weeds have been considered. Firstly, areas in a field that display a level of infestation that required treatment during a growing season could be precisely mapped. The map may then be used to direct the site-specific application of a residual/contact herbicide prior to the next season planting. Stafford and Miller (1993) have reported the development of such a system for winter cereal cropping, in which they propose applying a greatly reduced herbicide rate over the entire field and raising concentrations at previously identified weed locations.

An even greater reduction in spray area is promoted in the system described by Paice et al. (1995) whereby patch spraying of infested areas only is advocated. Paice et al. (1996) succinctly review the control requirements for such systems and conclude that the direct injection process offers the greatest benefits in economic and environmental terms. Qui et al. (1994), modelling the use of such continuously variable direct injection control equipment, reported a saving of up to 50% in herbicide application for the site-specific treatment of weeds in corn based on previously mapped weed density and soil OM. The authors bravely hypothesise that this treatment should also increase crop yield as the method will provide optimum weed destruction.

However, as indicated by Rew et al. (1997), these patch spray operations require the addition of a buffer zone to the identified patch area to account for position location errors, application activation delays and propagule spread by tillage. The authors concluding that a 4m buffer zone is optimum for the conditions under study.

Obviously the areal and quantitative reduction in herbicide usage from either of these systems would be controlled by the patchiness of the weed distribution and the application risk incorporated in buffer zone size or whole-field base rate. Rew et al. (1996) studied five fields with varying weed distribution and showed quantitative herbicide savings of between 9% and 23% for a blanket low rate with double blanket-rate patch spraying scenario and a 12% to 97% herbicide reduction for selective patch spraying only, when compared with mean uniform whole-field applications.

It may be necessary to study the effect of these two strategies over time to determine the most effective option. Paice & Day (1997) have attempted such a study using a 10 year stochastic simulation based on chemical cost and yield loss assessment in relation to initial weed distribution and spatial resolution of a sprayer. The results suggest that for the control of grass weeds in cereal crops, the low base dose with higher patch application is more cost effective. The fully spatially selective option apparently leads to increasing instability in the weed population over time and therefore significant increases in annual chemical costs and yield losses. Obviously the benefit is shown to be greater in population distributions that are less discrete. The simulation also illuminated the possibility that at courser sprayer resolutions (6m x 6m instead of 4m x4m) the costs over time for patch-only spraying may be significantly greater than uniform mean application.

Regardless of application philosophy, the technology to control variable rates is quite accurate. Stafford & Miller (1996) showed that at steady-state operation a direct injection system can provide delivered doses to within 5 % of the desired level at speeds between 1 and 3.5 m/s and flow rates of 0.75 to 5.01 litres/ha. The largest step change attempted (from 0 litres/ha to full operation) produced a 40% deviation in desired concentration for only 0.3 seconds. This equates to a 1m zone of misapplication at 3.5 m/s.

The second approach involves the employment of real-time weed recognition systems during treatment operations. Detectspray®‡, originally developed in Australia to commercial prototype by Felton et al. (1991), uses ambient light reflectance to identify green weeds in a fallow or stubble covered field. The detection activates the spraying mechanism so that only areas of weed infestation are treated. Biller et al. (1997) modified the operation of the Detectspray® to reduce calibration complexity and errors introduced by speed changes. They report herbicide savings between 30-70% with 100% kill. This type of system has an obvious use replacing fallow weed control by tillage and with total weed kill may prove superior to the temporally separated mapping and application methods.

More difficult to achieve is real-time detection of weed species in a photosynthesising crop. Brown et al. (1994) utilised aerial still-video camera images captured using four discrete spectral windows to discriminate between seven weed species in a corn field based on their individual spectral signatures. The process remains untested for efficacy from a ground-based platform and is therefore limited as a real-time treatment system.

‡ Detectspray International Pty Ltd, *Albury, NSW, Australia.*

More successfully, Green et al. (1997) used height-selective spraying equipment employing infrared light beams to detect and treat *Texas panicum* in peanuts. An 86% reduction in herbicide (with > 80% weed control) was reported. The height-selective sprayer was also shown to locate 21% more Florida beggarweed in a peanut field as compared with visual scouting maps. Long et al. (1997) employed a similar light beam system to selectively spot spray topped tobacco plants with sucker controlling chemicals and demonstrated a reduction in chemical application of 50%, having effectively removed wind drift and wasteful soil application. This technique could be applied to other row crops with discrete plant spacing and operates at 4-7 km/hr.

At the furthest realm of real-time control, Hague et al. (1997) have demonstrated the use of an autonomous vehicle guided through row crops by a vision system that can discriminate between crop and weed plant using image analysis. The vehicle operates at speeds of 1m/s (3.6km/hr) and allows individual plant treatment, be it weed or crop, with pesticides or fertiliser. Deployed in early crop growth stages the authors suggest that 90% of blanket chemical application may be saved by such accurate targeting.

The temporally separated mapping and treatment operations require some prior knowledge of the distribution of weeds or pests, unlike the real-time sensing and treatment techniques. For most insect pests, the real-time option is not a viable alternative. For weed infestations Stafford & Miller (1996) believe that temporally separated mapping allows for more complete chemical type and rate decisions based on knowing the whole field infestation. They also cite technically easier weed detection, greater flexibility in the timing of detection and spray operations, an ability to spray pre-emergent herbicides based on previous maps and the opportunity to discern the magnitude of error in the maps prior to treatment as positive attributes of the system.

The best option appears to rest on the efficacy of kill and the optimum time for treatment of particular weeds. Location errors in the temporally separated methods must be accounted for by low dose base-level spraying over the whole field. At present real-time sensors may only be used early in the growing season or with tall weed species.

2.3.8 Application of Irrigation Water

Variable-rate application of irrigation water to broadacre crops remains in its infancy. Much irrigation is based on a flood system mainly due to the relatively low cost of water compared with the higher costs of alternative irrigation systems. Undoubtedly this contributes to some gaseous and percolatory loss of chemicals from areas of a field that receives extended saturation periods. Field textural and structural variation may already be contributing to variation in infiltration and introducing significant error into the present prescriptions for the optimal use of irrigation water (Feinerman & Bresler, 1985). Textural differences could possibly be considered as an external control of variable-rate irrigation if the spatial variation in soil texture was known. Research in the immediate future may focus on textural monitoring and more frequent but smaller water applications to ensure more control of soil water movement.

Simulations by Warrick & Gardner (1983) suggest that variability in irrigation application may be just as influential on crop yield as variability in moisture-related soil physical attributes. The investigation of superior methods of application control may soon appear warranted on the basis of financial, social and environmental considerations.

Drip irrigation management poses particular problems with annual cultivation and flow control but could offer solutions to high value crops such as cotton in the future. More promising is the use of automated travelling sprinkler systems. King et al. (1995) developed a prototype control system to apply site-specific quantities of water from continuous moving irrigation systems. In field trials they succeeded in attaining water and chemical application uniformity similar to a conventional sprinkler system. The design was considerably more expensive owing to the use of 2 or 3 sprinklers at each delivery point to attain variable flow rates.

The system was fitted it to commercial centre-pivot by King et al. (1996) and successfully applied step-wise variable amounts of N with equivalent or greater accuracy than conventional uniform applicators, achieving the targeted amounts of N with little error. Evans et al. (1996) achieved similar success using a command system for cycling sprinklers within each zone of a moving irrigation system, and noted that the greatest difficulty remains in determining sensible application prescriptions.

The principle appears to be robust and achievable. Operation in windy conditions would reduce the accuracy of these systems and only some chemicals are registered for use with sprinklers. The future development of variable-rate sprinklers will drastically reduce the cost and technical complexity of these systems.

Table 2-4 is provided as a summary of the possible points for differential management intervention and the tools currently available or designed for the operations.

	Diierential action	
Management practice	Aspect	Technology
Tillage	Implement type and depth	Ultrasonic range finders.
		Draught transducers.
		Cone penetrometers.
	Surface condition	Image analysis.
		Ultrasonic range finders.
		Draught transducers.
Fertiliser application	Spreading	Master controlled metering device and variable disc height.
	Pneumatic (variable rate and mix)	Master controller governing individual bin slave controllers.
	Anhydrous ammonia	Flow controller governing actuators.
	Liquid manure	Separate flow controller for twin tank/boom system.
Gypsum/lime application	Spreading	Master controlled metering device and variable disc height.
	Slurry injection	Flow controller governing actuators.
Sowing	Seed quantity	Speed independent electric or hydraulic master controller.
	Depth	Sensor feedback loop governs actuators for depth control.
Pesticides	Insecticide application	Map guided patch spraying.
	Herbicide application	Map guided patch spraying.
		Master control of direct injection.
		Photoelectric real-time detection and spot treatment.
		Infrared height selection and spot treatment.
		Real-time image analysis vision detection and spot spraying.
Irrigation	Travelling sprinkler	Master controlled zones with autonomous nozzle arrays

Table 2-4. Management options for differential treatment and the available technology.

2.4 MANAGEMENT DECISIONS BASED ON OBSERVED SPATIAL VARIABILITY

The preceding sections outline the techniques and extent to which data on spatial variability may be gathered and the presently available options for differential treatment. The critical link between these two operations is the agronomic rationale or decision on which to base spatially variable treatments. This is potentially 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. Figure 2-5 provides a skeletal example of the decision process that could be employed following a study of field variability. This model begins with the premise that variability in crop yield is the initial signal that uniform application of ameliorants is a possibly inefficient use of resources. Another model may begin with the observation of soil variability. However, until the environmental cost of fertiliser wastage is imposed as a grower penalty in Australia, the economic imperative of optimising crop yield will no doubt guide management decisions.

In this model, differential treatment is then examined as an option based on the degree of variation, the cause/s of variation and their suitability for management intervention. Continuously variable treatment or division of a field into management sub-units is determined based on the spatial dependency observed. Again, this decision marks the point of a conceptual schism. If variability and treatment can be observed and controlled at a fine scale, should fields be treated as continuously variable in yield potential or can some classification into management units of 'homogeneous' yield potential be accepted? If the later is chosen, should these units be treated with uniform rates of ameliorants if the controlling factor for application was not used to define the management unit? The answers to such questions are most likely complex and, I believe, as yet unknown. Options at this point in the model are more than likely governed by limiting factors such as technology, economics and lack of research.

Finally, some form of predictive model must be employed to enable a scientific and agronomically sensible examination of the implications of differential as opposed to uniform treatment, and the interpretation of the results in the form of a spatial management plan. Research relevant to this realm of site-specific management will be examined.

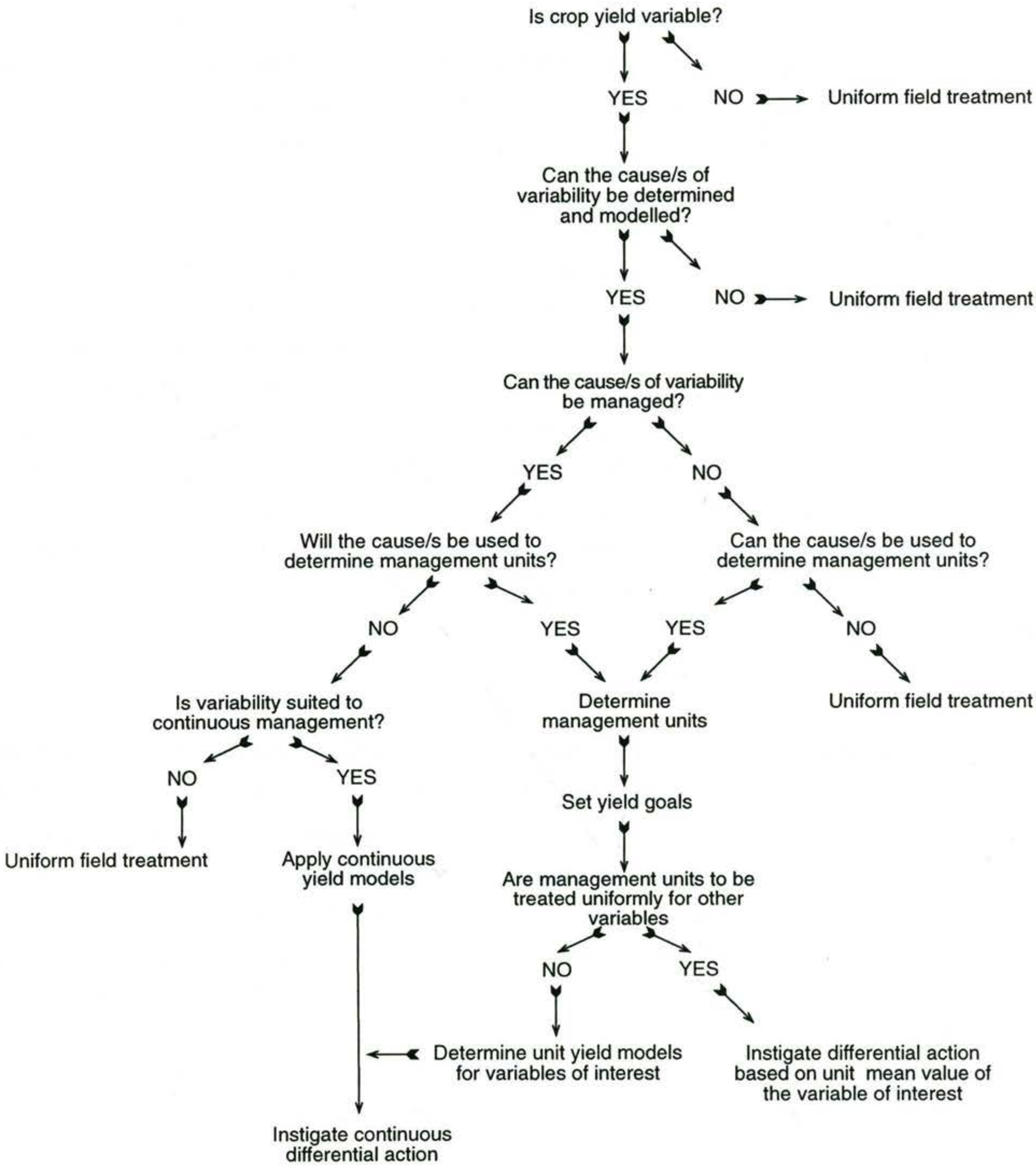


Figure 2-5. Management decision tree for Site-Specific Crop Management – a simple model based on the economic imperative.

2.4.1 Determining Causal Effects

Chapter 1 has examined the individual impact of variability in many soil and crop attributes on crop yield and provided an indication of the variability that may be expected within a field. Table 1-5 confirms the observations of Harris (1920) who had developed a yield heterogeneity index based on a form of nearest neighbour correlation with which he inferred that heterogeneity in soil factors such as soil moisture, nitrogen and carbon was occurring at the same scale as that observed in crop yield. The importance of characterising soil variability at the within-field scale in an attempt to understand crop yield variability at the same scale is only now becoming more widely accepted (Robert, 1993).

For site-specific management, the question is whether one factor can be considered to dominate the yield potential in a field or shall the complex interrelationships between observable factors be utilised in decision making. The former assumption simplifies management. The latter may be optimal in terms of optimising yield and environmental benefits, but economically inviable (at present).

Under the controlled environment of sprinkler irrigation Bresler et al. (1982) found that soil physical factors were dominantly the cause of observed within-field variation in crop yield. Under similar conditions Guitjens (1992) reported that areas with an increase in sand content produced a spatial pattern of soil water deficit that governed yield variability. A correlation between grain yield and clay content has also been reported by Miller et al. (1988) as the most significant contributor to spatial yield variability. Khakural et al. (1996b) suggest that more spatial variability in corn and soybean yield can be explained by physical soil or landscape features than soil fertility factors.

The significant effect of soil moisture on crop yield variability is shown by Power et al. (1961) where 53 % of wheat yield response to P is explained by spatial variability in soil moisture at seeding. With the addition of rainfall variability between tillering and heading the authors explained 81% of the spatial yield variability. Studies over 3 years in dryland crop production by Lark & Stafford (1997) provide evidence that the spatial variation in soil moisture significantly effected the spatial variability of crop yield. While noting a significant spatial correlation between texture and sorghum yield over two years, Williams et al. (1987) also found that in a year with a very dry finish the correlation with soil moisture storage also became significant. Similarly, Thomsen et al. (1997) found that in 'dry years' the spatial variability in water holding capacity (calculated by water balance modeling) was a highly significant contributor in yield variability but was not significant in years with 'sufficient' moisture.

Other soil factors have also been shown to predominate in the explanation of yield variance. Nolin et al. (1996) found soil pH to be the most significantly spatially correlated soil attribute to corn yield. Dobermann (1994) also reported that spatial variability in soil pH was strongly correlated with rice yield in Russia and suggested its dominance could be used as a simple parameter to infer fertility gradients.

The relationship between topography and crop yield, in particular slope position and aspect is well known (Hanna et al., 1982). Measuring these attributes can provide an indirect indication of variability in soil physical and chemical attributes along with climatic gradients (McCann et al., 1996). Sudduth et al. (1996) found that understanding the causes of yield variability was compounded by the interrelationship of factors affecting it, but when comparing seven soil parameters (K, P, pH, OM, topsoil depth, CEC and elevation) they found elevation to be the most significant.

The spatial variation in nutrient supplying capabilities with a field and the associated yield effects have also been well documented (e.g. Rennie & Clayton, 1960; Ferguson & Gorby, 1967). Using 10 tonne samples of 4 soil types sampled in duplicate from two different counties to grow a variety of crops over 10 years, Lyttleton-Lyon (1932) noted large differences in yield response to fertiliser application. In some instances the variability was greatest within than between soil types. They also observed the same spatial variability in field experiments and conclude that it would be very difficult to justify the use of one response model for a single soil type let alone a field with a suite or gradation of soil types.

More recently, in a comprehensive nitrogen fertiliser response trial using sugar beet and potato at over 200 sites, Neeteson & Wadman (1987) showed the confidence range for the economic optimum N rate to be over 300 kg/ha (equivalent to the maximum rate applied) for up to 60 % of the trials. This also dramatically demonstrates that very large spatial variation in fertiliser response may be encountered within a field and so spatial correlations between soil nutrient levels and yield may routinely prove insignificant or negative.

One plausible explanation for such variability is that the soil nutrient status has also been related to variation in the complex interrelationships existing between the spectrum of edaphological influential soil physical and atmospheric factors (Malo & Worcester 1975). Nolin et al. (1996) proposed using the strong spatial correlation between altitude and a range of major chemical nutrients as a means of inferring fertility gradients. Goovaerts & Chiang (1993) found a temporal persistence in the spatial pattern of numerous soil properties studied before and after winter which they postulate may be due to a correlation with a deterministic attribute such as soil texture.

These results tend to suggest that spatial variability in the soil water regime and physical properties controlling soil water movement and nutrient supply may be the most significant causal factor in the spatial variability of crop yield. Using the variation in indicator factors such as soil texture or elevation to delineate areas of homogeneous yield potential may prove useful. The response to these factors will be site-specific, but the significance of their influence may not.

2.4.2 Management Unit Determination

The information provided in Section 2.4.1 suggests that the use of more static variables to delineate map units may be supported agronomically. Obtaining data on the spatial variability in these soil attributes directly is but one option. The expense and labouriousness of the sampling regime has fostered the examination of alternative methods.

Soil Attributes

Mulla et al. (1992) used grid sampled soil P and N to calculate required fertiliser using a mass balance approach and divided the field into three management zones based on fertiliser application thresholds. They determined yield goals based on the probable water deficits calculated from subtraction of available water plus expected precipitation from the non-limiting water requirement for growth. Field results showed a significant difference in yield for each zone which correlated well with soil profile moisture measurements and organic carbon which were not used in management zone construction.

Following this lead Mulla (1993) used the spatial variability in soil OM to infer fertility variability and divide a field in management zones. The zones possessed significantly different wheat yield potential, soil moisture and residual N. Calculated differential Fertiliser N and P treatments for these zones were much lower than uniform option traditionally employed by the grower. Field results in this year revealed no significant difference in yield between uniform and differential fertiliser applications within the zones but with considerably less fertiliser applied, a economic benefit could be assumed.

Management unit delineation based on soil texture was employed by Nolin et al. (1996) and found to reduce the unit variation (expressed as %CV) in other soil attributes significantly. This was a comparison of total field CV to a weighted mean for all the soil units. Dobermann (1994) used factor analysis to construct a soil fertility factor that the author suggest could be classified and mapped to produce fertility zones.

As noted earlier, discrete soil sampling may provide a useful method for research purposes where sampling costs are less limiting, but at a practical level the number of samples and the sampling design are likely to be both influential and cost prohibitive. To explore this point, Franzen & Peck (1995) used grid sampling on a 25m, 66m and 100m grid to determine management zones based on required P and K fertiliser. Their results show that the 66m grid approximated the delineations apparent in maps produced on the 25m and were far superior to the 100m grid example. They concluded that a 66m grid could be used as a compromise between economics and accuracy.

Wollenhaupt et al. (1994) reported that a 30m grid provided the most accurate representation of soil spatial variability and that a loss of at least 30% in map accuracy could be expected if the sampling grid was increased in size. Birrell et al. (1996) also show that sampling pattern and intensity greatly influences the map and the associated error. This error changes with soil attributes and much detail can be lost in simply moving from a 25m to a 100m grid. The influence of sampling design on management unit delineation is further highlighted by Wollenhaupt et al. (1994) in a comparison of grid point sampling to grid cell sampling. They report that cell sampling could lead to incorrect determination of fertiliser requirements in more than 40% of a field when compared to maps made on grid points. Confirmation of the significant effect of soil sample density and design on fertiliser application mapping accuracy is provided by Gotway et al. (1996a).

Few studies have used continuous sampling of soil attributes to overcome the sampling density, design and cost aspects, however Jaynes (1996) did employ EM induction estimates as a surrogate for organic carbon and the depth to clay pan to successfully map and define management units.

Continuous Yield

Based on the premise that spatial variability in crop yield is influenced by spatial variability in soil factors at a similar scale, researchers have begun to examine the patterns observed in crop yield maps obtained from continuous monitoring.

Using a classified yield map from the previous year Kitchen et al. (1995) report the successful determination of yield potential zones. Their success was quantified by applying variable N fertiliser according to yield goals calculated for each zone, and observing a reduction in residual soil nitrate in comparison with uniform treatment within the zones and (as may be predicted) especially in the zones of low yield potential.

When more than one year's yield maps are available for a field, the recognition of stable response patterns becomes important for the determination of management units. Stein et al. (1997) suggest the simple use of correlation coefficients between the nodes on a map for pattern comparison. Van Uffelen et al. (1997) propose a weighted taxonomic distance measure to quantify the similarity between patterns in yield maps. The authors applied the technique to simulated yield maps but were forced to arbitrarily select the dominant pattern as that most repeated over the 8 years of simulation. A benefit of the simulation process is that yield levels displayed in the dominant pattern may be utilised as the yield goals for the management units.

In a more rigorous approach using actual yield data, Lark & Stafford (1997) employed a fuzzy multivariate clustering analysis to three years yield data in an attempt to define regions of a field that may present similar factors limiting/governing yield. The years were considered variates in the technique which was optimised with 4 clusters and produced reasonable continuity in maps of maximum class association.

Again using a form of fuzzy cluster analysis Burrough & Swindell (1997) classify maps of 3 years yield data into four membership classes. They employ an innovative technique to determine boundaries between the classes whereby points in the maps where the maximum membership values are most similar between the classes indicate zones of confusion. These zones are used to define the boundaries between classes or management units. While the process appears promising, it is only applied in this instance using 80 yield values which were obtained as 20m block kriged estimates on a 2.5m grid. The clustering is performed and then the membership values kriged onto a 2.5m grid. This methodology is likely to produce smooth spatial representations and thus continuous yield boundaries that may be unrealistic.

Another novel idea is presented by Swindell (1997) which suggests the use of normalised yield classification and the summation of these classifications over mapped years to determine a relative yield potential variation in a field. This technique is likely to falsely represent the overall field variability as each year must have a full range of classifications under the normalisation process, but in some years there may be little variance in the absolute yield values recorded. It could not be accurately used as a quantified yield potential map. Further, the author alludes to the use of the technique to combine crop types within one field but it is arguable as to what information would be gained as various soil attributes are likely to effect different crops differently.

Not all studies suggest that crop yield is the optimum indicator. Khakural et al. (1996b) believe that management units based on yield maps may maximise differences in yield between units but this may not necessarily be equated to the optimum delineation of management units based on maximum differences in soil properties. This is presumably possible due to other external factors significantly influencing crop yield.

Aerial Reconnaissance

A further step away (in terms of distance) from directly sampling the soil is the use of remote sensing from an aerial or satellite platform. Anderson & Yang (1996) delineated management units by aerial photography into zones of homogenous spectral response. During ground-truthing, considerable variability in crop yield data (CV between 9% and 180%) and plant and soil nutrient levels were recorded within each zone. McCann et al. (1996) used panchromatic aerial photographs of bare soil enhanced, categorised and ground-truthed to delineate 4 management units which the author believed to basically reflect slope position.

Using satellite imagery with a 20m ground resolution, Steven & Millar (1997) calculated the NDVI for a number of field crops and typically explained 50% of eventual yield variability. The results showed that spatial pattern persistence was poorly detected in most cases between years but depending on time of capture, could be quite good within years.

These studies highlight the error introduced by the temporal gap between image capture and final harvest and also may allude to the eventual need to manage differentially within management zones with uniform yield goals. These images may find their greatest use as an aid to determining causes of spatial yield variation by providing in-season growth information or as an adjunct to other delineation methods.

As an example, by augmenting soil unit delineations from survey maps with aerial photographs Carr et al. (1991) derived within field management units. Fertiliser application rates were calculated based on mean soil nutrient tests, traditional fertiliser recommendations and yield goals. They report some success at 5 sites over two years but temporal variability in the crop yield achieved highlighted the need for accurate yield goals, accurate soil tests and reliable fertiliser response calculations.

Combining DEM derived attributes with aerial photographic survey data proved most cost and labour efficient for Thompson and Robert (1995) in delineating map units as compared with grid soil sampling and interpolation.

Elevation and Terrain Attributes

Delineating management units based on landscape characteristics has been suggested by Larson & Robert (1991). They discuss numerous landscape characteristics of which they consider position the simplest and most effective. Landscape or terrain mapping (to provide position information) may prove effective in management unit delineation because terrain significantly influences the distribution of hydrological processes and soil temperature which in turn govern the majority of soil and microclimate attributes that influence crop production potential (Moore et al., 1993).

Terrain attributes calculated from a digital elevation model (DEM) were shown to account for 50% of the spatial variability in soil OM and depth of top soil attributes in a study by Bell et al. (1995) and to significantly represent the spatial variation in soil N (Hollands, 1996). Showing the diversity of information that may be related to elevation, Mathews & Blackmore (1997) used a DEM to estimate the variability in incident solar radiation as a function of elevation. They combined this information with a crop growth model to estimate changes in nitrogen response curves within the field and calculated management units. Under field conditions, 15% less fertiliser was applied than under uniform management to achieve the economic optimum yield.

It is important to remember with these surrogate techniques that the accuracy of the derived attributes is a function of the accuracy of the DEM, which in turn is a function of the method of collection (Spangrud et al., 1995).

Comparisons

A few studies have been undertaken to compare strategies for management unit delineation. Wibawa et al. (1993) found that soil sampling on a 50 m grid spacing produced a good estimate of soil fertility as indicated by increased yield from differentially fertilising to yield goals determined for the delineated management units. In comparison, using existing soil survey map units as management units did provide significant differences in crop yield, however the soil nutrient levels did not follow the soil unit pattern providing less than optimum yields. While the authors report grid sampling to be the most successful in terms of yield and fertiliser synchronicity, the cost of grid sampling meant that this option was not the most profitable. The study does suggest that a process of delineating management cells based on yield potential may benefit from differential treatment within based on spatial variability in indigenous attribute levels.

Intensive soil sampling also proved the most successful for mapping P and delineating management units in a study by Delcourt & De Baerdemaeker (1994). They compared this procedure with apriori knowledge (soil survey maps) and yield maps correlated over two years. The soil unit management delineations suffered a similar error as described above and the yield mapping proved difficult to delineate units from using correlation analysis due to large temporal variability.

Long et al. (1995) reports that aerial imagery of crop reflectance produced more accurate and precise estimation of soil unit delineations than a final yield map. Importantly, they condition such results on the aerial photographs being taken at the correct time of season to truly represent the yield variability induced by soil variability. The period post-anthesis is suggested as the optimum window.

These studies suggest that intense grid sampling of soil attributes is the most accurate method of determining management units (at least for single nutrient fertiliser application). Techniques for the use of multiple year yield maps in management unit delineation are in their infancy. Intuitively, management zones developed on an integrative attribute such as crop yield or vegetative index should be more robust for the application of a range of differential treatments.

While these techniques are researched and refined, operations should continue based on the soil sampling process. Initially zones defined in this manner will be treated as homogenous, described by a single response curve for individual attributes. Thrikawala et al. (1998) show that in a simulated field efficiency gains increase with decreases in management unit size even with a single fertiliser response curve and that this result is enhanced by greater spatial variability. The authors determine efficiency is as returns less fertiliser application costs with no inclusion for the cost of information.

However, as has been previously suggested, while management zones may be drawn on the grounds of homogeneous yield potential, the response to treatment within the zones may be governed by internal variability. Using N fertiliser as an example, Vetsch et al. (1995) experimentally determined the variability in response to N fertiliser within a field and particularly concluded that variability existed in the intercept, slope and economic optimum N rate, but not in the predicted optimum yield.

Continuously variable treatment may eventually be applied in such cases (and across whole fields) but some guidelines for management cell size within the units will be required. Sensibly, the minimum cell size should be determined based on the application equipment dimensions, the accuracy of positioning systems and the speed with which application controllers can vary rates without considerable error. The maximum cell size requires some agronomic or statistical basis. Han et al., (1994) propose using the 'mean correlation distance' based on the normalised complement of the semi-variogram model of the attribute of interest. This distance is a function of the sill and range of the semi-variogram and while it does assume one variogram model for the whole field or management unit, provides a non-arbitrary assessment. The technique must be an improvement on that proposed by He & Peterson (1991) whereby simulation based yield goal estimation from soil OM, moisture and indigenous N are combined with a rule-based expert system to calculate variable N rates for 80 x 80m blocks within a field.

2.4.3 Modelling Yield Variability as a Function of Causal Effects

As experimental work continues on the most effective method of delineating differential management zones, the tools necessary for predicting the spatial effects of inherent and induced variability on crop yield is also being examined. Models are required that predict outcomes for all the differential treatment processes described in Section 2.3.

A comprehensive summary of the attempts and requirements of including bio-economic spatial weed models into management decisions is provided by Johnson et al. (1997). Although there has not been a great deal of success as yet in this endeavour due to sampling scale problems, Steckler & Brown (1993) circumvented the dilemma by using classified aerial images to identify weed patches. They developed rule-based, expert system to calculate herbicide application within each treatment unit based on spatial distribution of weed species, thresholds, crop stage, climatic conditions and herbicide resistance.

Far more attention is being focused on the variable-rate application of fertiliser and modelling the spatial yield response.

Modelling crop yield may be achieved through a number of conceptually different techniques. An 'empirical' model may be constructed purely on the basis of statistical analysis of experimental data, while a 'mechanistic' model attempts to predict yield on the basis of contributory functional components of growth. These two general types of models maybe further classified as 'deterministic' whereby prediction is aimed at a singular outcome for a set of input conditions, or 'stochastic' providing a probability distribution for the outcome.

Most traditional modelling approaches for the effect of varying the rate of single or twin causal factors on yield follow the empirical response curve technique as described in Section 2.3.2. These models can be incorporated into spatial analysis for site-specific management

(McBratney & Whelan, 1995b) and their simplicity enables relatively swift data manipulation. However, their usefulness may be restricted to combining linearly related factors.

Sudduth et al. (1996) analysed a number of simple empirical models in relation to site-specific management and indeed found that interrelationships in the causal factors of spatial yield variability makes modelling difficult. These relationships are often nonlinear making modelling operations that are linearly constrained (i.e. correlation and multiple linear regression) unsuitable. The authors found that non-parametric, non-linear methods such as projection pursuit regression (PPR) were better performed when dealing with numerous factors. A yield map constructed from the PPR derived response curves compared favourably with the initial yield map, however this may be due to the large number of parameters overfitting the experimental data.

In an attempt to improve interpretation of multiple regression by reducing the correlations between variables, Mallarino et al. (1996) employed factor analysis to aggregate highly correlated variables into new 'latent' variables. Factor analysis defines these 'latent' variables using covariance analysis. They found that a latent variable reflecting early corn growth was considered the most important to final yield, and in two of three fields studied the aggregate variable 'weed control' was important. Only a low to moderate proportion of yield variability could be explained by this technique ($R^2 = 0.28$ to 0.71) and the authors stress the importance of measuring and including in analysis the truly influential causal factors. This technique offers relative simplicity in the incorporation of interrelationships but the variability in R^2 reported by Mallarino et al. (1996) suggests that variables may be interrelated differently between fields and that 'latent' variables may not be stable in space.

In a similar vein, Khakural et al. (1996b) produced a Soil Fertility Index (SFI) which ranged from 0 to 1 based on a number of soil and terrain attributes. The SFI was used to linearly predict maximum crop yield and a variable stress factor based on climatic and soil moisture characteristic information was then superimposed to calculate actual yields. When applied to a 17 ha area, the predicted yields provided a good spatial correlation with the actual mapped yield.

Wendroth et al. (1997) used the same principle of SFI, in conjunction with a vegetative index (VI) formed from aerial infrared photographs, in a state-space approach to modelling yield variation. The method is basically an autoregressive approach incorporating spatial covariance and cross covariance in a transition or autoregressive coefficient matrix. The autoregressive analysis can only operate in one dimension but most interestingly it can be yield. The authors found that yield could be predicted well with SI and VI in combination with only minimal auxiliary yield data. They suggest the addition of variables such as multiple year yields, multiple year VI or soil nutrient concentrations could help in determining which parameters are optimal for prediction.

Neural networks are another non-parametric, empirical process that have recently been employed in crop yield modelling. A neural network 'learns' by experience from statistically approximating the input and output functions of a process using sample data. The neural network is recognised as capable of non-linear processing and signal noise reduction (Kosko 1992). Sudduth et al. (1996) employed neural network analysis in the previously described study and found the models generated to be only slightly less successful than PPR.

Quite sophisticated empirical models with stochastic prediction have been developed for crop yield. As an example Bresler (1987) models crop yield in a field with spatially variable soil parameters and boundary and initial conditions as an indirect random function of the spatial co-ordinates. It can be considered as a direct function in the form of Equation 2–1:

$$Y_{(\underline{x})} = f[\underline{R}_{(\underline{x})}, \underline{\alpha}_{(\underline{x})}] \tag{2–1}$$

where:

$Y_{(\underline{x})}$	=	Vector of crop yield for a given space coordinates vector
$\underline{R}_{(\underline{x})}$	=	Vector of man-controlled random functions (i.e. boundary/initial conditions) for a given space coordinates vector
$\underline{\alpha}_{(\underline{x})}$	=	Vector of spatially random functions for a given space coordinates vector

The authors used this model to estimate the moments (mean and variance) of the integral of all $Y_{(\underline{x})}$. For an application to site-specific management the individual estimates of $Y_{(\underline{x})}$ would be useful or integrals over management units. For this model to be applicable however, the changing nature of the functions in space that comprise the vectors $\underline{R}_{(\underline{x})}$ and $\underline{\alpha}_{(\underline{x})}$ must also be considered.

These empirical models are finding application in spatial analysis at the field level through incorporation as GIS data analysis tools. Yost et al. (1988) outline the preliminary development of an 'expert system' for the determining lime requirement using rule-based functions on model output. Moltz et al. (1993) preview a more sophisticated approach in the form of a specific GIS for site-specific management that spatially analyses input data (detrending and variogram analyses) then uses empirical and Boolean (logical) functions to manipulate the data and form fertiliser treatment maps. Schroeder et al. (1997) report the development of a similar approach.

Mechanistic models are more complex and computationally demanding but have routinely been employed in simulation studies of crop growth because they are often regarded as superior to empirical models which are usually single-site based and consider little phenological effect (Barnett et al., 1997). Numerous commercial growth simulators are available in the public domain for a range of crops using component soil moisture, soil chemical, soil erosion, root growth, nutrient uptake, climatic and transpiration sub-models (see for example Hanks & Ritchie, 1991).

However, traditional mechanistic simulation models do not operate at the spatial resolution required for site-specific management. Either the simulations must be run using input data representative of small areas only or the models must be modified to accommodate spatially variable data.

Hoogenboom et al. (1993) attempted to circumvent this dilemma by linking a commercial GIS to a crop simulation models. The GIS could call the simulation model to run in batch mode for different soil units identified within a field or farm to give a representation of soil spatial variability to the model output. Han & Goering (1993) and Han & Evans (1994) also employed a GIS and simulation models to simulate corn and potato yield along with nitrogen movement and added a decision rule module to interpret the output and recommend spatially variable pre-season fertiliser and lime application.

Boone et al. (1996) provide a discussion of this developing use of GIS and growth simulation models in combination with expert interfaces for interpreting model output as management decisions. These software linkages have been collectively termed 'decision support systems' (DSS) and Olesen et al. (1996) show the use of a sophisticated example that includes submodels for crop vegetative development, soil water balance and crop yield all modelled as a function of available water and available nitrogen. The modelled spatial variability in yield for a single field provided a reasonable correlation with mapped and hand harvested wheat in one year but not the proceeding year.

This example highlights the apparent fact that factors affecting spatial variation in crop yield may change with time. More accurate is the possibility that the influence of certain physical causal factors changes with temporal climatic variation. While these simulation models attempt to incorporate some influence of climate, it is spatially and temporally non-linear and therefore complex to predict (Schueller 1992). The simulation studies of Hoogenboom et al. (1993) show that the effect of temporal variability in climate on crop yield models is far greater than soil spatial variability and that there appears to be a difference between crops in their response to soil and climate variability.

This large temporal variability in climate reinforces the need for the inclusion of climatic simulation models and the necessity of historic climatic data in any yield prediction process (Karlen et al., 1997). Booltink et al. (1996) have attempted such a procedure by combining crop simulation models within a commercial DSS with spatially variable soil data and a weather generator (predictive simulator). The weather simulator is based on historical climatic data and the model outcomes are used to predict fertiliser applications for optimum yield and minimum nitrogen wastage. The predictions had not been field tested at the time of publication.

While these systems are honing in on the requirements of a comprehensive site-specific DSS, there remains contentious or problematic areas. While Acock & Pachepsky (1997) argue that mechanistic models using limiting factor sub-models for the interaction of parameters (and operating with less than daily analysis) are the most suitable for a site-specific management system because they are better at operating outside the conditions on which they are developed than empirical models, Barnett et al. (1997) do not agree. The authors attempted to validate in the UK a number of well known mechanistic wheat yield models developed from other countries. They found very poor correlation between predicted and actual yields and believed that the complex weather processes included in the models for crop physiological growth simulation are basically irrelevant in the UK. A parsimonious statistical model was formulated that was applicable across a range of sites and incorporated phenological growth stage factors providing a reasonable predictive power for yields.

Passioura (1996) concurs with Barnett et al. (1997) in the belief that mechanistic models as management tools are flawed, and bases the opinion on the inclusion of usually difficult to prove assessments of the processes that control crop growth in the models. Passioura (1996) suggests that empirical models applied under the environmental conditions in which they were formulated are the most suitable for management. Obviously it will be important to ensure that site-specific causal factors (including climate) are relevantly modeled and included in any DSS for local application.

It also should be acknowledged that uncertainty exists in the final yield estimate as a result of uncertainty in the input data and errors in the models. Chen et al. (1997) used first order uncertainty analysis to examine the effect of uncertainty in input data on the model outcome of a mechanistic phosphorus decision support system. They reported a large uncertainty which was contributed mostly by variability in specific model parameters (crop critical P level and the soil buffering coefficient). Uncertainty may also be contributed by the use of models and input data designed for larger scales than the current application. In explanation of this, Heuvelink (1998) point to the fact that different processes are important at different scales, that reduced input data is available at larger scales and the support for data points changes dramatically. The implication is that a DSS for site-specific management should not include commercial models developed for larger scale predictions.

Uncertainty estimation is essential for a thorough risk analysis of any decisions generated from a DSS. A stochastic element must be introduced to the model or the input data. Pachepsky & Acock (1997) use stochastic imaging to achieve this aim by generating possible images of variability in soil input data (available water content). These realisations are applied in crop growth models to assess yield response and the associated uncertainty. Gomez-Hernandez (1997) also show the use of stochastic simulation by generating alternative spatial estimates of parameter values for input into water flow models and obtain frequency distributions of the response variables.

Finally, the majority of models discussed (with the exception of Wendroth et al., 1997) are designed to utilise input data that has been previously gathered. Figure 2-1 suggests that the ultimate aim of site-specific management may be to gather some information, make decisions and instigate action all in real time. While this may appear futuristic, there are a number of other techniques that may be investigated to achieve this goal. Or & Hanks (1992) suggest the use of a Kalman filter algorithm[§] that combines data from separate sources such as model predictions and actual measurements into an estimate with minimised variance. Alternatively, Goovaerts & Journel (1995) used indicator algorithms to merge soil classification data with sparse sample data to improve predictions of deficiency in trace elements.

While progress continues to be made in DSS, it appears imperative that the errors and uncertainty associated with measuring variability and modelling responses be estimated. It is also evident that and DSS must incorporate the significant effects of temporal variability induced by climatic variables.

[§] The theory of Kalman filtering can be reviewed in Merminod (1989) and Grewal & Andrews (1993).

2.5 SUMMARY

The premise underlying site-specific management, namely that soil heterogeneity influences the productive potential of agricultural land, can not be regarded as a new concept. Equally, the knowledge that measuring the degree of heterogeneity and using this as base data with which to manipulate farming operations is long held. In most cropping systems, the field variation in soil type, moisture content, structural integrity and nutrient levels, will contribute to site fluctuations in the potential yield.

Acquiring data on the short-range variation of these influential soil attributes is essential to the operation of a SSM system. A true description of small and large scale variation in such soil properties has historically been difficult and costly to obtain. Sampling on a large-scale grid is logistically troublesome and provides data on variability at a very coarse scale. Alternatively, a fine-scale grid sampling scheme may provide more detail on variability but will incur high costs in order to cover a significant area. Obtaining a more thorough understanding of the extent of soil variability at a site will require the continued development of methods that allow observations to be made at a diverse range of scales and with greater continuity. Until such time, more efficient direct sampling designs and machinery should be investigated.

Numerous systems are now commercially available to monitor the variability in crop yield in 'real-time' during harvest operations. Combining these technologies with vastly improved ground positioning systems is now allowing detailed mapping of crop yield variability within a field. There are however a number of error sources in the data gathered by these systems that requires quantification, or more appropriately, removal.

The results of mapping variability patterns in this manner should be a wealth of new production information for the land manager. Small-scale variation in pertinent soil factors can be identified and any fluctuations in productivity potential across a site quantified. While this review has only touched on the formal processes of spatial representation of this data (i.e. map making), the different methods and their associated assumptions can produce widely varying results. With the vast quantities of data available per field for yield map construction, these methods and assumptions should be examined in terms of accurate variability representation and uncertainty propagation and the most appropriate method determined.

The degree of variation will in turn influence the differential treatment strategies required to maximise yields and resource application. It should be obvious that the technology to apply variable rates of ameliorants within a field is well developed. The agronomy and decision processes at these fine-scales has been little developed. While it can be envisaged that the entire data acquisition–processing–decision procedure may be undertaken in the field during relevant farming operations, thereby avoiding an increase in the traffic loading and increasing timeliness, the reality appears relatively distant. Much research is being undertaken in an endeavour to rectify this situation.

In general, applying the theories of Precision Agriculture to the practicalities of broad-acre farming will rely on successfully handling the ramifications of uncertainty in information, i.e. information pertaining to the spatial and temporal variation of those factors which determine yield components and/or environmental losses. It is clear that annual temporal variation is much larger than the spatial variation within single fields. This leads to the conclusion that if Precision Agriculture is to have a sound scientific basis and ultimately a practical outcome then accurate measurements of variability and assessments of the spatial structure must be ensured and uncertainty reduced in soil and yield maps and crop growth models. Some of these important areas will be addressed in the following research Chapters.

SECTION II

STUDIES OF WITHIN-FIELD VARIABILITY IN SOIL AND CROP ATTRIBUTES UNDER AUSTRALIAN CONDITIONS

CHAPTER 3

CHAPTER 3

Spatio-Temporal Monitoring and Modelling of Soil Moisture Content

3.1 INTRODUCTION

Considering the climate, soil types and managerial practices of the north-west NSW dryland cropping region, by far the most critical spatio-temporally variable attribute governing crop yield is the moisture content of the soil. Moisture content must be within recognised parameters for trafficability at cultivation, sowing and harvest times. It is also crucial to the germination, vegetative and reproductive growth of the plant.

The soil moisture content at any point in a field can also be viewed as a random realisation of the effects of a number of soil physical attributes that themselves vary in space and time. These would include soil type, soil texture, soil structure and structural stability to wetting along with surface features such as crusting. This ability to broadly reflect the variation in a number of physical attributes of the soil, when combined with the crucial role soil moisture occupies in all aspects of plant growth, provides a potentially powerful singular parameter with which to characterise the spatial and temporal variability of soil in the cropping fields in northern NSW.

3.2 METHODS OF IN SITU SOIL MOISTURE MEASUREMENT

The requirement for robust methods for the measurement of soil moisture content in situ has continued to extend the ingenuity of soil scientists. Gravimetric sampling provides an indisputably accurate method however its destructive nature, the requirement for constant physical site access and the inability to resample observation points ultimately limits its use to space- and time-finite surface sampling if a crop experiment is to remain minimally disturbed through the growing season.

Stafford (1988) comprehensively reviews the techniques for remote, non-contact and in situ measurement of soil moisture. Of relevance here are the widely available in situ techniques. They all rely on the measurement of physical properties of the soil that vary in a definable relationship with soil moisture. Each of these 'indirect' techniques require calibration to approximate a soil moisture content and each varies in applicability to field-based crop growth experiments.

3.2.1 Tensiometry

Tensiometers measure the energy status or potential of the soil water, the matric component of which can be related to the water content of the soil. In operation, an hydraulic equilibrium is established between the soil water and the water supply inside the tensiometer. The moisture potential of soil surrounding the porous ceramic tip of the tensiometer is then measured by monitoring the pressure exerted on free water inside the tensiometer. Tension is exerted on the tensiometer water by a drying soil, producing an outflow and a reduction in the internal water pressure (the value becomes more negative). The reverse occurs if water is added to the soil and equilibration requires a flow into the tensiometer.

Cassel & Klute (1987) consider the applicability of tensiometers to cover irrigation scheduling, root zone delineation and hydraulic gradient measurements. The inference being that the method is less suitable as a technique for indirect measurement of soil moisture content. This reservation is increased in shrink/swell soils where the matric potential is further influenced by the overburden load imparted on the soil around the tensiometer cup (Mahony 1975). The safe operating range of the tensiometer is generally regarded as 0 kPa to -100 kPa (with Field Capacity = -10 to -30 kPa and Permanent Wilting Point -1500 kPa). The range of moisture contents that can be estimated is therefore similarly restrained. Coupling tensiometers with electrical transducers does facilitate digital data logging, allowing a number of units to be automatically monitored.

3.2.2 Electrical resistivity

The electrical resistivity of a porous medium is also a function of its moisture content (Gardner 1987). Typically, a porous gypsum block buried in the soil will achieve a matric potential equilibrium with the surrounding soil that can be measured using suitable electrodes. This potential can be calibrated to approximate the moisture content of the specific soil surrounding the block. Porous blocks used in this method are unsuitable for measuring moisture at the wetter end of the scale, operating with greater precision in the -60 kPa to -1500 kPa range.

As with the tensiometer, the relationship between moisture potential and content can be effected by hysteresis and calibration is more successful in the soil drying cycle. Adequate and realistic contact between the soil and the instrument surface is also a point of concern. The application of the above two techniques would appear best suited to monitoring soil moisture potential and the interpretation of these measurements for the availability of soil water for plant growth. Extrapolation to a precise moisture content appears to over-extend the techniques.

3.2.3 Neutron Thermalisation

The Neutron scattering technique has found wide acceptance in irrigation scheduling throughout Australia. It operates using a radioactive source (Americium 241/Beryllium) in tandem with a multi-directional sensor that is shielded from the source. Fast moving neutrons are emitted into the surrounding environment, thermalised on contact with atoms of a similar size and mass and detected as slower moving neutrons by the sensor (Gardner & Kirkham, 1952). In the soil, hydrogen (H^+) is effectively the only atom with the necessary characteristics and is present in clay minerals, organic matter and water. The fraction of H^+ in the mineral/organic soil matrix at a site is extremely low and essentially fixed in comparison to quantities monitored during fluctuations in moisture content. This lead to the effect of soil constituents other than water being neglected in analysis and the development of a universal calibration (Holmes, 1956).

The use of a universal calibrations has been questioned more recently. Chanasyk & Neath (1996) cite changes in soil chemistry, bulk density and organic matter levels as attributes which will significantly effect the accuracy of absolute moisture values using a universal calibration. The neutron scattering technique is also sensitive to the volume of soil available for sampling and is therefore less reliable at the soil surface (Chanasyk & Neath, 1996).

3.2.4 Time Domain Reflectometry (TDR)

TDR is used to measure the apparent dialectric constant of soil (ε) surrounding a configuration of metal probes. The technique involves determining the travel time (t) of an electromagnetic pulse propagated along the probes and relies on the correlation between pulse travel time and soil moisture content for a fixed probe length (L). Top et al. (1980) reported an empirical relationship for many soil materials of the form:

$$\theta = -0.053 + 0.29\varepsilon - 0.00055\varepsilon^2 + 0.0000043\varepsilon^3 \tag{3-1}$$

The apparent dialectric constant is calculated using the velocity of light in free space (c) in Equation 3.2

$$\varepsilon = (ct/2L) \tag{3-2}$$

This simple technique has been made available for soil moisture measurement due to the rapid improvement in instrumentation electronics. Probe lengths between 0.2m and 1.0m require the ability to measure reflection times in the nanosecond (ns) range. This speed of measurement also means that the sampling process is extremely swift and the use of buriable probes allows for repeatable non-destructive sampling of a single soil volume. Coupled with these advantages is the ability to multiplex a large number of probes to automatically collect data at many points. These attributes make the TDR the best choice to examine the spatial and temporal variability of soil moisture over a growing season.

3.3 MATERIALS & METHODS

3.3.1 Site Description

Soil of North-West NSW

The soil of the North West Plains of NSW composes a mosaic of types that vary in both genetics and crop production potential. Northcote (1966), Stannard & Kelly (1977), and Butler & Hubble (1978) provide detailed descriptions of the variability in soil profiles to be found in the region. However, it is the deposition of alluvium derived from basaltic parent material in the ranges to the east that has resulted in the predominance of Cracking Clay soil in the semi-arid/sub tropical cropping sectors of this region. These Cracking Clay soil types are at the fore in agricultural production potential in Australia.

The Cracking Clay soil classification encompasses the Australian soil groups - Grey, Brown and Red Clays and Black Earths (Stace et al., 1968). In terms of US Soil Taxonomy (Soil Survey Staff 1975) these soil types are recognised as Vertisols. Northcote (1971) generally characterised these soil types as possessing a uniform, clay dominant texture profile and a shrink/swell nature that results in seasonal cracks of a minimum 6mm width, 30cm depth and 1 m^2 spatial frequency. A more complete description of the qualities that define this classification would include the following attributes (Hubble 1984).

- A texture profile with a maximum range of one texture group.
- Generally uniform profile colour ranging from black – grey – brown to red-brown. Below 1 m the colour gradually becoming paler with ochreous mottling in poorly drained soil and occasional changes to more yellow clays in deeper soil.
- A 2 – 5 cm surface layer that is either self-mulching composed of loose granular or polyhedral units; self-mulching with a thin laminar crust of dispersed soil that cracks on drying; or massive to weak medium blocky.

- An abrupt boundary to a moderate medium blocky ped structure that graduates into a parallelepiped structure.
- Environmentally induced occurrence of carbonate, ferromagnesian and gypsum segregations, concretions or coatings.
- As a consequence of the amount and type of clay present, the soil may exhibit >70% base saturation, relatively high soil water contents at Field Capacity and Wilting Point, variable water infiltration into dry soil and low saturated hydraulic conductivity.
- The soil reaction may range through strongly alkaline – alkaline – alkaline/acid – acid.
- Montmorillonite, illite or kaolinite may dominate the clay mineral suite; as a consequence the Cation Exchange Capacity may vary between 200 and 800 millimoles '+' / kg soil with a grade between calcium dominance (low Sodium Adsorption Ratio (SAR)) and magnesium co-dominance combined with higher sodium concentrations (high SAR); exchangeable potassium concentrations are relatively high.
- Nutrient status and organic matter contents vary from high to low according to site-specific factors.

Soil at the Experimental Site

The soil monitoring experiment was conducted at the I.A. Watson Research Institute, Narrabri, NSW. The Institute is located within the northern grain/cotton belt as shown in Figure 3-1. The region has a summer dominant rainfall pattern enabling both summer and winter crops to be grown.

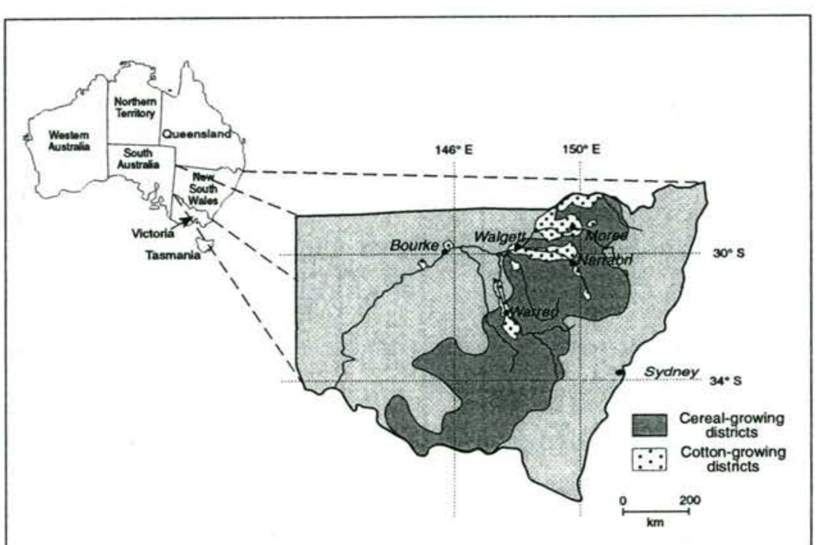


Figure 3-1. Regional location of the experimental site.

(a)

Layer Depth (m)	Texture	pH	E.C. (mS/m)	Cl (mg/kg)	O.C. (%)	P (mg/kg)	Ca (mmol+/kg)	Mg (mmol+/kg)	K (mmol+/kg)	Na (mmol+/kg)	$\sum$ Cat (mmol+/kg)
0.0 - 0.3	Medium Clay	8.6	15	5	0.8	39	213	104	8	7	332

(b)

Layer Depth (m)	Sand (%)	Silt (%)	Clay (%)	pH	E.C. (mS/m)	Cl (mg/kg)	$CaC0_3$ (%)	O.C. (%)	P (mg/kg)	Ca (mmol+/kg)	Mg (mmol+/kg)	K (mmol+/kg)	Na (mmol+/kg)	$\sum$ Cat (mmol+/kg)
0.00 - 0.02	28.9	13.5	56.0	8.3	12	1	0.1	0.9	–	263	147	22	13	444
0.00 - 0.10	32.3	12.3	53.9	8.1	17	6	0.1	0.8	82	219	160	16	17	410
0.10 - 0.20	30.5	13.2	55.0	8.5	20	25	0.1	0.7	41	210	163	12	33	416
0.30 - 0.40	32.9	15.3	50.0	8.9	25	23	0.7	0.6	28	187	174	10	54	425
0.70 - 0.80	27.2	13.9	56.9	9.1	35	78	0.9	0.6	50	166	220	12	99	497
1.20 - 1.30	24.5	16.2	56.6	8.9	66	298	1.7	0.5	53	148	214	14	119	495
2.50 - 2.60	22.1	15.7	60.1	9.0	67	262	1.6	0.1	12	141	250	11	134	535

(c)

Layer Depth (m)	Sand (%)	Silt (%)	Clay (%)	pH	E.C. (mS/m)	Cl (mg/kg)	$CaC0_3$ (%)	O.C. (%)	P (mg/kg)	Ca (mmol+/kg)	Mg (mmol+/kg)	K (mmol+/kg)	Na (mmol+/kg)	$\sum$ Cat (mmol+/kg)
0.00 - 0.02	37.2	12.3	48.0	8.9	17	2	0.9	0.9	–	242	135	15	18	410
0.00 - 0.10	42.5	11.0	43.0	8.9	19	10	1.5	1.1	14	219	150	15	39	422
0.10 - 0.20	40.6	10.8	45.2	9.1	25	15	1.8	0.9	13	189	157	12	49	407
0.30 - 0.40	28.1	10.8	50.2	9.4	41	25	9.9	0.5	5	123	242	9	101	473
0.70 - 0.80	32.0	10.4	49.9	9.6	67	128	7.0	0.3	4	35	239	13	174	461
1.20 - 1.30	24.1	15.3	54.9	9.5	96	314	5.1	0.2	12	26	247	14	234	520
2.30 - 2.40	56.2	10.5	30.9	9.5	69	295	2.1	0.1	11	19	149	6	101	275
2.50 - 2.60	31.4	15.8	50.6	9.3	89	482	1.8	0.1	6	36	243	9	171	459

Table 3-1. Physical and chemical characteristics of the soil at the experimental site (a) and from samples 500m south-east (b) and 700m north east (c).

The general physical and chemical characteristics of the topsoil at the site are displayed in Table 3-1(a). Tables 3-1(b) and 3-1(c) show the physical and chemical analysis of entire profiles located respectively 500m south east and 700m north east of the experimental site (unpublished data (McGarry et al.)). The soil is classified as a Grey Clay or Pelustert. All the sampling points are under the same management cycle.

3.3.2 Moisture Monitoring Equipment and Installation

The project employed a commercially developed TDR system utilising buriable sensors (waveguides) that could all be monitored within the same hour of the day. The waveguides were installed in a horizontal orientation at the site. This orientation was primarily chosen to provide data from the profile zone where soil moisture would be drawn by the plant roots for the majority of the growing season. It also reduced the effect of variability in the integration process used to measure moisture content from the soil surrounding the probe. A waveguide installed vertically into the topsoil would encounter a steep gradient in moisture content as the soil surface dried and insulated the deeper soil from the evaporative effect of the troposphere. The resulting soil moisture measurement would be an integration of the varying dielectric qualities observed in the soil down the length of the waveguide.

Waveguide Layout

The experiment was initiated on a 36 m × 36 m site subdivided into 144 plots, each 3 m × 3 m, with a centrally located TDR waveguide (0.2 m long) inserted horizontally at a depth of 0.25m (Figure 3-2). At this depth the greatest extraction of soil moisture by the fibrous wheat root system is expected. Ten additional waveguides (5 pairs at 0.3 m separation) were used to examine shorter-range variation. Techniques and tools for the installation of the sensors into undisturbed soil at an appropriate depth were developed.

Inserting Waveguides

An undisturbed soil environment is desirable to ensure the moisture measurements reflect real growing conditions. To this end the waveguides were buried prior to the first crop being sown and they remained in position for the subsequent years. It is considered important for correct operation of the three-probe waveguides that the parallel planar orientation of the probes is maintained. To ensure this condition was met in the heavy textured soil, a pre-insertion tool was designed to prepare a pathway for each probe into the soil. This tool was constructed of high tensile steel that would allow significantly more pressure to be applied without deformation. The tool and associated equipment are drawn in Figure 3-3.

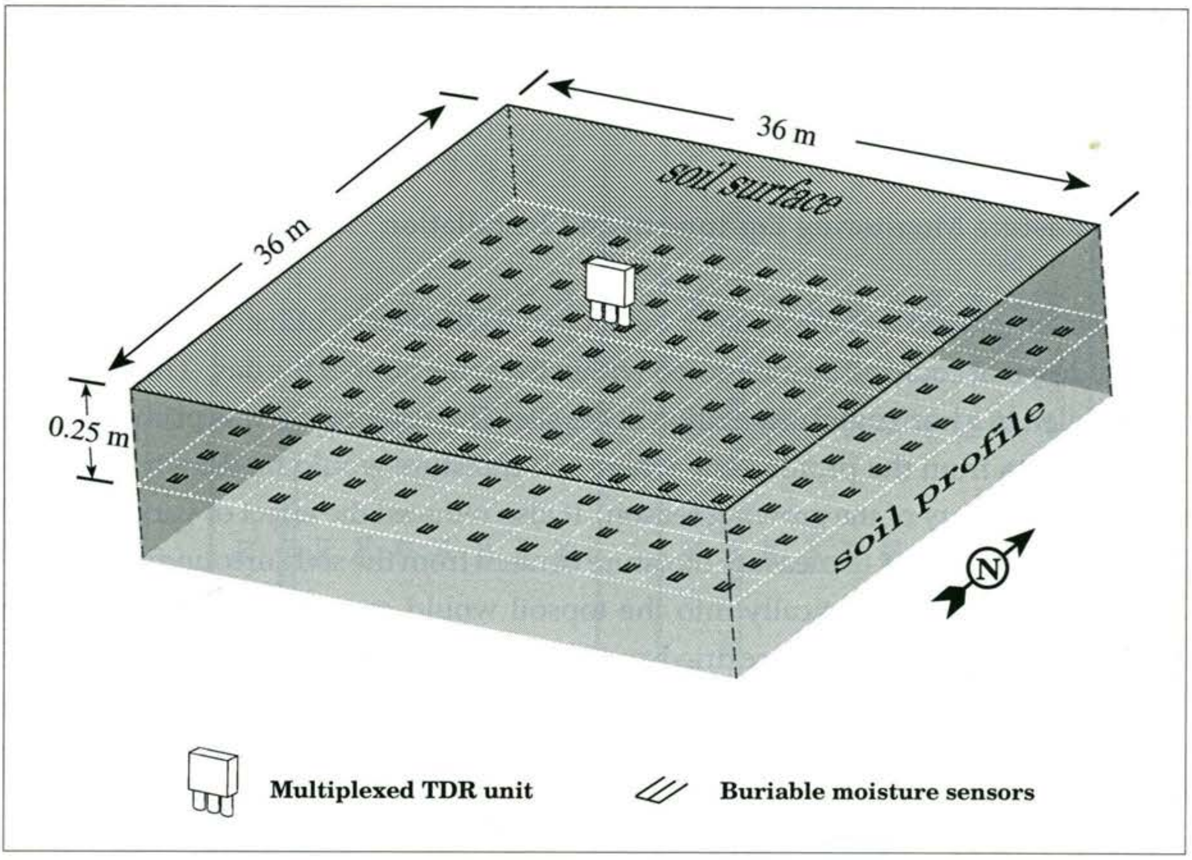


Figure 3-2. Experimental setup for waveguides.

The waveguides were to be installed in the centre of each plot so a hole was dug along the central north-south axis to expose a planar soil face 0.1m south of the central east-west axis in each plot. The 0.25m depth was established and the pre-insertion tool guide installed horizontally into the soil face using a spirit level. Once the pre-insertion tool was correctly aligned using the spirit level and set square, it was gradually pushed into the undisturbed soil. The spirit level was used to ensure the tool maintained a flat plane during the process. Removal of the tool left three channels for the probes of the waveguide to follow. The diameter of the tool probes was smaller than that of the waveguide probes so that good soil to probe contact could be established when the waveguide was finally inserted. Figure 3-4 shows the pre-insertion procedure in operation.

Following installation of the waveguides into the prepared positions, their 1m coaxial cable was buried as the access hole was back-filled, to leave only 0.1m of cable and the terminating connector exposed above the soil surface. The site was left to equilibrate for

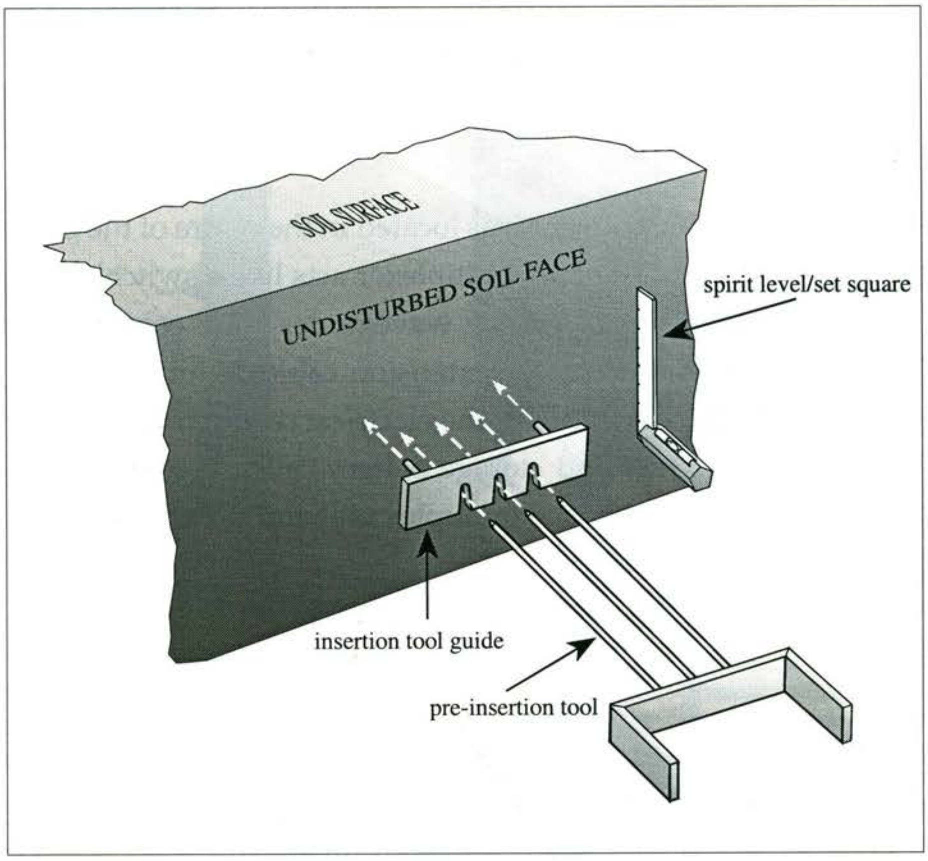


Figure 3-3. Pre-insertion tool and associated equipment

Figure 3-4. Pre-insertion procedure in operation.

3 months prior to sowing, at which time a bright pink marker ribbon was attached to each connector to improve location of the cables post sowing. The sowing operation over the waveguides was completed each year with the loss of only 2 waveguide cables.

Multiplexed TDR network

A weatherproof Trase® TDR instrument was located in the centre of the experimental site and linked to a multiplexing unit. The multiplexer acts like a switchboard when under command of the TDR instrument. All the waveguides were connected to individual channels of the multiplexer via coaxial extension cables which enabled the TDR to interrogate each waveguide in sequence. The electrical requirements for operation were provided by a solar panel array and storage battery cells. Figure 3-5 shows the TDR instrument and a single waveguide, the multiplex unit and the whole monitoring station set-up during the growing season.

Observation Schedule

The mean time for a moisture reading was estimated at 13 seconds, giving an approximate total of 35 minutes for a complete measurement cycle. Readings were programmed to occur on a 12 hour cycle beginning at 6.00am. This time-frame was chosen in an attempt to gather data on water usage during the daily transpiration period and any redistribution changes that may occur during the evenings. The twice-daily readings were also considered the most efficient trade-off between instrument memory and data requirements, while remaining within the power supply capabilities of the solar array. The instrument was expected to remain self-sufficient for 3 week periods.

3.4 RESULTS & DISCUSSION

The operation of the TDR instrument proved problematic during much of the experimental period. At the time of initialisation (1993), the unit and multiplexer were, although recently commercially released, still under refinement. The multiplexer was in fact the first of its size to be used under full field conditions.

Technical errors with the pulse generating board caused the instrument to fail and abort the monitoring program. With an updated board the instrument functioned as expected until periods of high temperature apparently caused the internal circuit breaker to trip again aborting the monitoring program. The cause of this problem was not diagnosed by the USA-based instrument supplier until towards the end of the experimental period.

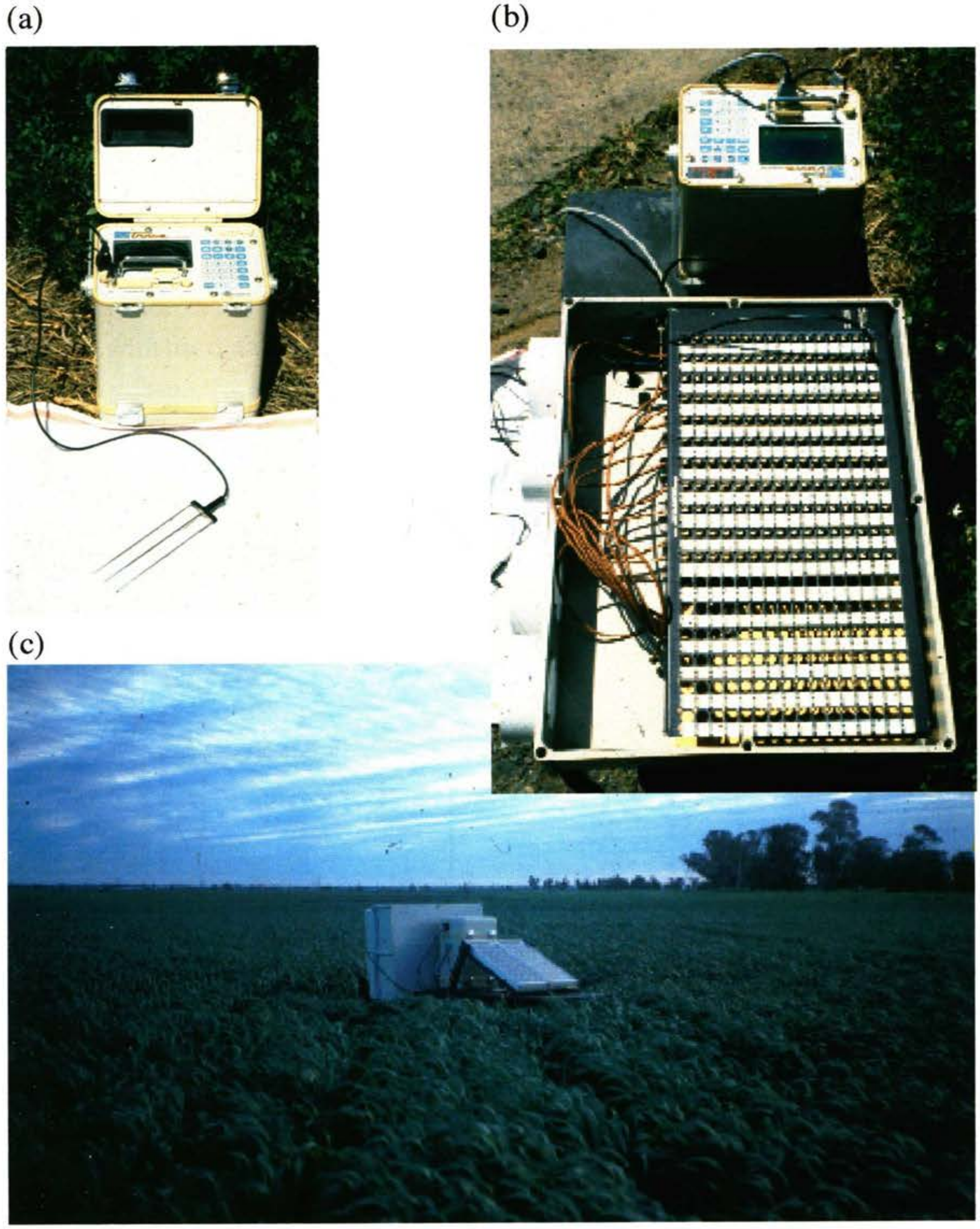


Figure 3-5. TDR instrument with single waveguide (a), TDR and multiplexer unit (b), instrument array in the field during the growing season (c).

These malfunctions meant that the unit could not be expected to reliably operate over extended periods. International repair requirements, remoteness of the site from the university campus, and the lack of additional personnel meant that often the unit was not operating or operating satisfactorily. Missing data in the years 1993 and 1995 reflect these operational difficulties. In 1994, technical problems became unimportant as the region was subjected to severe drought and it was impossible to sow a winter wheat crop. The 1994 year of data collection was abandoned.

Results for the 1993 and 1995 experiments will be presented and discussed. The less-than-optimal operation of the TDR set-up meant that the full aims of the experiments could not be explored with the data available. Modelling of the spatial, temporal and spatio-temporal variation in volumetric soil moisture content at the site will be examined.

3.4.1 Soil Moisture Variation in Space and Time

The data gathered in 1993 and 1995 are graphically displayed in Figure 3-6. Substantial variation about the mean of the site can be seen in both space and time during both years.

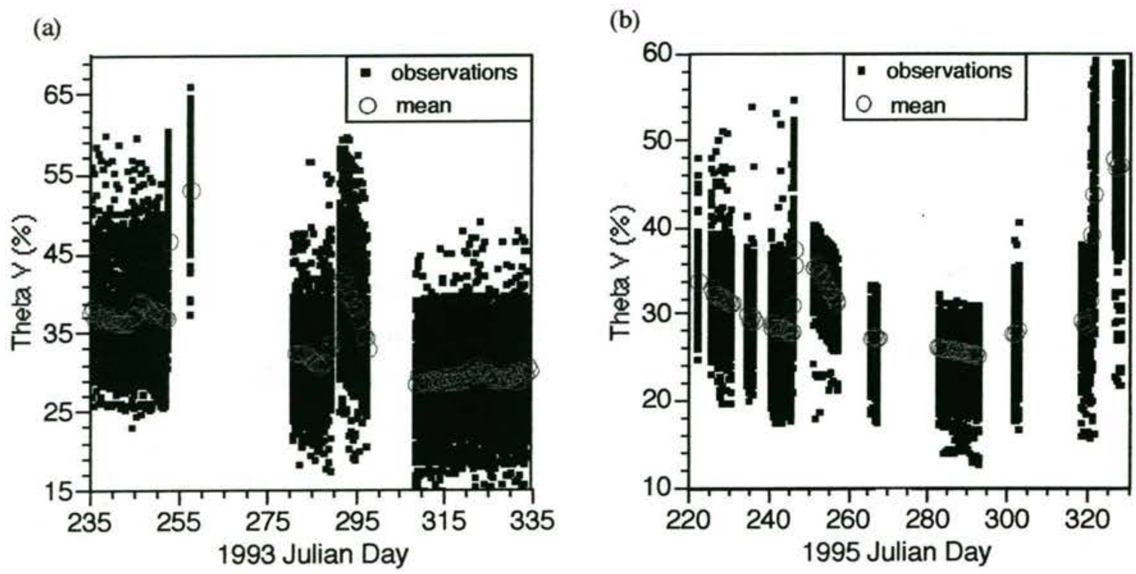


Figure 3-6. Soil moisture observations at the site for 1993 and 1995.

Table 3-2 presents the moments of the data for 1993 and 1995. The small change in mean moisture content between the years does not provide a significant change in the observed variability. The CV is double the median value listed in Section 1.3.4 for spatial variation. This is most likely a function of the data set density and temporal span.

Moment	1993	1995
No. of observations	14095	11612
Minimum θv (%)	15.0	13.1
Mean θv (%)	33.7	30.0
Maximum θv (%)	66.2	59.6
Std. Deviation θv (%)	6.9	6.1
Variance (θv $\%^2$)	47.6	37.1
CV (%)	20.5	20.3
Duration (days)	99	105

Table 3-2. Descriptive statistics for the observations of soil moisture content in 1993 and 1995.

3.4.2 Modelling the Spatio-Temporal Variability in Soil Moisture Content

The embryonic nature of space-time models has been discussed in Section 1.5.3. In general a number of generic models can be described and categorised based on the stationarity of the data mean.

Equation 3-3 describes a stationary model:

$$\psi(x,y,t) = m_{x,y,t} + r(x,y,t) \tag{3-3}$$

where:

ψ	=	soil moisture content ($m^3m^{-3} \times 100$)
x,y,t	=	space and time coordinates
m	=	data mean or trend
r	=	residual

In understanding this model, the use of subscripts may be read as 'value does not depend on the listed coordinates' and the enclosing brackets ( ) are to be read as 'value is dependent on the listed coordinates'. Equation 3-3 therefore states that soil moisture content is dependent on all coordinates but has a fixed mean. Other models can be written to describe the non-stationary situation (Equation 3-4) or intermediate cases (Equation 3-5 and Equation 3-6).

$$\psi(x,y,t) = m(x,y,t) + r(x,y,t) \tag{3-4}$$

$$\psi(x,y,t) = m_{x,y} + m(t) + r(x,y,t) \tag{3-5}$$

$$\psi(x,y,t) = m(x,y,t) + r_{x,y}(t) \tag{3-6}$$

The non-stationary model is best applied to the data under examination in this experiment. Suitable models for the trend in the non-stationary case ($m(x,y,t)$) would include generalised linear models e.g. polynomial trend surfaces (McCullagh & Nelder, 1989), generalised additive models e.g. smoothing splines (Hastie & Tibshirina, 1990), regression-tree models (Clark & Pregibon, 1992) or a deterministic function describing a physical process. The usual model for residuals, $r(x,y,t)$, assumes the condition stated in Equation 3-7.

$$E[r(x,y,t)] = 0 \tag{3-7}$$

Description of the residual is commonly performed by a covariance or semivariance function. Assuming spatial isotropy, one positive-definite model for the semivariance (Christakos, 1992) is shown as Equation 3-8.

$$\gamma(\lambda,\tau) = C0 + C\left(1 - \exp\left(-\sqrt{\left(\frac{\lambda^2}{(a')^2} + \frac{\tau^2}{(b')^2}\right)}\right)\right) \tag{3-8}$$

where:

$\gamma(\lambda, \tau)$	=	semivariance as a function of the spatial lag (λ) and the temporal lag (τ)
C_0	=	nugget semivariance
C	=	sill semivariance minus the nugget semivariance
a'	=	the range of influence in space
b'	=	the range of influence in time.

Trend Modelling

To define the three-dimensional trend component of the data, a polynomial trend surface, a generalised additive model and a regression-tree were applied and tested for goodness of fit (Table 3-3). The most successful of these, the regression tree model, is a hierarchical model that determines the relationship between variables by devising a set of regression rules for prediction using recursive partitioning (Clark & Pregibon, 1992). Figure 3-7 presents the fitted models for a single measurement point in the 1993 and 1995 growing seasons.

Model	% Variance Explained 1993	1995
Polynomial trend surface	24.4	1.1
Generalised additive model	32.0	37.0
Regression tree	62.9	66.9

Table 3-3. Percentage variance in the soil moisture data explained by each trend model.

It is obvious that the regression-tree, while far from perfect, models the trend in the data with greatest efficacy. The other models are likely to fail in capturing the variation in soil moisture content in three-dimensions due to the 'step-input' effect of rainfall events and subsequent drying cycles. The skeletons of the regression tree models are shown diagrammatically in Figure 3-8 and 3-9 where the spacing between levels is based on the deviance of parent and children nodes. To enable the criterion for each split to be viewed, the same regression trees are also shown with uniform spacing between the nodes in Figures 3-10 and 3-11.

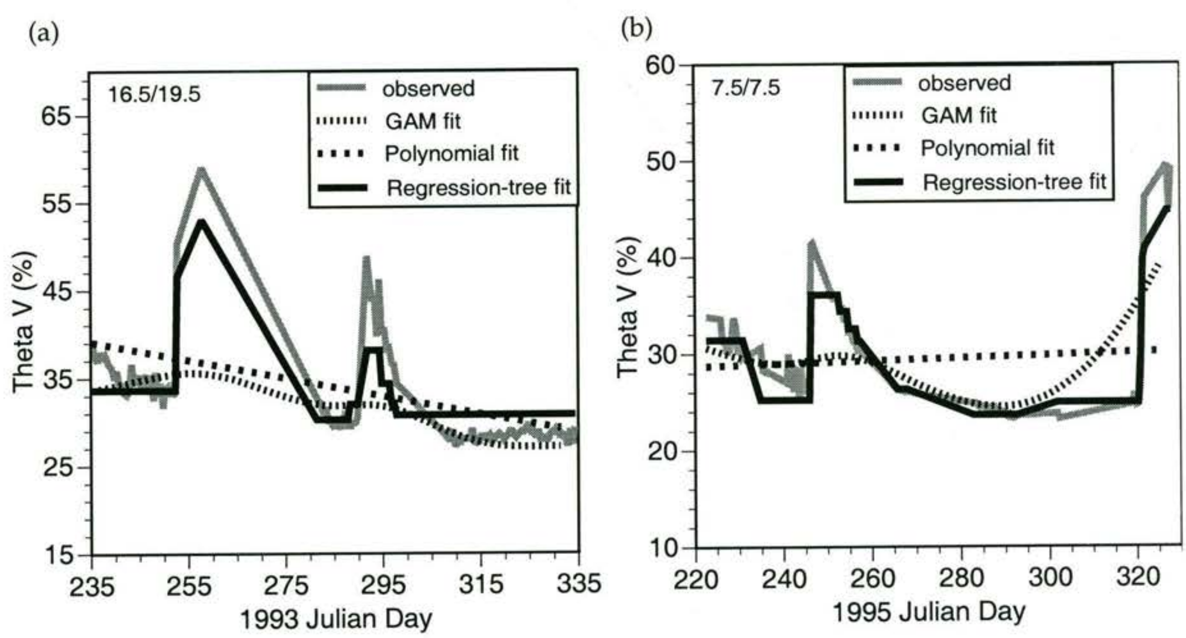


Figure 3-7. Experimental model fits for 1993 (a) and 1995 (b). Fit for one observation point over entire growing season (spatial location denoted by x/y co-ordinates (in metres) in top left corner of each graph).

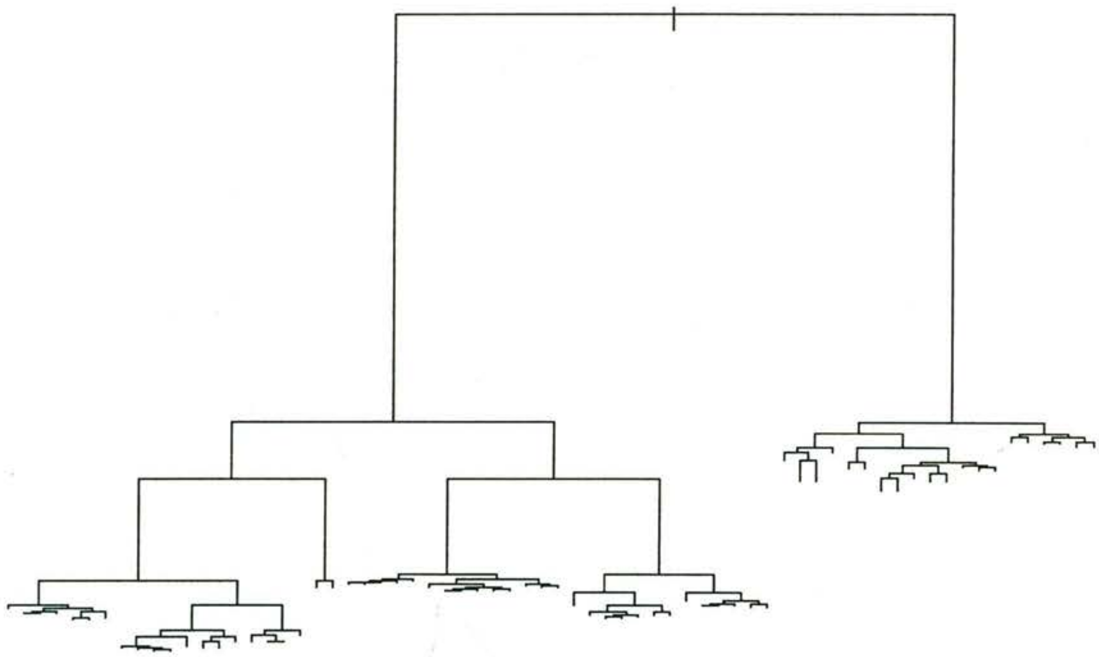


Figure 3-8. 1993 regression-tree skeleton showing separation based on deviance between parent and children nodes.

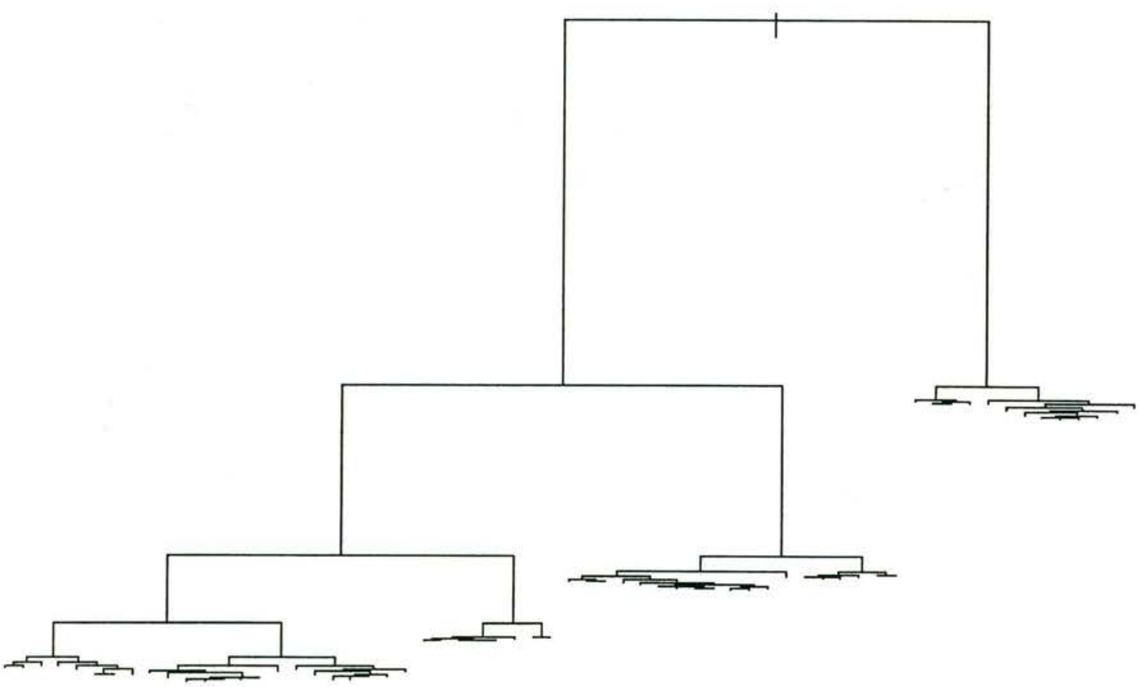


Figure 3-9. 1995 regression-tree skeleton showing separation based on deviance between parent and children nodes.

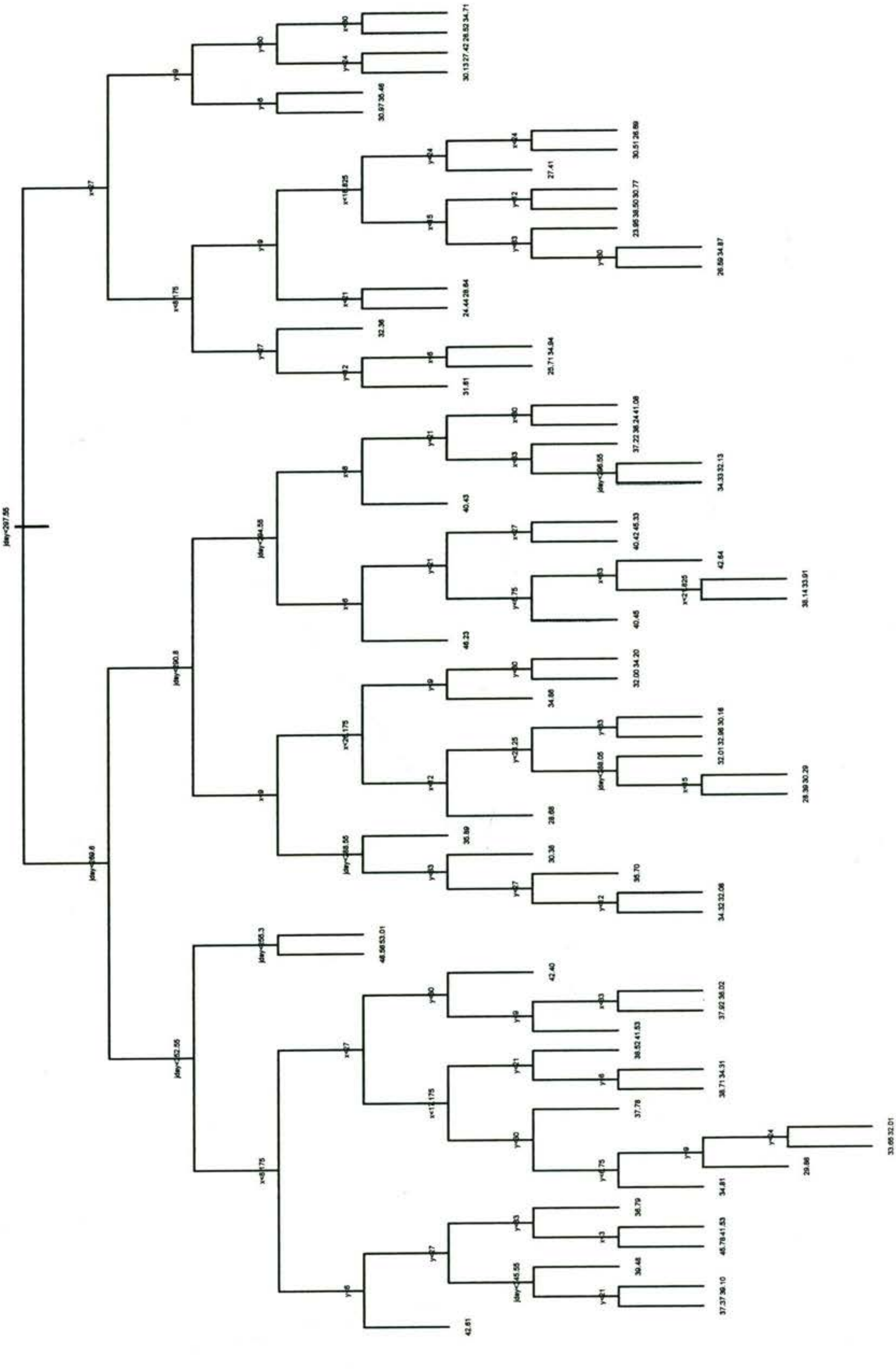


Figure 3-10. 1993 regression-tree skeleton showing criterion for separation (uniform node spacing).

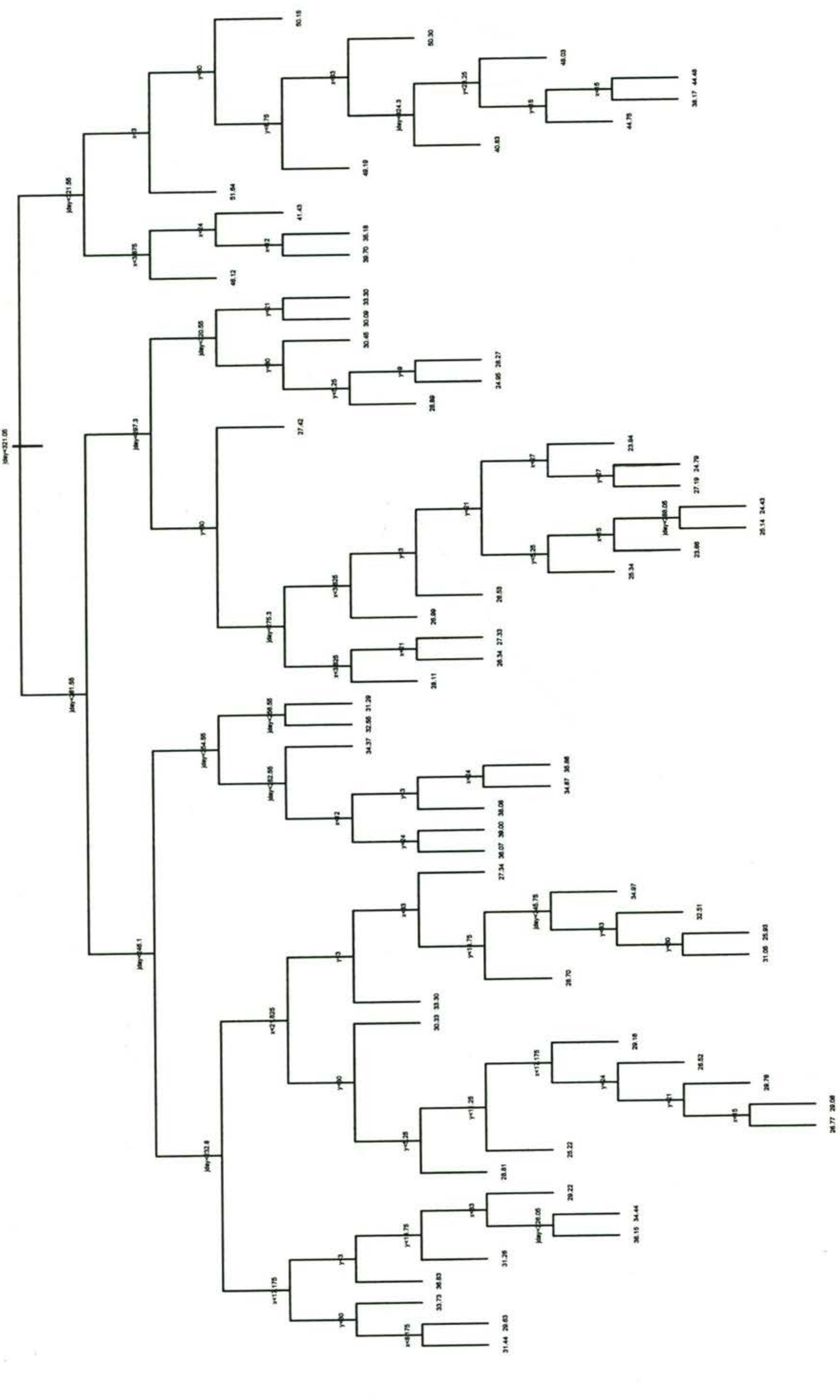


Figure 3-11. 1995 regression-tree skeleton showing criterion for separation (uniform node spacing).

The model is fitted to two spatial dimensions (X and Y co-ordinates) and a temporal dimension (julian day of observation). It is appears from Figures 3-8 to 3-11 that the major criterion for separation is temporal (jday). This is perhaps understandable given the intensity and sporadic nature of the rainfall events that lead to the recorded soil moisture content. A breakdown of the variance in the data sets that can be explained by modelling the time or space components separately is provided in Table 3-4. Modelling the soil moisture content with any degree of precision would seem difficult without the temporal indicator data.

	% Variance Explained	
Model component	1993	1995
All (jday, x, y)	62.9	66.9
Temporal (jday)	44.4	59.2
Spatial (x & y)	30.4	19.2

Table 3-4. Percentage variance in the soil moisture data explained by incorporating each component singularly in the regression-tree model.

Figures 3-12 and 3-13 are included to display the temporal fit of the regression-tree models at different locations within the site. The locations, the same in both years and identified by co-ordinates in the upper left of each graph, have been chosen to uniformly cover the site and are presented in a plan perspective of the site.

These figures show that in both seasons the trend model fits most poorly in the upper left and lower right corners of the site. From the lower left, through the centre, to the upper right of the site the trend model fits quite well. This is indicative of the direction of the trend at the site. Maps showing the modelled spatial variability in the trend across the site on a number of days during the growing seasons (Figures 3-14 and 3-16) also highlight the changing spatial pattern with time in each year. A comparison with the original observations on the same days is provided in Figures 3-15 and 3-17. The original data was recorded on the nodes of a 3m grid and the maps presented are not predictions but representations of the point observations as 3m × 3m blocks. The modelled trends (and indeed all Figures representing modelled attributes) are point predictions on the nodes of a 1m three-dimensional grid for improved spatial and temporal resolution. The data is represented as blocks for improved visual appreciation and it is not difficult to 'see' the modelled trend patterns in the original data maps.

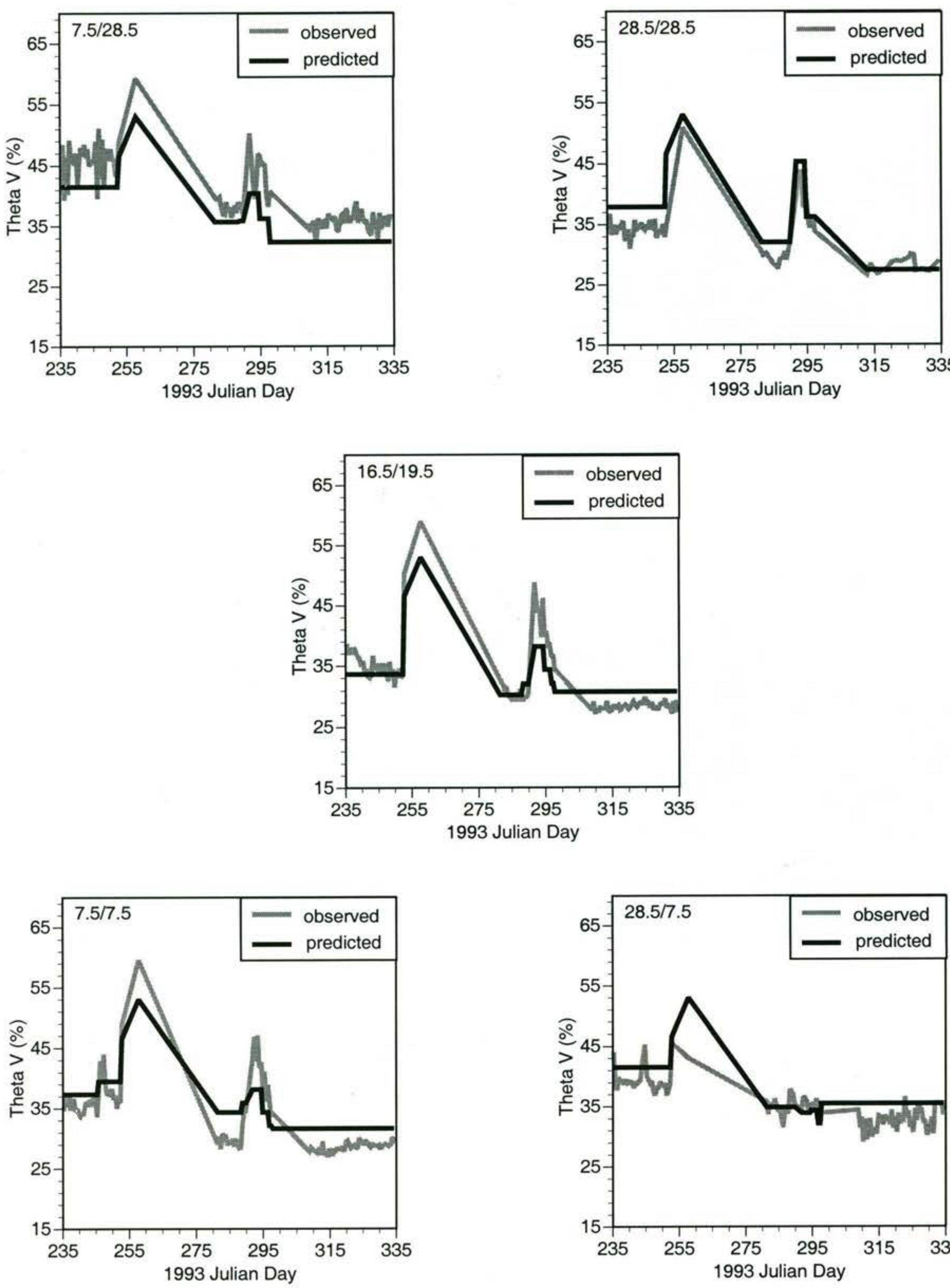


Figure 3-12. 1993 regression-tree fit for the entire season at a number of locations at the site (location coordinates in metres are shown in top left of each graph; graphs presented as a plan view of the site).

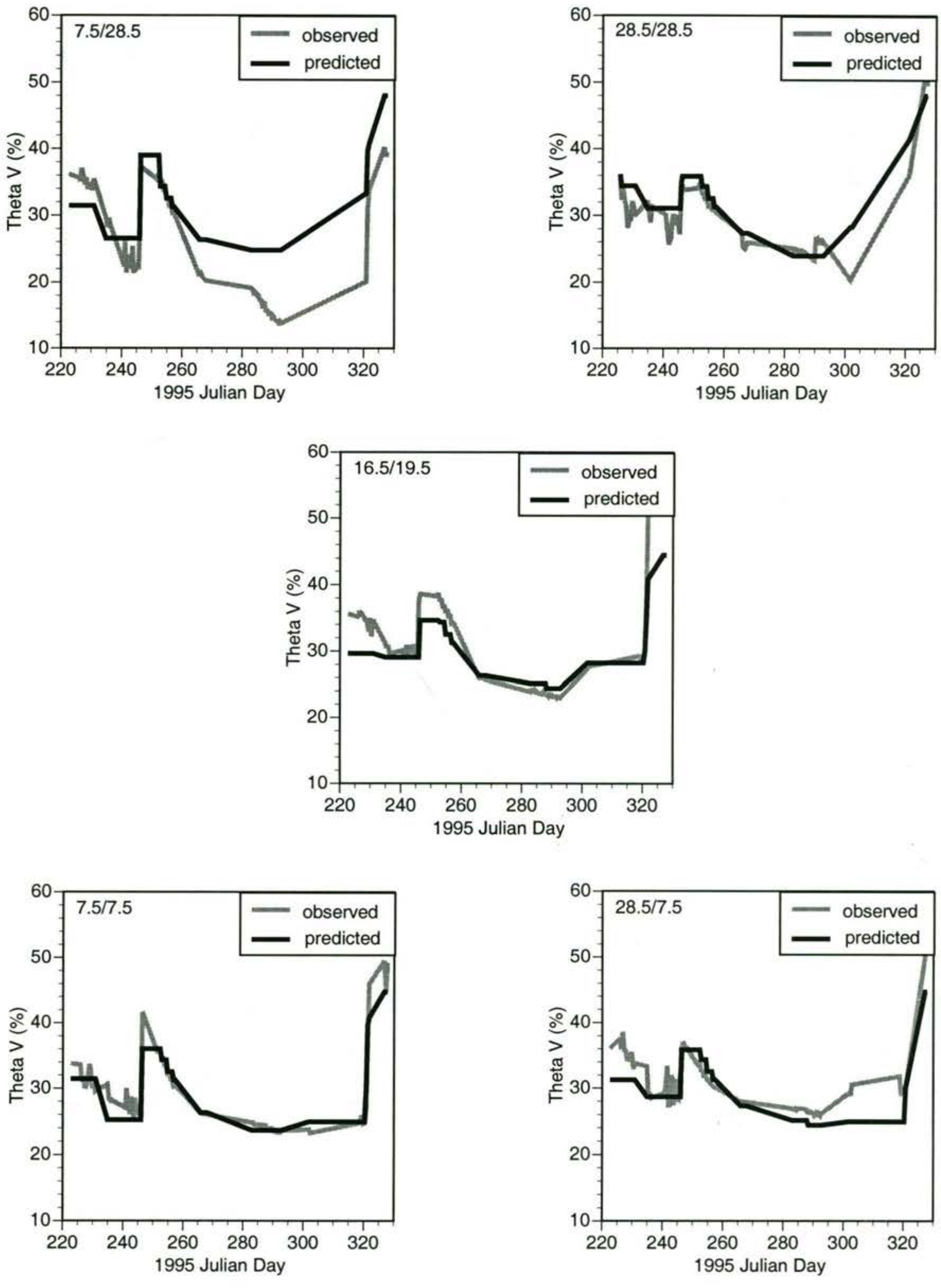


Figure 3-13. 1995 regression-tree fit for the entire season at a number of locations at the site (location coordinates in metres are shown in top left of each graph; graphs presented as a plan view of the site).

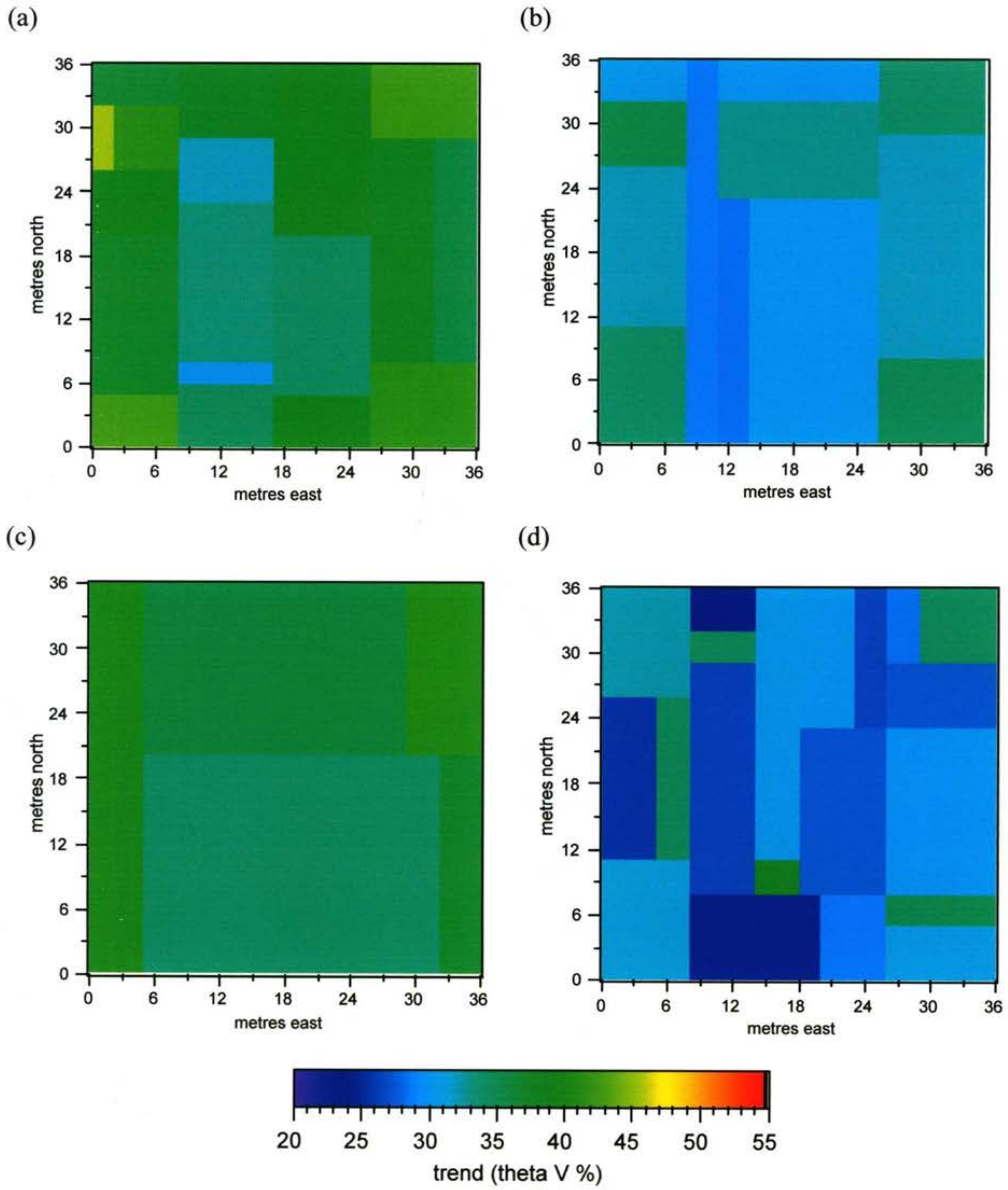


Figure 3-14. 1993 regression-tree trend prediction across the site on single days (a) julian day 240, (b) julian day 285, (c) julian day 295, (d) julian day 320.

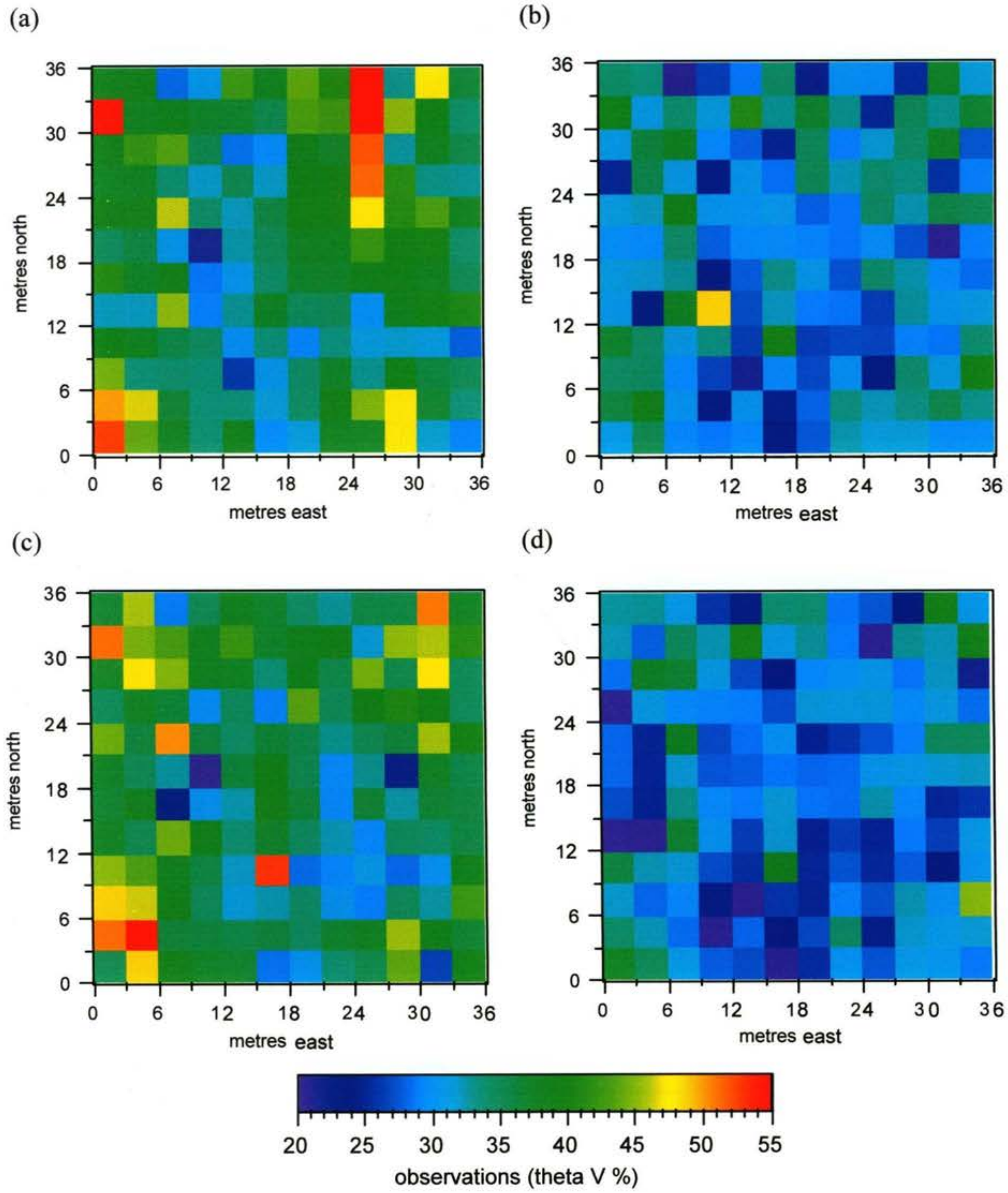


Figure 3-15. Observations of soil moisture content across the site on single days in 1993 (a) julian day 240, (b) julian day 285, (c) julian day 295, (d) julian day 320.

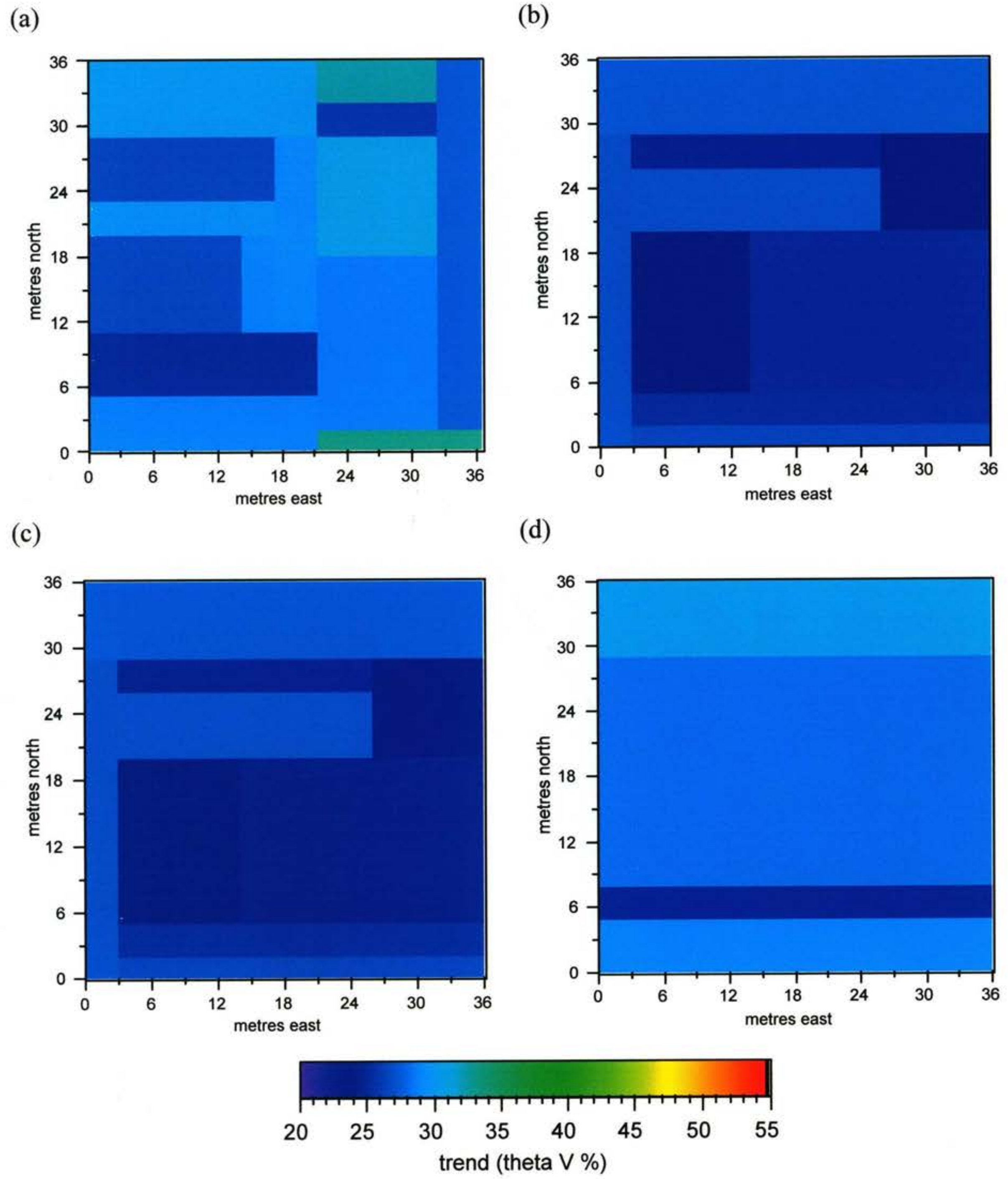


Figure 3-16. 1995 regression-tree trend prediction across the site on single days (a) julian day 240, (b) julian day 285, (c) julian day 292, (d) julian day 320.

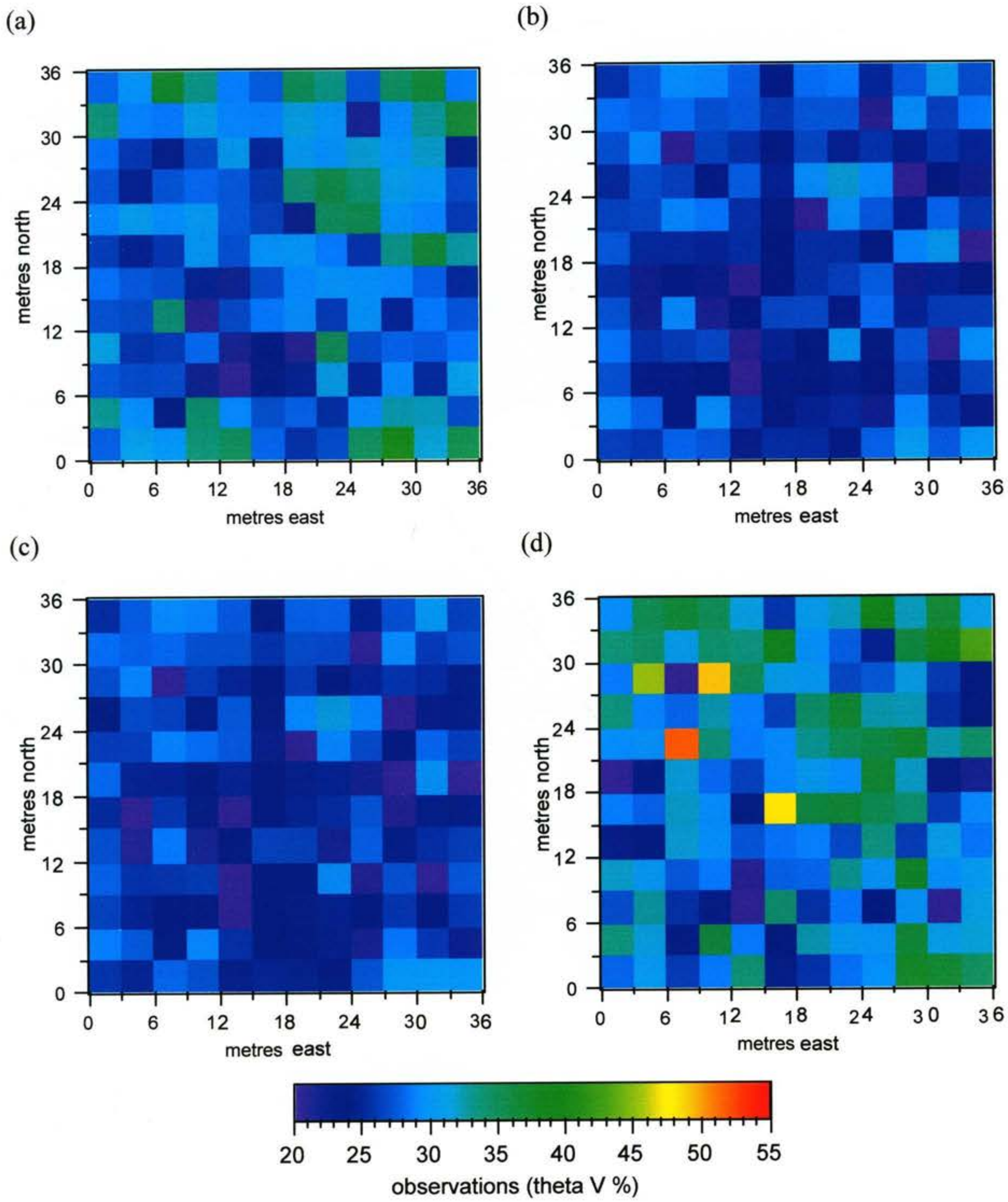


Figure 3-17. Observations of soil moisture content across the site on single days in 1995 (a) julian day 240, (b) julian day 285, (c) julian day 292, (d) julian day 320.

Residual Modelling

Modelling the residuals arising from the trend fit to the observations was undertaken using a three-dimensional semivariogram analysis. With the removal of the underlying trend, the residuals were assumed to possess spatial isotropy (X,Y plane) and anisotropy along the temporal (Z) plane. The semivariogram cloud was then constructed from observation residuals using isotropic spatial lags and 36 azimuth angles in the temporal plane. Visually representing such a semivariogram cloud is more difficult than a two dimensional example. Figures 3-18a and 3-19a show the residual semivariance estimated for observations with spatial lags up to 20m and temporal lags up to 50 days.

Modelling the semivariogram was achieved using Equation 3-9, a modified form of Equation 3-8.

$$\gamma(\lambda,\tau) = C0 + C\left(1 - \exp\left(-\sqrt{\left(\frac{\lambda}{a'} + \frac{\tau}{b'}\right)}\right)\right) \qquad (3\text{-}9)$$

where:

$\gamma(\lambda, \tau)$	=	semivariance as a function of the spatial lag (λ) and the temporal lag (τ)
C_0	=	nugget semivariance
C	=	sill semivariance minus the nugget semivariance
a'	=	the range of influence in space
b'	=	the range of influence in time.

The parameters for this three-dimensional model in both years are shown in Table 3-3.

Parameter	1993	1995
C0 (θv %^{2})	5.6	5.8
C (θv %^{2})	13.0	7.3
a (m)	3.2	1.7
b (days)	30.3	36.0
a/b (m/day)	0.1	0.05

*note: a and b are the apparent range equivalent (3 $\times$ a' or b')

Table 3-5. Model parameters for the 1993 and 1995 space/time semivariograms.

The fitted models are represented in Figures 3-18b and 3-19b. The models as shown have been predicted onto a regular grid to remove the undue influence of prediction points on the perceived pattern. This influence is considered responsible for the undulations in the radiating patterns displayed in the semivariogram clouds (Figures 3-18a and 3-19a). Semivariance estimations using points in the three dimensional array with small temporal separation (close to the zero time axis) and high spatial separation (further from the origin of the figures) are much less common, and the estimates are accordingly less reliable.

The models in both years depict a quite small dependence in the spatial as compared with the temporal plane. This can be best observed by examining the predicted residuals across space with time held constant. Figures 3-20 and 3-21 map the residuals for the same days shown in Figures 3-14 and 3-16. The maps (especially in 1993) show a high degree of small-scale spatial dependancy in the residual patterns. This is seen as sharp changes in colours within each map. The dominance of the spatial co-ordinates on the variability in residuals can also be gleaned from the fact that there is greater change in the colours within maps than between the maps of one year. The spatial patterns could also be considered as reasonably stable through the year.

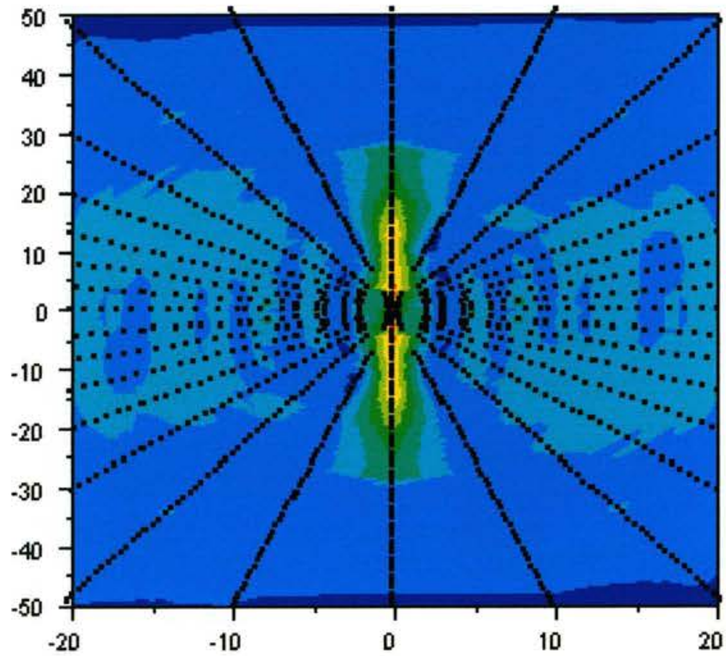
Combing Trend and Residual Analysis for Prediction

By combining the three-dimensional kriging estimates of residuals with the regression-tree trend predictions, the estimation of soil moisture content in both space and time should be enhanced. Figures 3-22 and 3-23 show this combined model fit to the observed data for each season at five locations within the site. These locations are the same as those showing the results of the regression-tree trend modelling in Figures 3-12 and 3-13. A comparison between these two sets of figures indeed suggests that the observations are more successfully predicted, however in areas where the trend model failed to reliably characterise the moisture content, the final estimate remains inadequate.

Figures 3-24 and 3-25 allow an insight into the spatial pattern in total soil moisture content that has been predicted accross the site at a number of given days in the season. The trend model can again be seen to dominate the moisture prediction.

As mentioned earlier, the moisture monitoring equipment performed less than optimally given the effort required for installation. A full season data set would have provided a far greater opportunity for examining the implications of this method of soil moisture modelling for crop parameters. Further exascerbating this attempt was the significant rain damage to the grain at harvest 1995.

(a)



(b)

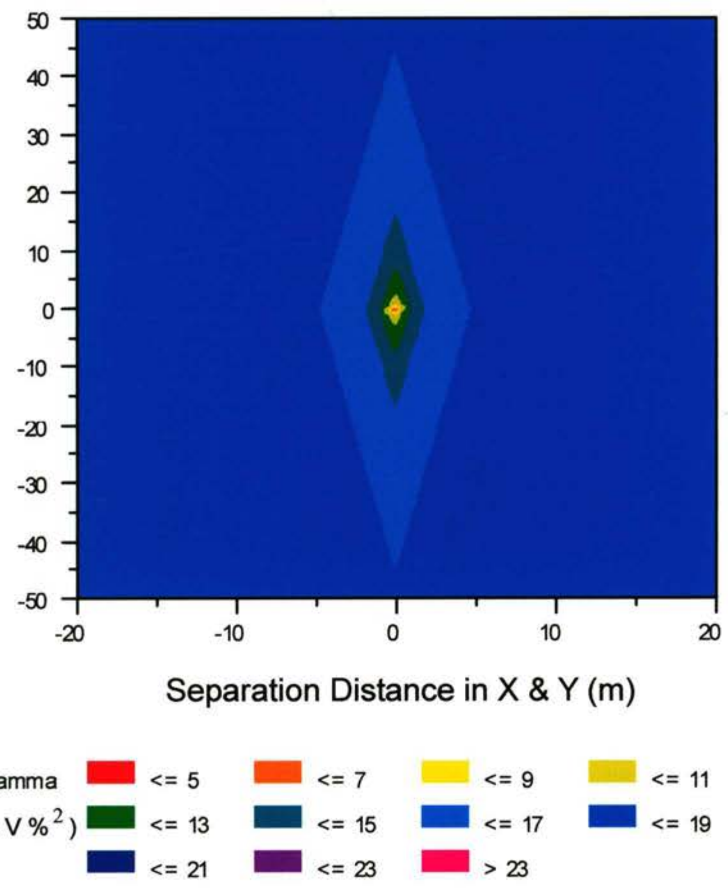


Figure 3-18. Representation of the three-dimensional semivariogram for 1993 - (a) semivariogram cloud calculated using the displayed rotation angles in the time dimension; (b) semivariogram model.

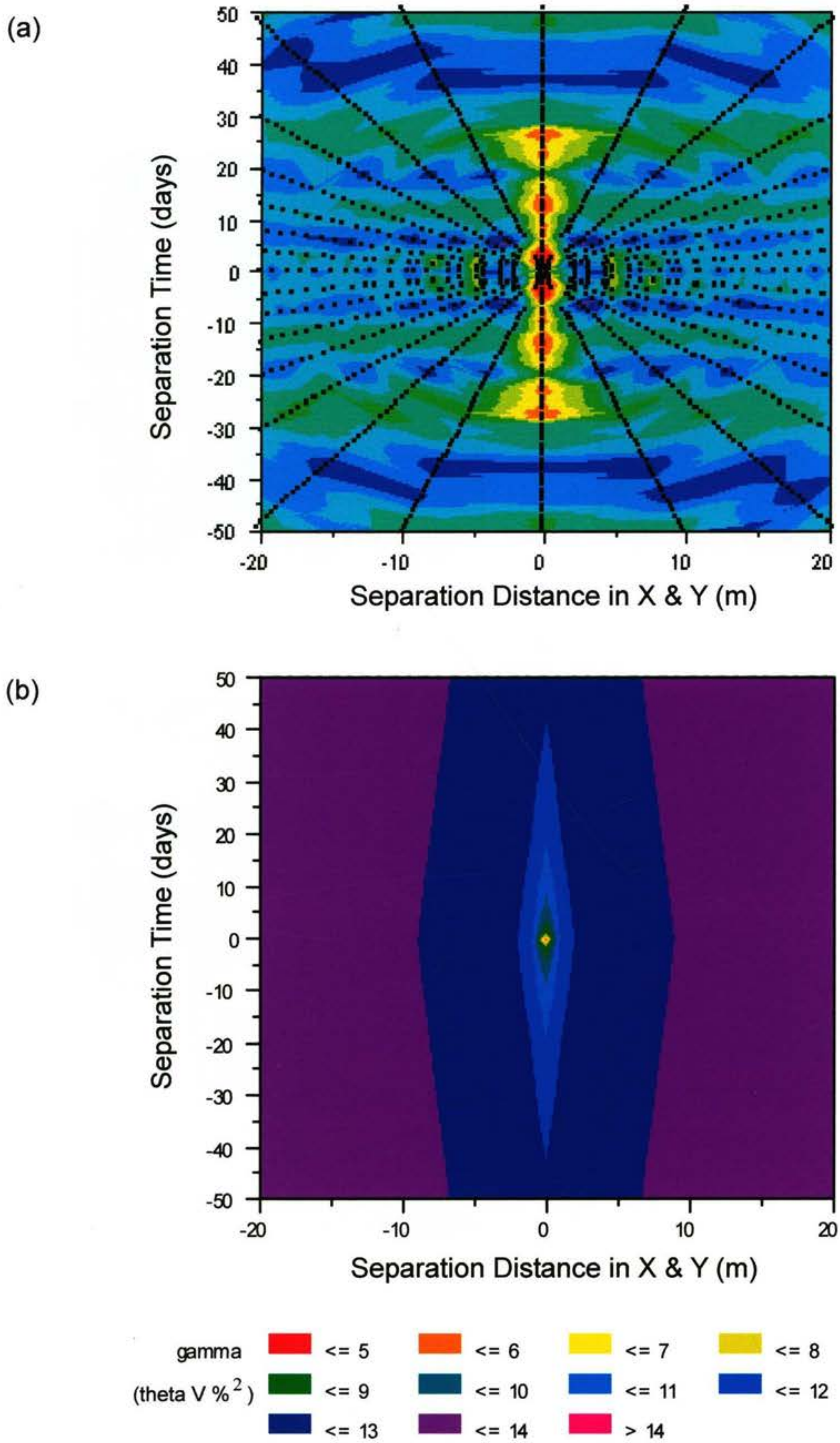


Figure 3-19. Representation of the three-dimensional semivariogram for 1995 - (a) semivariogram cloud calculated using the displayed rotation angles in the time dimension; (b) semivariogram model.

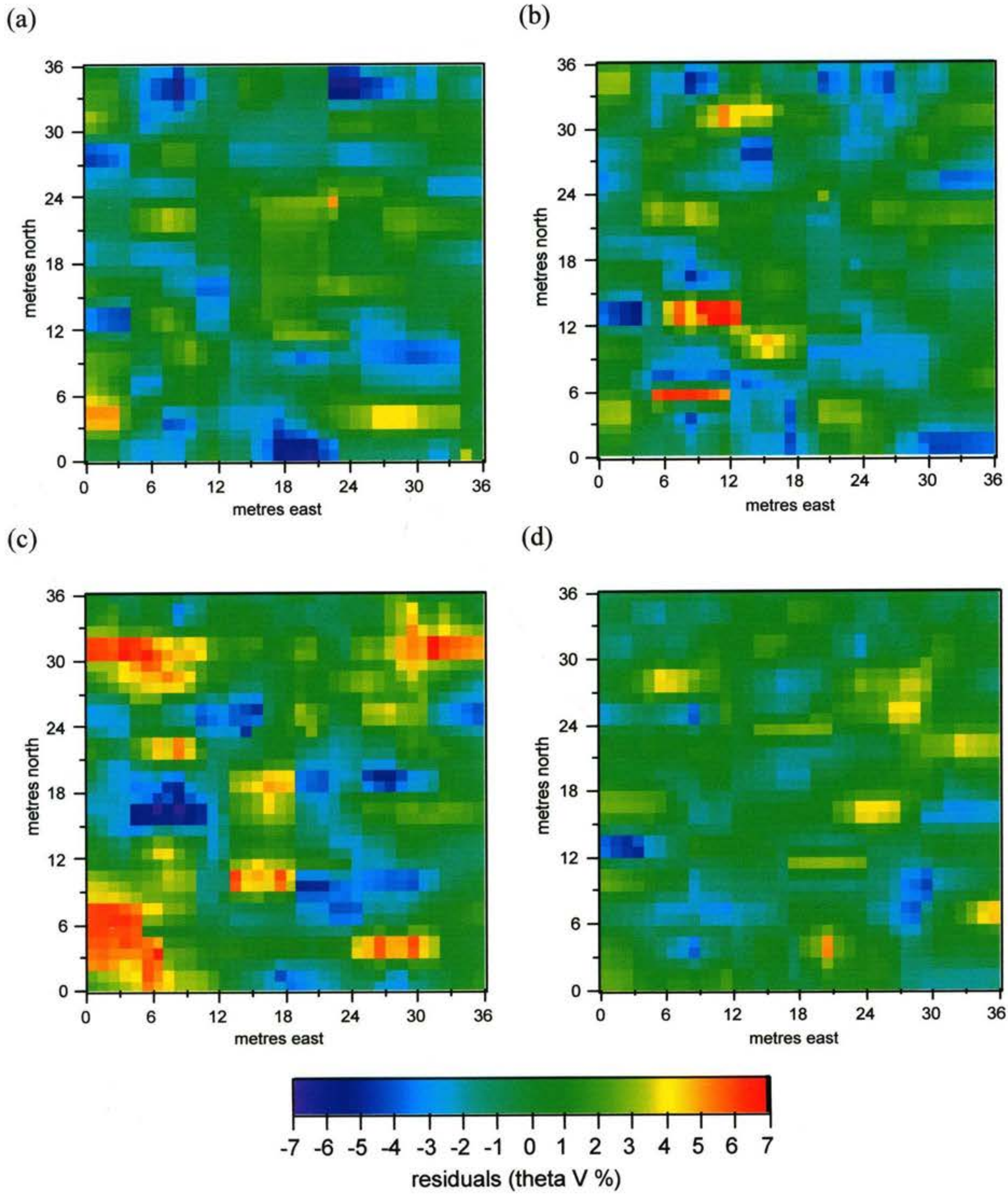


Figure 3-20. 1993 kriged residual estimates across the site on single days (a) julian day 240, (b) julian day 285, (c) julian day 295, (d) julian day 320.

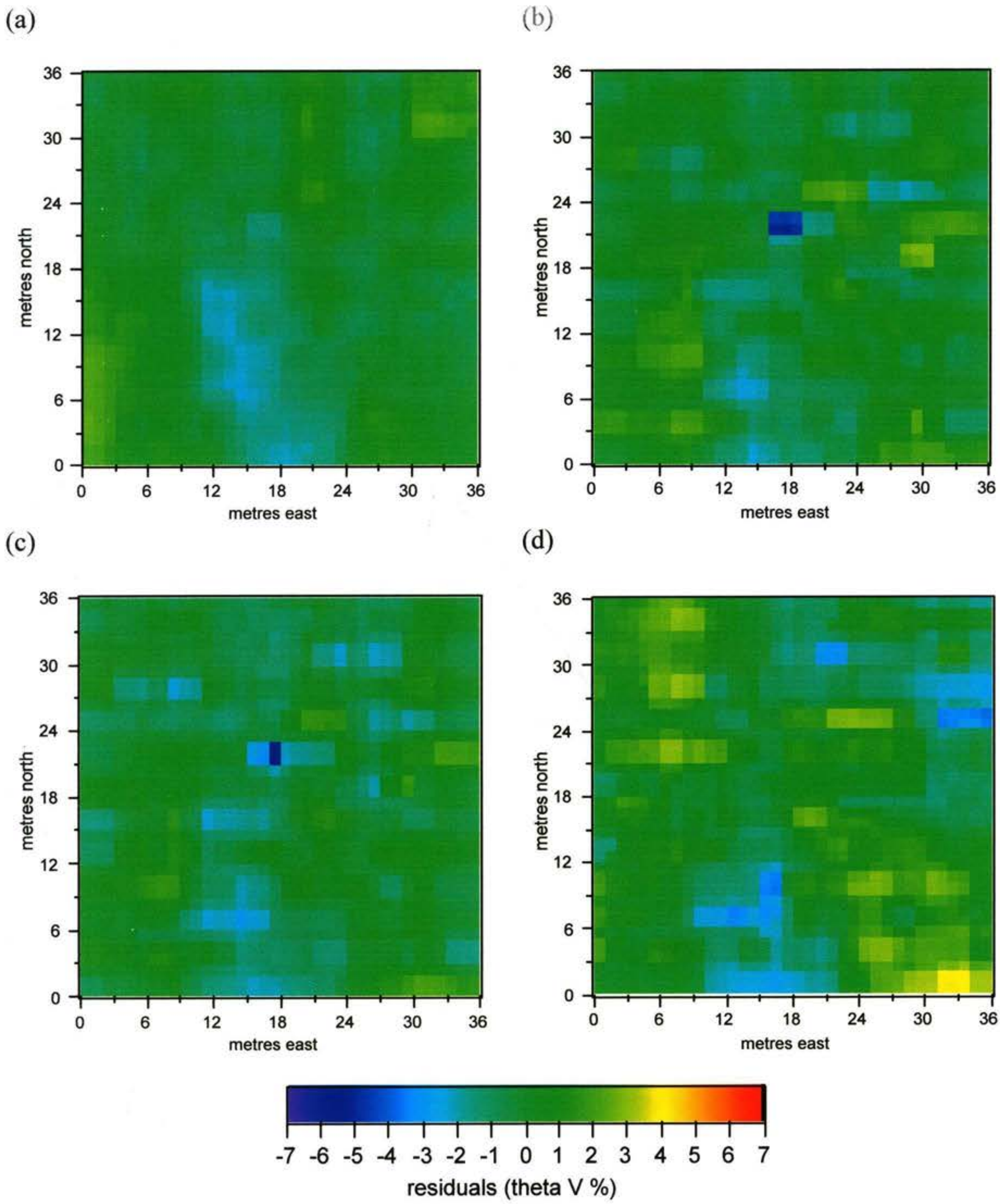


Figure 3-21. 1995 kriged residual estimates across the site on single days (a) julian day 240, (b) julian day 285, (c) julian day 292, (d) julian day 320.

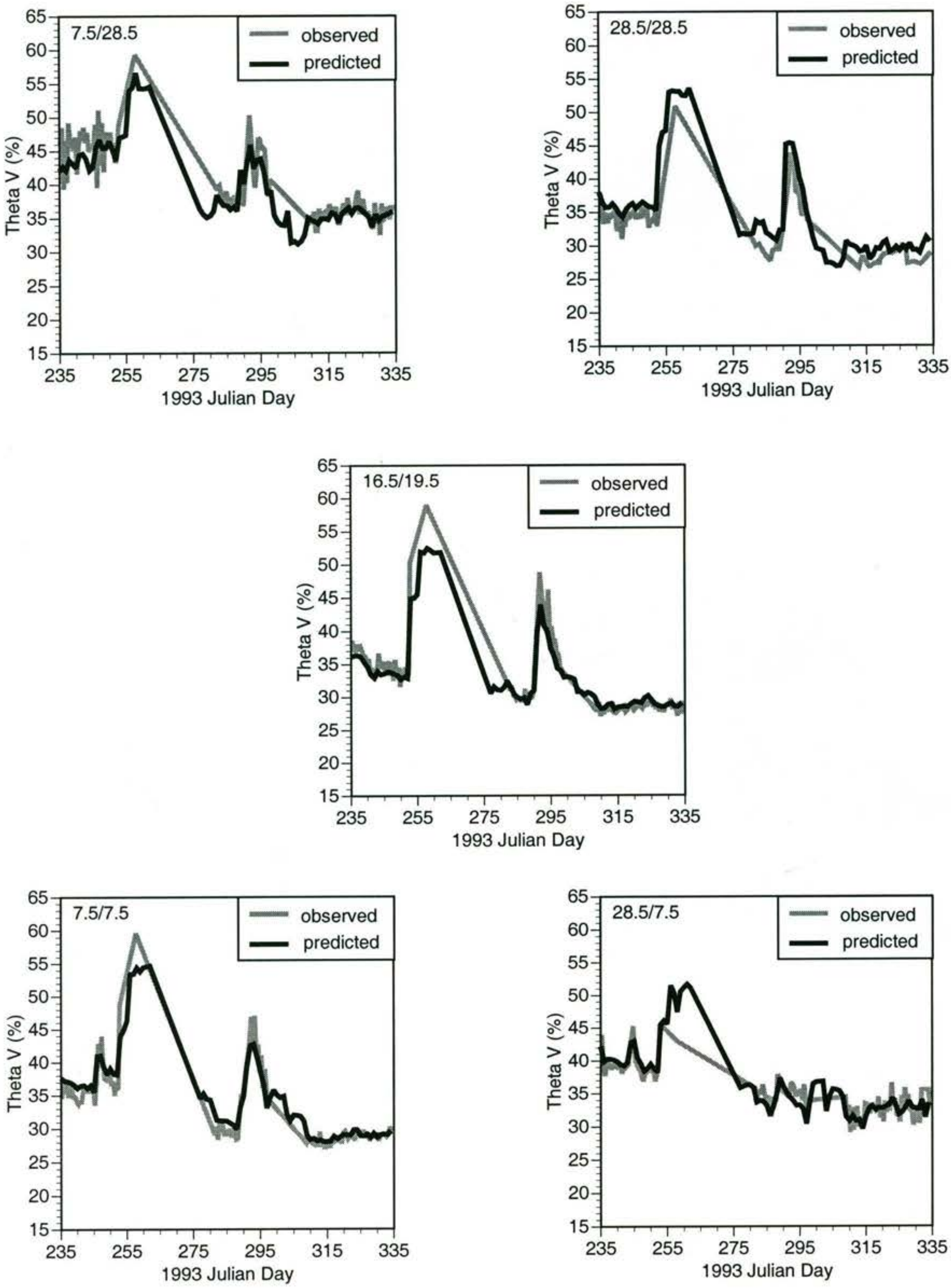


Figure 3-22. 1993 combined trend and residual estimates for the entire season at a number of locations at the site (location coordinates are shown in top left of each graph; graphs presented as a plan view of the site).

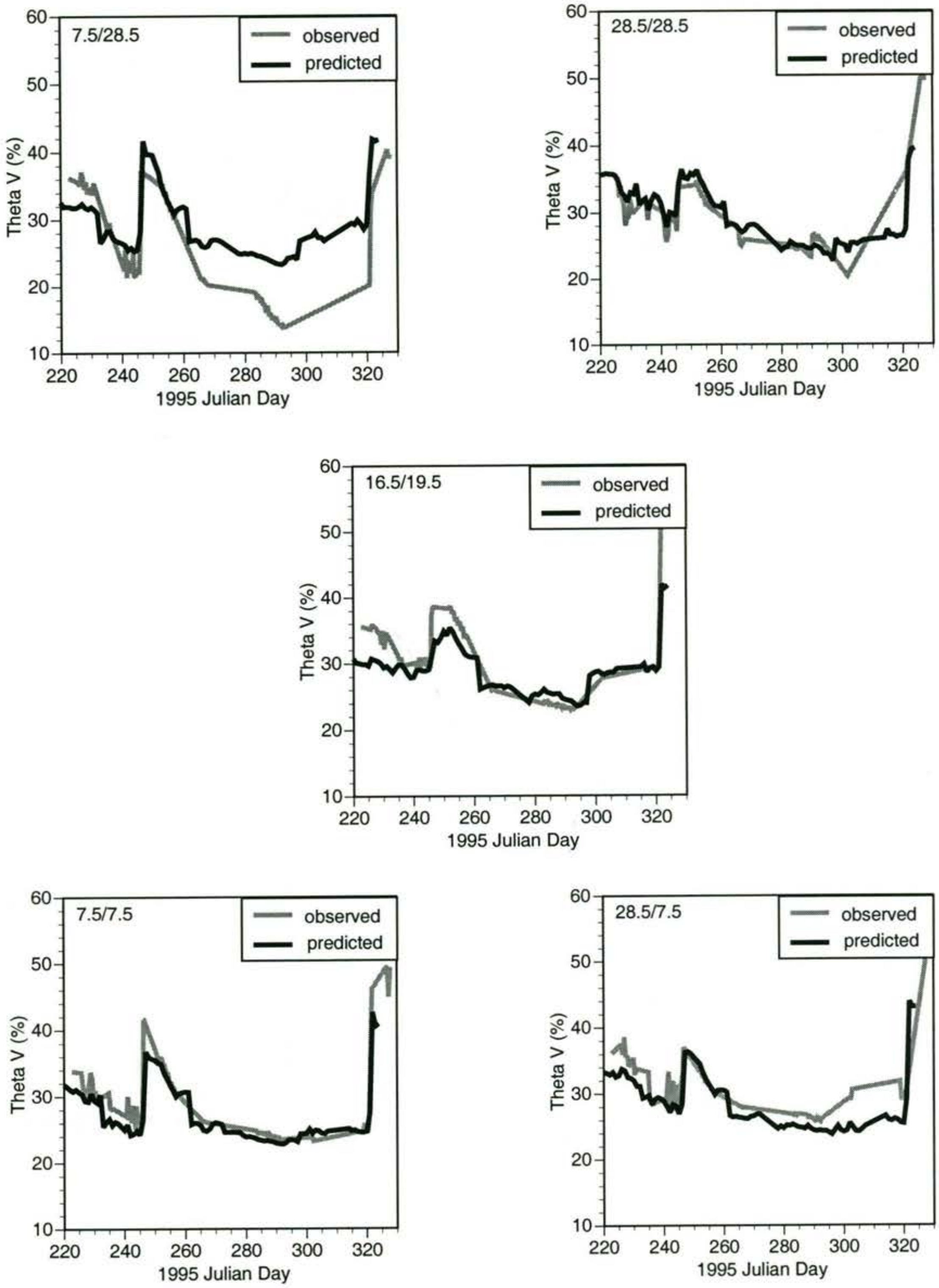


Figure 3-23. 1995 combined trend and residual estimates for the entire season at a number of locations at the site (location coordinates are shown in top left of each graph; graphs presented as a plan view of the site).

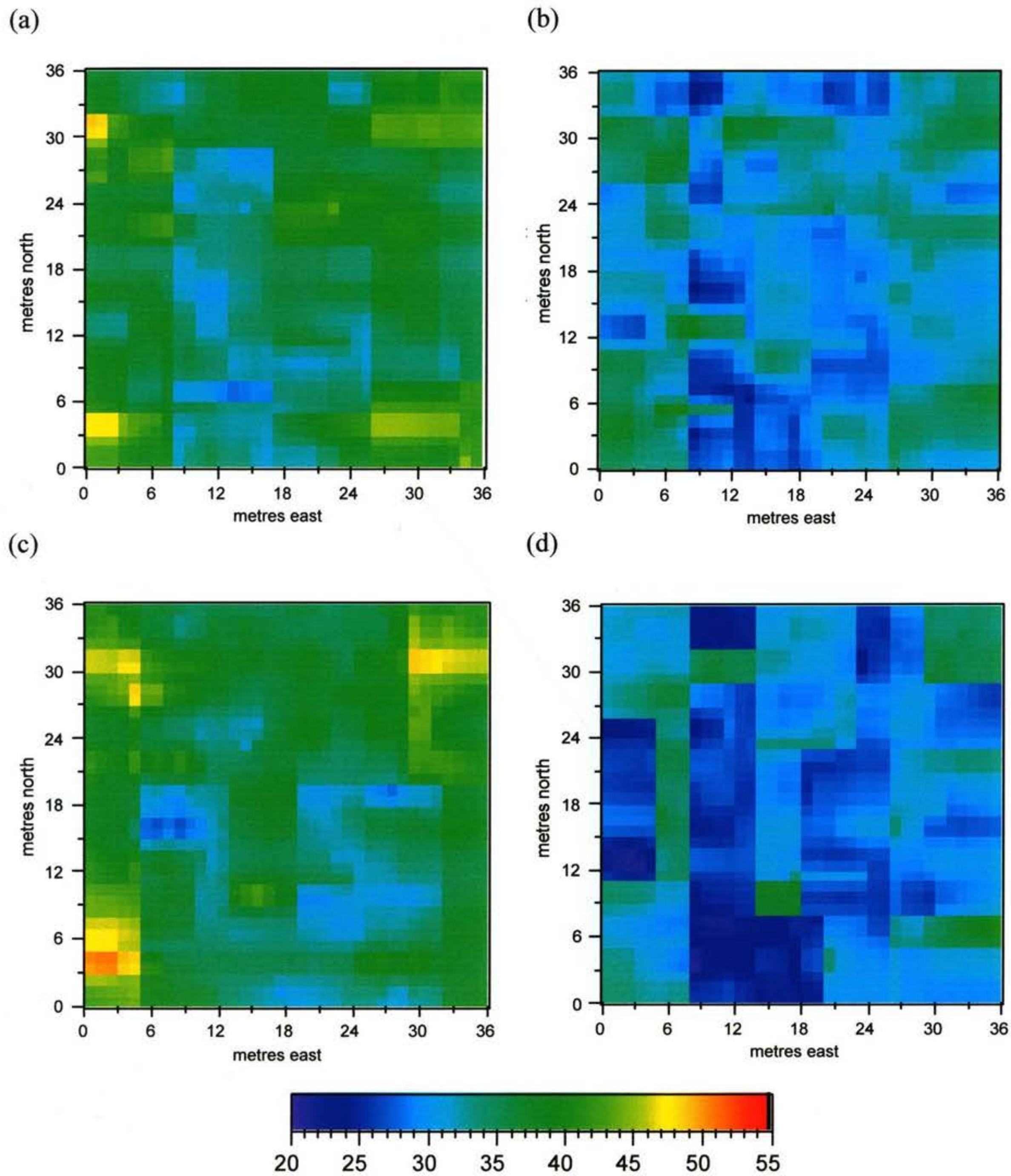


Figure 3-24. Combining trend and residual estimates for soil moisture across the site on single days in 1993 (a) julian day 240, (b) julian day 285, (c) julian day 295, (d) julian day 320.

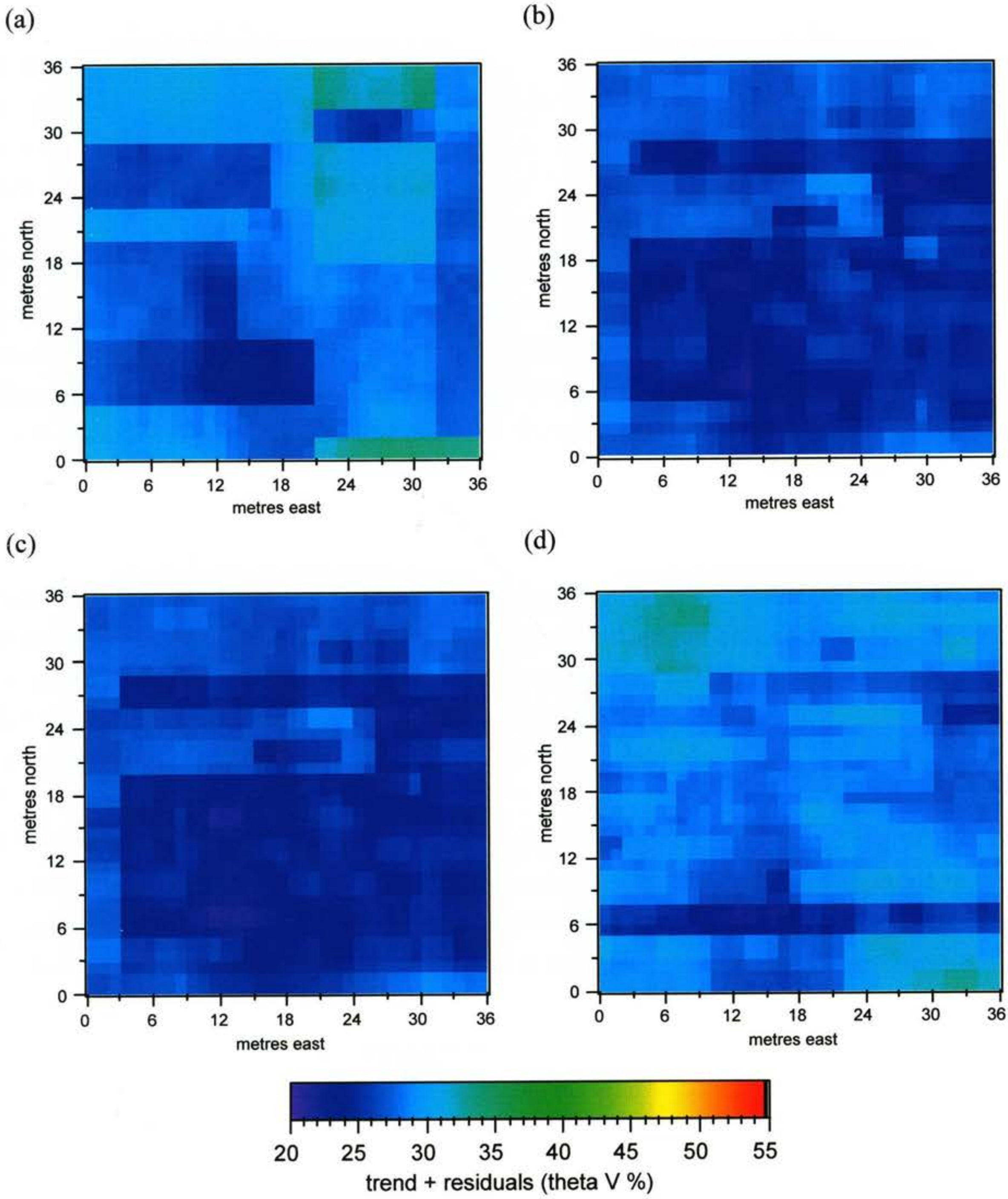


Figure 3-25. Combining trend and residual estimates for soil moisture across the site on single days in 1995 (a) julian day 240, (b) julian day 285, (c) julian day 292, (d) julian day 320.

The significant temporal variability observed in these experiments suggests that the successful completion of such work will be required if variation in soil moisture content is to be usefully employed in the Precision Agriculture Decision-Support Systems of the future.

3.5 CONCLUDING REMARKS

The results presented in this Chapter suggest that the variability in soil moisture content across a field during a growing season is predominantly influenced by time. The trend model based on the spatial co-ordinates and the Julian calendar day of the observations show that the initial (and most significant in terms of variance partition) tree nodes separate on the temporal parameter. However, the spatial component of this trend model cannot be ignored. The spatial patterns in the trend model maps shown in this Chapter are rarely similar.

With the dominant temporal variability being significantly removed by the regression-tree, the variation in residuals shows a more dominant spatial influence. In fact the variation in residuals found over 1 metre in 1993 was equivalent to that experienced over 10 days. In 1995 the ratio suggests that 1 metre of spatial variation equalled 20 days in the temporal dimension.

While this study provides only a small insight into the complex nature of space-time variability in soil moisture content, the dominance of the trend component may have significant implications for the use of real-time soil moisture sensors and Decision-Support Systems in Precision Agriculture. While it is apparent that the trends are dominated by time in this instance, a region with more regular rainfall (or irrigation) should show a greater influence of spatial parameters in the model. In such circumstances, the ability to rely on trend information only would mean substantial savings in computation complexity and time if soil moisture was to be eventually incorporated into real-time Decision-Support Systems.

In areas where spatial parameters were found to dominate trend models, then modelled soil moisture content could be used to stratify management units within fields. From the results presented here, the region under investigation could not be considered suitable for such delineation and real-time sensors would best be employed to provide data for agronomic operations (e.g. sowing) that are performed in temporal proximity to the moisture measurement.

In the future it may prove suitable to monitor inherent trends in the temporal variability of soil moisture content within fields and use this information for growth assessment and risk-based analysis of within season operations such as fertiliser and pesticide applications. An understanding of the trend in soil moisture variability appears to provide the most useful information for crop growth management. Fine tuning using the residual model may add little of use for management.

CHAPTER 4

CHAPTER 4

Real-time Monitoring of Crop Yield - Spatial & Temporal Variability

4.1 INTRODUCTION

As Chapter 1 documents, the quantification of crop yield variability within a field has to date relied on random broad-scale sampling, transect sampling or small-scale labour intensive comprehensive sampling operations. Extending the information gained using such procedures to whole fields requires the assumption that the sample variance is representative of the true field variance. The true field variance has been economically and perhaps physically impossible to obtain, however gathering detailed yield variability data on a broad-scale (i.e. whole field basis) during the normal commercial harvest operation could provide this information.

This chapter presents work aimed at documenting and examining the detailed spatial and temporal variability in grain crop yield within and between fields in north-west New South Wales using real-time crop yield monitors.

4.2 MATERIALS & METHODS

4.2.1 Harvesting Process

A conventional combine harvester (John Deere 7720) was used to harvest winter wheat crops in November/December 1995 and 1996 and summer sorghum crops in February/ March 1996 and 1997. The wheat harvest in 1997 involved two harvesters often operating in tandem within a field. Both harvesters were fitted with 7 metre wide cutting-tables. The fields, all located within a 40km radius near the village of Biniguy in north-west NSW, are farmed by one family. The crops were agronomically managed using a traditional uniform approach to ground preparation, sowing rates, fertiliser and pesticide application.

Beginning in 1995, the harvesters were equipped to monitor crop yield by recording grain mass flow rates and determining the area to which each measurement should be allocated. For this purpose a number of instruments are required. A real-time mass flow sensor was installed between the exit point of the clean grain elevator and the grain bin bubble-up auger intake (Figure4-1a). At this point a free-flowing stream of clean grain can be intercepted by the flow sensor (Figure4-1b) which comprises a strike-plate and potentiometer to measure applied force (Figure4-1c) - see section 2.2.2 for a full description.

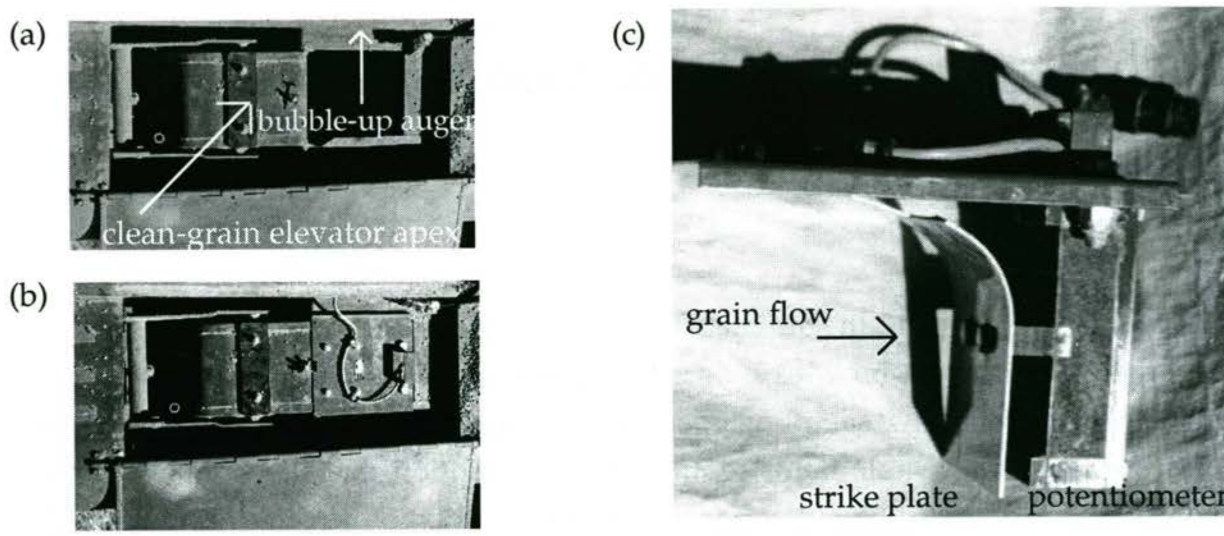


Figure 4-1. Grain-flow sensor installation: (a) mounting position (b) installed (c) sensor. An AgLeader ®† mass flow sensor was employed.

A capacitance-type moisture meter was installed into the bubble-up auger where the flow of clean grain over the capacitance plate registered grain moisture content continuously (Figure 4-2). The grain moisture content is used to adjust the final yield calculation to a constant grain moisture content.

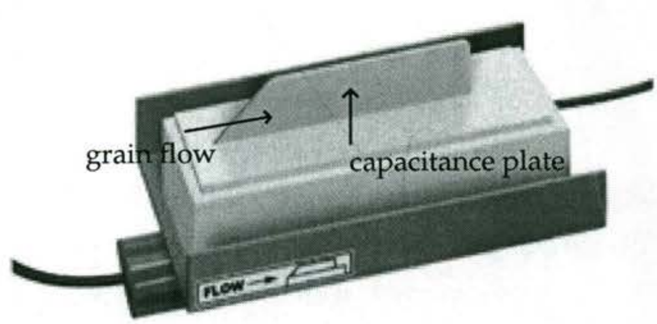


Figure 4-2. Capacitance plate moisture sensor .

A dGPS receiver (Motorola Encore 8 channel with OmniStar demodulator) was installed in the harvester cabin behind the operators seat and connected to two externally mounted aerials. The GPS aerial was located along the central axis of the harvester on the top edge of the grain-bin front 'hungry board'. This location gives an uninterupted satellite view and ensures that position readings refer to the central axis of the harvester close to the perpendicular plane on which the yield sensor is mounted.

† AgLeader Technology, 2202 South Riverside Drive, Ames, IA 50010.

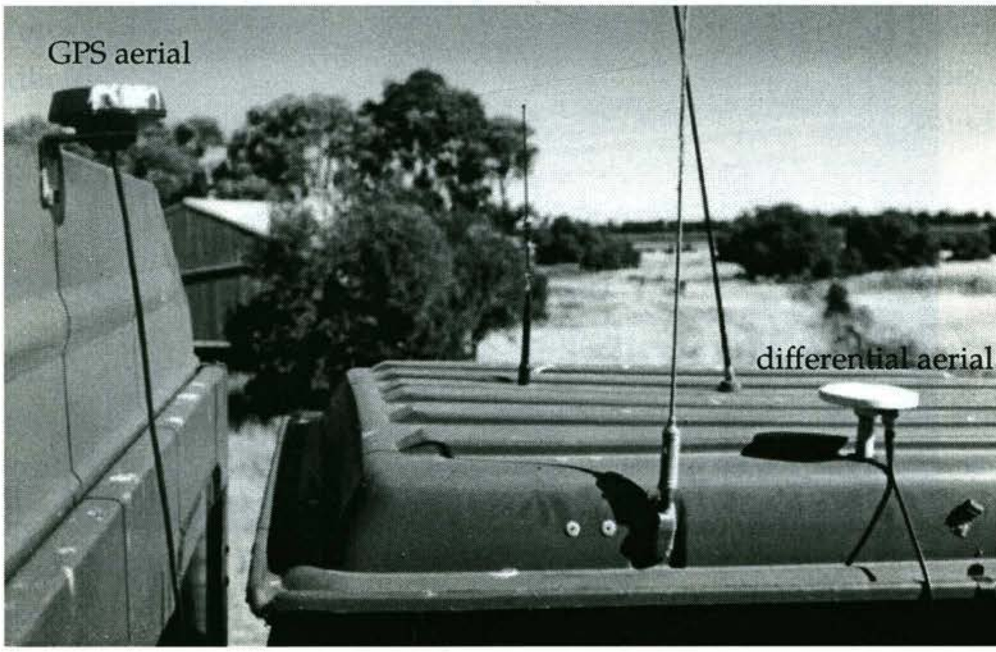


Figure 4-3. dGPS aerial array.

The differential correction aerial has no positional restrictions other than ensuring an uninterrupted sattelite view. The mounting positions for both these aerials can be seen in Figure 4-3. The dGPS system and the yield sensor were linked to a cabin mounted monitor that combines a basic computer with a static RAM (SRAM) PCMCIA card port for data storage (Figure 4-4). Each second during harvest operations, incoming grain flow force data from the yield sensor is matched with a georeference point from the dGPS and stored on the PCMCIA card. Additional information required to convert the force to mass per unit area is also recorded by the monitor. These attributes include GPS time, harvester speed, cross auger speed and comb cutting width and were also stored each second.

Calibration

Together these instruments produce a monitoring system which requires some basic initial calibration. Distance monitoring is effectively calibrated by travelling over a known distance. The signal from the grain sensor registers force and this must be converted to a mass flow rate. Firstly, the underlying mechanical noise effects of harvester operation on signal output are identified by running the harvesting mechanisms at full operational speed with no grain flow. This provides a signal level that equates to zero yield. Quantitative yield calibration is then achieved through comparison of cumulative mass measurement using a mobile grain bridge (10 kg resolution) and an integrated sensor

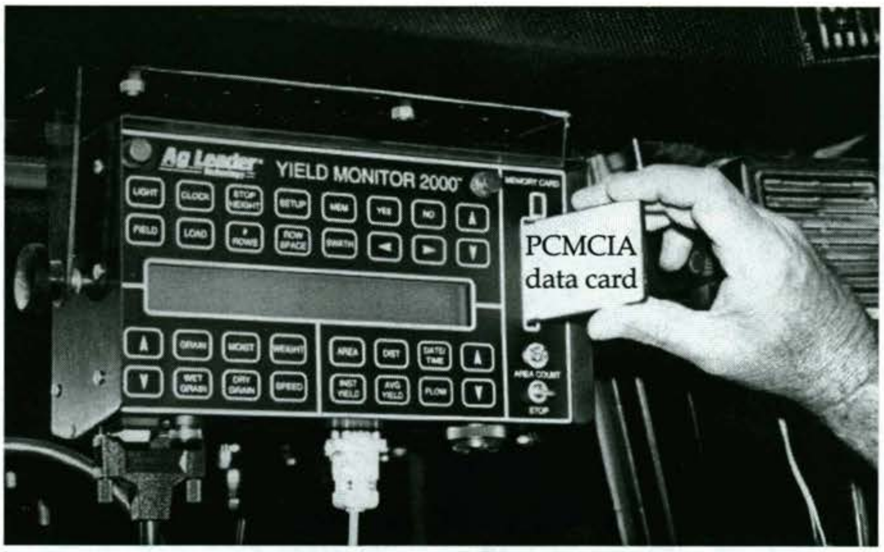


Figure 4-4. Cabin mounted monitor showing PCMCIA data storage card and the connections to external sensors.

signal. Total grain mass was measured on six to eight harvest loads, collected at a range of harvest speeds to simulate variation in grain flow rate within the harvester. These comparisons were performed for each crop in each year and used to construct signal/yield calibration curves for the harvest.

4.2.2 Grain Yield Calculation

The sensed data may be used to calculate a yield quantity per unit area for a given harvest duration (*t*) by Equation 4-1.

$$\mathrm{Y}_{(t)} = \left(\frac{f_{(t)} \times 10}{d_{(t)} \times w_{(t)}}\right) \times (1 - (m_{(t)} - sm)) \qquad (4\text{-}1)$$

where:

$\mathrm{Y}_{(t)}$	=	grain yield (t ha^{-1})
$f_{(t)}$	=	grain mass flow (kg)
$d_{(t)}$	=	distanced travelled (m)
$w_{(t)}$	=	cutting width (m)
$m_{(t)}$	=	moisture content (m^3 m^{-3})
sm	=	standard moisture content (m^3 m^{-3})

The wheat and sorghum yields referred to in these experiments has been corrected to 12% and 13% moisture content respectively, which is the desired level for delivery of grain to bulk handling facilities. A detailed description of the methods and practicalities of obtaining the operational measurements used in the grain yield calculation can be found in Pierce et al. (1997).

4.2.3 Rectifying Yield Quantities & Harvest Location

The calculated grain yield in mass per unit area remains matched with spatial co-ordinates that refer to the position of the harvester at the time the yield was sensed. With the yield sensor positioned at the end of the threshing and separating processes as previously described, there is a delay period between crop entering the harvester and flow being registered at the sensor. Both the yield sensor and dGPS are recorded at a frequency of 1 hertz, therefore shifting the yield measurements backward relative to the position information by an amount equal to the delay period should approximately rectify the yield with the relevant spatial co-ordinates.

The results shown herein have used a 10 second delay which has been determined as the mean travel time for grain through the harvester at harvest speed. Chapter 5 will discuss this important aspect of the yield monitoring process in more detail.

4.3 RESULTS & DISCUSSION

4.3.1 Position Accuracy

The dGPS instruments utilised in the monitoring process were subjected to a number of accuracy and repeatability tests involving start and end point correlation while mapping field boundaries and repeated measurements of a single fixed point. In Figure 4-5 a surveyor's trigonometric point (where the exact location is known to within 0.001 m) is monitored once per second over a 5 minute period. The results show that in the dGPS mode, accuracy reaches the sub-metre level (mean = 15cm east/4cm south) with a precision of 1 metre (97cm 2RMS). These results are only a guide to the quality of position determination as the error budget for the system varies with time as discussed in Section 2.2.1. However, as will become evident in the proceeding results, the dGPS employed in these experiments provides highly suitable position determination for crop yield monitoring.

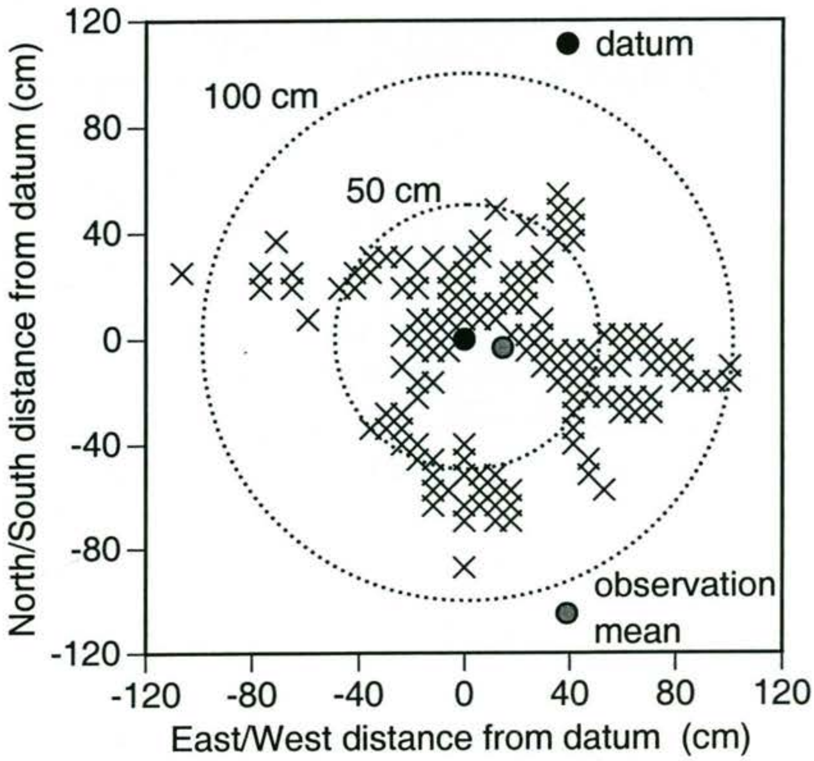


Figure 4-5. dGPS accuracy and precision determination from 286 observations at a known trigonometric station.

4.3.2 Mass-flow Calibration

Appendix A1 catalogues the calibration weights and errors for each load, each year, in each crop. The mean error for both crops ranged from 0.45% to 1.37% with a maximum individual load error of 3.20 %. The calibration operation was undertaken at a range of speeds to cover the expected flow rates under normal operation. This is more important at this scale than evenly covering a range of total harvest mass.

Figure 4-6 graphically documents the results following the 1995 wheat and 1996 sorghum calibrations. While these measurements are necessarily made using small tonnages to retain the operation on-site and maximise the weighing accuracy, the results at this scale can be compared with entire season calibrations. The full 1996 sorghum harvest, monitored as a total of 1974 tonnes using the yield sensor, was delivered for sale and recorded 2054 tonnes at the grain handling silo. This equates to an absolute mean error of 4.1% using much less sensitive scales and less rigourous grain handling techniques than the localised calibration.

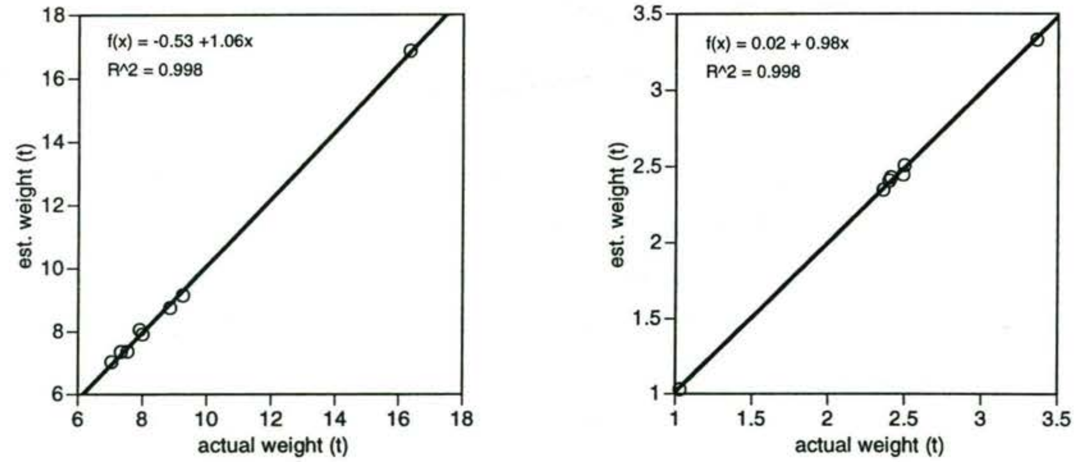


Figure 4-6. 1995 wheat and 1996 sorghum actual versus sensed weight following calibration.

4.3.3 Spatial Variability in Grain Yield

The yield monitoring system records a quantitative yield determination once per second during harvesting operations. The distance between observations is governed by harvester travel speed in the direction of operation and by the cutting-table width in the direction normal to operation. Figure 4-7 shows an example of the spatial observation detail obtained from this system in the 1996 sorghum harvest where the harvest speed was 3.25 km/hr, resulting in observations every 0.9 m.

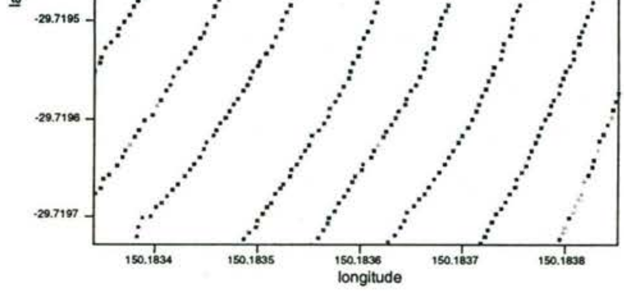


Figure 4-7. View of yield observation spacing in header runs using a real-time yield monitor. Observations are 0.9m seperation along and 7m between the runs.

Figure 4-8 displays the spatial and frequency distribution of 26,161 yield observations in a 40.9 ha area that is divided into 3 contour bays. It highlights a number of important process errors that result in unusually high or low yield values. Points where the full width of the cutter-bar is not utilised during a harvest run result in the area allocated to a crop yield being exaggerated and the yield values per unit area will appear unrealistically small (refer Equation 4-1). This will occur in headland areas when harvesting is carried out in a circular pattern, when harvesting across irregular terrain or highly irregular shaped areas, and where the cutter-bar remains lowered when moving but not harvesting. Unrealisticaly high yields are observed where the harvester is brought to a sudden halt and grain yield is allocated to a nonrepresentatively small area. These points are evident in the histogram as outliers below 2 t/ha and above 10 t/ha and as black symbols in the spatial distribution.

These erroneous data points should be removed to improve the accuracy of further analysis. After examining the spatial and frequency distribution data from all fields in all years monitored, it was evident that these outliers could be removed from the vast majority of fields by trimming the data using equation 4-2.

$$Y_v = Y \text{ if } \overline{Y_o} + 3\sigma \geq Y \geq \overline{Y_o} - 3\sigma \qquad (4\text{-}2)$$

where:

Y_v	=	valid yield estimates
Y	=	observed yield estimate
$\overline{Y_o}$	=	observed yield mean
σ	=	observed yield standard deviation

Comparing Figure 4-8 with Figure 4-9 shows the effect of this procedure. In Figure 4-9, yield estimates have been removed that were erroneously high along with artificially low yields in areas such as oversown roadways where the crop was damaged by vehicle passage prior to harvest, slopes where a full swath width could not be achieved and areas in headlands. In this instance, the procedure has removed 697 data points (from a total of 26161) and has increased the mean yield from 6.76 t/ha to 6.90 t/ha. The process decreases the standard deviation of the data sets, here reducing the figure of 1.58 t/ha to 1.22 t/ha, with a comensurate decrease in CV (23% to 18%).

Tables 4-1 to 4-5 present the trimmed yield data for the fields monitored over two seasons. Appendix A2 provides summaries of the original yield sensor data for comparison. The spatial distribution of the trimmed yield data as farm block and individual field yield

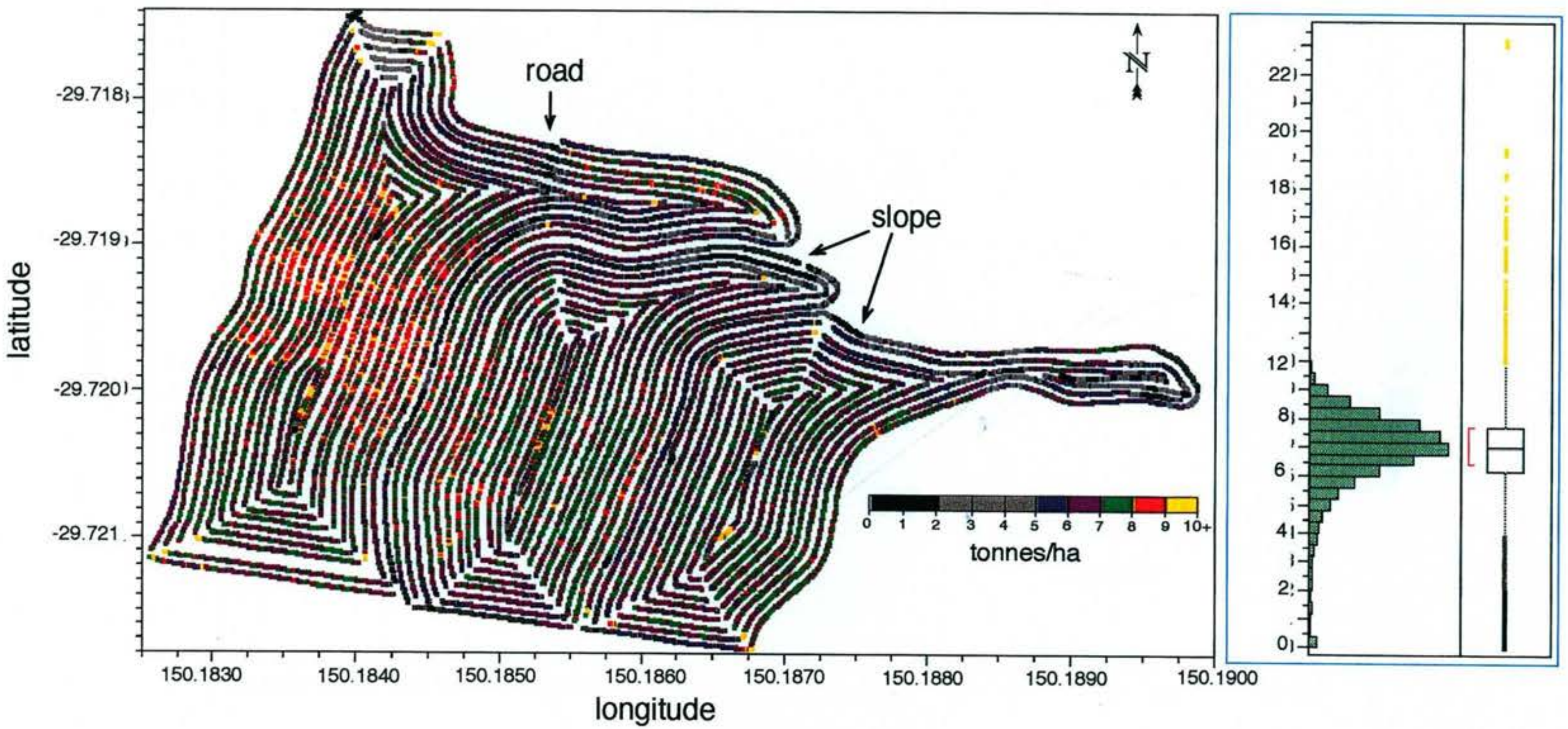


Figure 4-8. **Harvest data showing spatial and statistical distribution. Areas of low yield attributable to harvest artifacts are highlighted as black.**

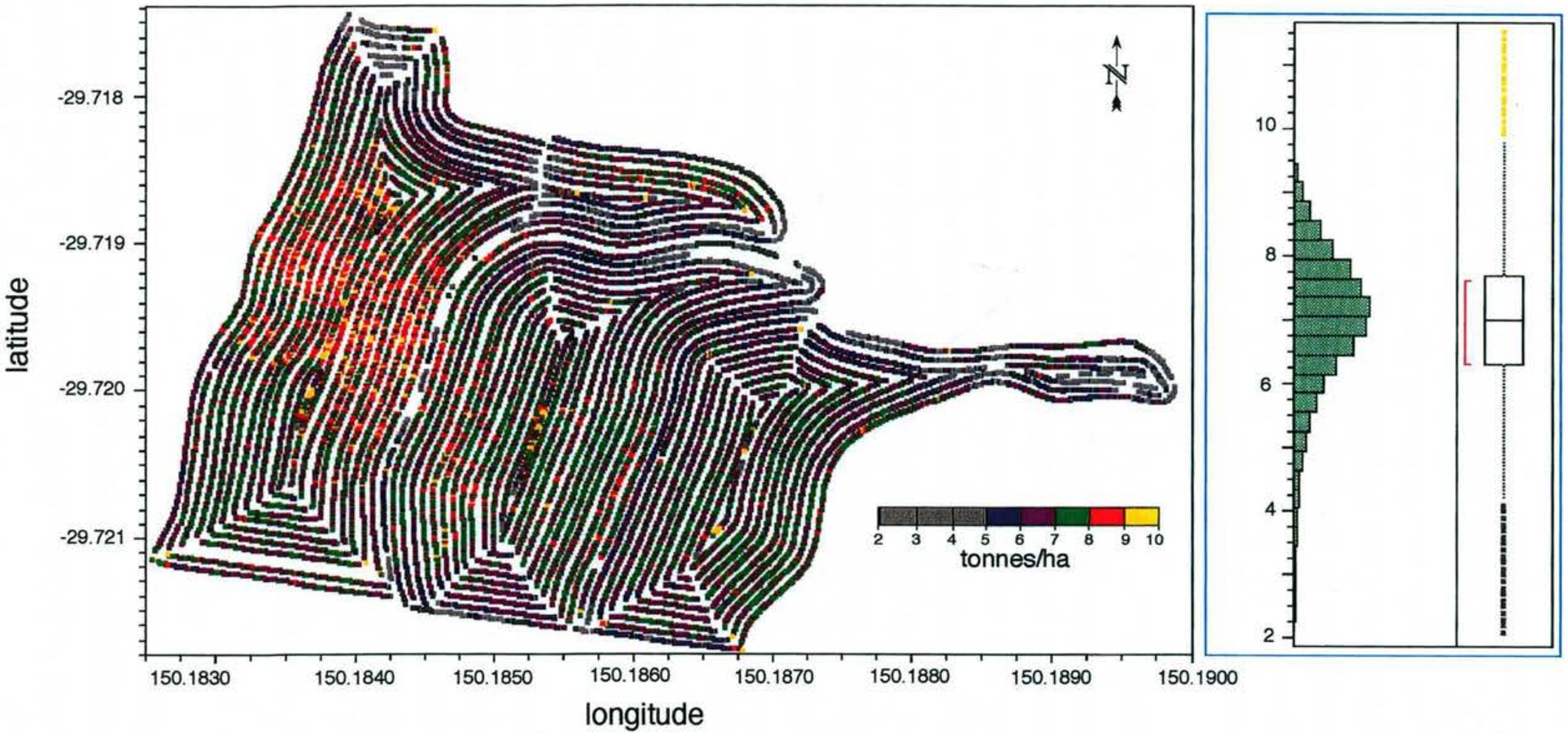


Figure 4-9. Erroneous yield estimates attributable to harvest artifacts are removed using three sandard devaitions of the data distribution as upper and lower cut-offs.

data maps is presented in Appendix B. These maps have been prepared using a 5 m radius moving window averaging process on a prediction grid spacing of 3.5 m. Linear interpolation onto a 1 m grid followed to improve map resolution. Prediction onto a regularised grid is necessary because of the irregular observation spacing produced by variation in harvester travel speed and path (refer Figure 4-7). These maps are not neccessarily the best depiction of the true yield variability within each field because the method applied here has been chosen to best present the yield data obtained from the monitoring process without undue smoothing. The 5 m window radius allows the information in individual header runs to remain obvious while producing a continuous prediction surface for improved spatial representation and visualisation.

The farm-wide season summaries in Tables 4-1 to 4-4 show substantial differences in mean yields between the two years for wheat (1.56 t/ha & 4.28 t/ha) and sorghum (6.20 t/ha & 3.08 t/ha). The mean standard deviation for wheat increases slightly from 0.75 t/ha to 0.88 t/ha with the decrease in mean yield. Sorghum shows an increase in mean standard deviation from 1.07 t/ha to 1.31 t/ha with the decrease in mean yield. It would appear that sorghum yield is more variable across the farm than wheat yield , even with its greater overall mean yield. At a finer scale, Table 4-5 shows significant differences between farm block mean yields during each season and each crop. Again the sorghum yield appears consistently more variable than the wheat yield.

At the within-field scale of observation, the mean standard deviations of each crop are lower than for the larger farm units. However the range of these values is greater at the field level because less variability is encompassed in each estimate. The range of standard deviation values for wheat extends from 0.44 t/ha to 1.02 t/ha, and from 0.67 t/ha to 1.62 t/ha for sorghum. With 3 standard deviations encompassing 99% of the normal distribution (Mead & Curnow, 1987), these figures intimate that within a single field the wheat yield may vary between ± 1.32 t/ha and ± 3.06 t/ha from the mean. Sorghum yields may show variability from the field mean of between ± 2.01 t/ha and ± 4.86 t/ha within a single field. These figures translate to coefficients of variation ranging from 10% to 80% (mean = 22%) for both crops combined.

At this scale, the median CV = 17%, as compared to CV values of 16% (mean) and 14% median for all experiemnts in Table 1-12, 14% for both mean and median of the continuous experiments reported in Table 1-12, and 19% (mean) and 20% (median) for continous experiments reported by Pringle et al. (1993).

As a simple analysis that provides some insight into the comparitive spatial variabilities of the crops is shown in Figure 4-10. Here the variance at all scales is regressed against the square root of the applicable field area (a surrogate distance measurement). The results confirm the earlier indication that the sorghum crop displays greater variability than the wheat in both seasons. The 1997 sorghum harvest fields show the greatest increase in variability with increasing representative distance.

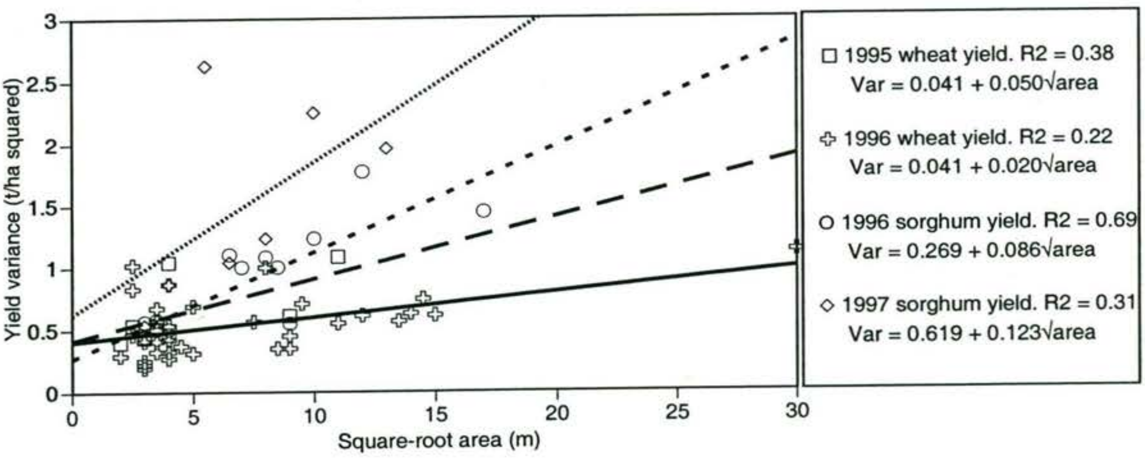


Figure 4-10. Regression analysis of yield variance against square-root field area. This provides a basic comparison of the increasing variability with increasing harvested area.

This variability may also be quantified and assessed using the uniformity index proposed by Fairfield Smith (1938) (refer Equation 1-15). The slope of the regression equations displayed in Figure 4-11 are used as an index (*b′*) of uniformity in yield with increasing crop area. A larger value for b' indicates a greater uniformity in the crop yield across space. A comparison of the values in Figure 4-11 with those reported by Fairfield Smith (1938) and documented in Table 1-11, show the wheat yield for these experiments to be in the higher range for uniformity. This may suggest that the sorghum crop would show greater response to differential treatments, but there is as yet little information with which to provide a benchmark for the index.

As with the analysis shown in Figure 4-10, the regression model cannot be expected to fully describe the spatial variability in crop yield but the index (b') does provide a tool for classifying or ranking variability. This may be an even more valuable tool for SSCM if used at the within field scale, by calculating variance over increasingly larger subunits. With such analysis the index would be a tool for segregating crop fields into variability classes and eventually formulating a benchmark index above which differential treatment may be non-viable.

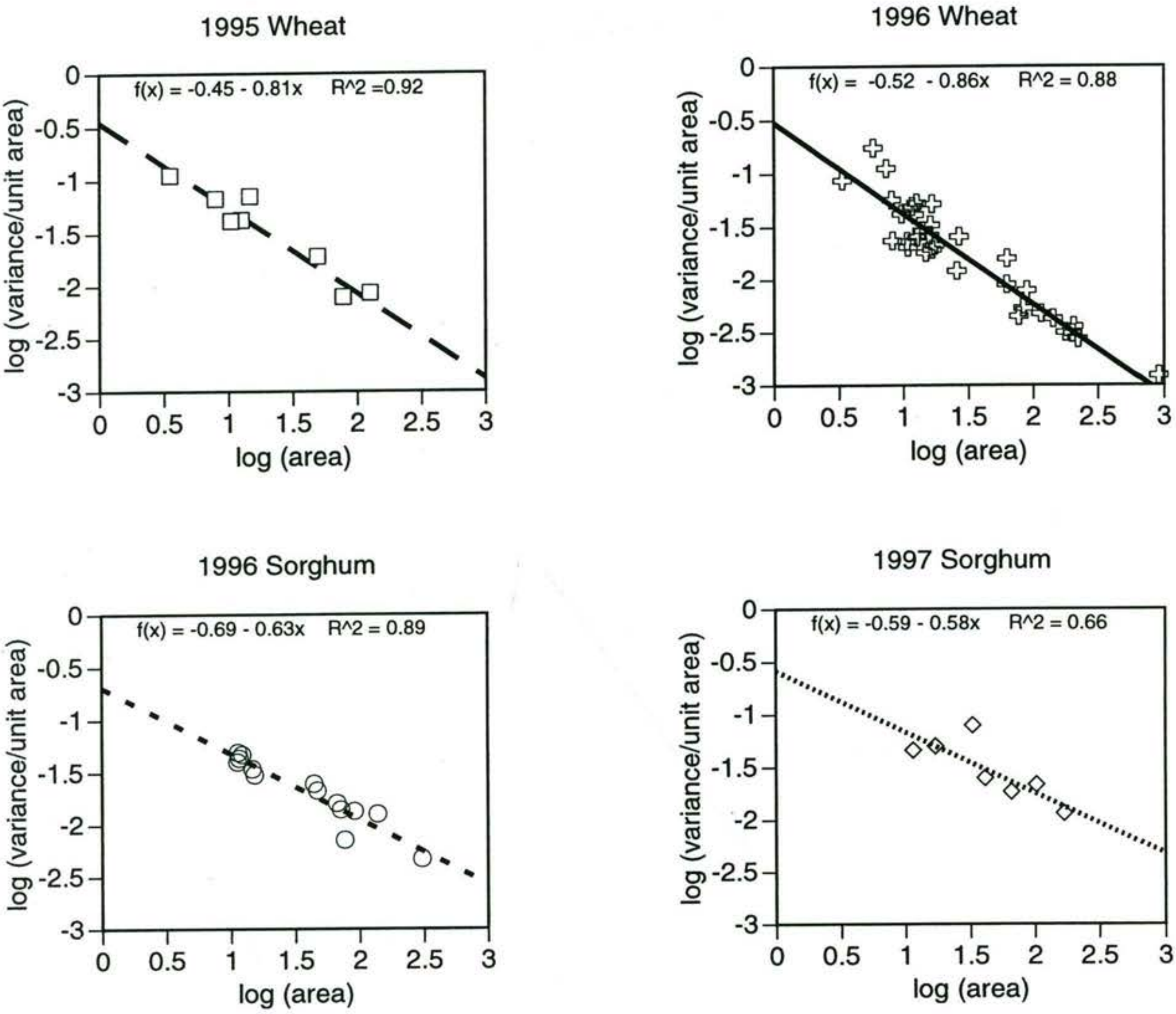


Figure 4-11. Regression analysis based on the Fairfield Smith (1938) 'uniformity index'. The regression line slope provides the index (*b'*). Sorghum yield in both seasons shows greater variability.

The degree of within-field variation that is evident in these analyses is most strikingly demonstrated in the yield data maps (Appendix B). Each field is classified using 0.5 tonne class intervals. These maps also show the spatial distribution of the yield variation which should provide a much greater benefit for management decisions than the information gleaned from the classical statistical analyses. However, to reliably examine the nature of temporal and spatial variation exhibited at the within field scale, it is neccessary to examine these maps for fields that have been sown to the same crop for more than one year.

Field Name	Area (ha)	N	Yield Mean (t/ha)	Yield Std Dev. (t/ha)	Yield C.V. (%)	Moisture Mean (%v/v)	Moisture Std Dev. (%v/v)	Moisture C.V. (%)
B1	3.53	2611	2.21	0.63	28.5	9.94	0.53	5.3
B2	12.52	7966	1.04	0.73	70.2	8.72	0.35	4.0
Horse	10.43	10182	2.67	0.66	24.7	9.86	0.21	2.1
B4	7.91	6636	1.90	0.73	38.4	12.54	0.96	7.7
N3	14.61	11404	2.24	1.02	45.5	9.73	0.44	4.5
Maidens	77.29	32082	0.96	0.78	81.3	8.81	0.44	5.0
Season Summary	125.68	70881	1.56	1.04	66.7	9.50	1.20	12.6

Table 4-1. 1995 trimmed wheat yield data for monitored fields.

Field Name	Area (ha)	N	Yield Mean (t/ha)	Yield Std Dev. (t/ha)	Yield C.V. (%)	Moisture Mean (%v/v)	Moisture Std Dev. (%v/v)	Moisture C.V. (%)
N2	12.25	18804	6.68	0.76	11.4	12.69	0.65	5.1
N6	14.64	22100	6.70	0.71	10.6	12.81	0.47	3.7
N10	15.24	22087	6.47	0.68	10.5	12.53	0.61	4.9
S2	11.60	17234	6.15	0.71	11.5	12.96	1.06	8.2
S6	11.23	15709	6.21	0.67	10.8	12.64	1.21	9.6
S10	11.39	15337	6.27	0.75	12.0	12.39	0.49	4.0
Creek	71.25	106734	7.00	1.00	14.3	13.20	0.80	6.1
Pine	66.84	82315	5.27	1.04	19.7	13.00	1.34	10.3
Cabro West	44.20	58994	5.40	1.05	19.4	12.04	0.49	4.1
Cabro East	46.72	77080	6.25	1.00	16.0	13.24	1.03	7.8
Season Summary (all fields)	305.36	434804	6.20	1.20	19.4	12.90	1.20	9.3

Table 4-2. 1996 trimmed sorghum yield data for monitored fields.

Field Name	Area (ha)	N	Yield Mean (t/ha)	Yield Std Dev. (t/ha)	Yield C.V. (%)	Moisture Mean (%v/v)	Moisture Std Dev. (%v/v)	Moisture C.V. (%)
B1	3.36	4035	3.32	0.54	16.3	10.67	0.86	8.1
B2	12.78	14100	3.48	0.57	16.4	9.53	0.51	5.4
Horse	10.85	12199	4.67	0.47	10.1	11.10	0.60	5.4
B4	8.12	9366	4.00	0.68	17.0	11.86	0.50	4.2
B5	14.05	12738	3.87	0.64	16.5	10.26	0.53	5.2
Field 80	25.80	28809	4.41	0.56	12.7	12.61	2.76	21.9
N1	10.78	13006	4.62	0.50	10.8	10.66	0.22	2.1
N4	15.97	18348	3.93	0.65	16.5	9.38	0.58	6.2
N5	17.47	18312	3.55	0.61	17.2	8.85	0.61	6.9
N8	12.68	17369	3.92	0.82	20.9	11.16	0.74	6.6
N9	16.61	19212	4.20	0.93	22.1	11.28	1.71	15.2
S1	11.70	12628	3.70	0.76	20.5	8.06	0.36	4.5
S4	14.88	18363	3.51	0.52	14.8	10.16	0.63	6.2
S5	9.74	10199	4.07	0.64	15.7	9.23	0.89	9.6
S8	8.25	17103	3.72	0.44	11.8	9.95	0.66	6.6
S9	16.67	19691	3.39	0.57	16.8	9.56	0.68	7.1
S12	12.15	12050	3.02	0.71	23.5	10.85	0.71	6.5
Maidens	77.29	110942	4.54	0.59	13.0	10.88	0.66	6.1
Bommera	26.78	27789	2.52	0.83	32.9	10.51	0.64	6.1
Bull	7.36	9344	4.94	0.91	18.4	9.63	0.77	8.0
South Dam	16.11	21103	5.54	0.73	13.2	13.05	1.30	10.0
Skurr	5.84	7380	5.24	1.01	19.3	13.12	0.69	5.3
Creek	83.66	110530	5.44	0.67	12.3	11.25	1.48	13.2
Lease	89.14	96311	5.68	0.84	14.8	10.64	1.10	10.3
Cabro West	142.40	170300	3.66	0.78	21.3	9.47	0.75	7.9
Cabro East	62.74	73923	3.77	1.00	26.5	11.39	0.69	6.1
KWee North	114.78	133227	4.16	0.74	17.8	11.49	0.83	7.2
KWee South	62.39	78862	4.35	0.75	17.2	11.30	0.74	6.5
Season Summary (all fields)	910.35	1097239	4.28	1.06	24.8	10.94	1.38	12.6

Table 4-3. 1996 trimmed wheat yield data for monitored fields.

Field Name	Area (ha)	N	Yield Mean (kg/ha)	Yield Std Dev (kg/ha)	Yield C.V. (%)	Moisture Mean (%v/v)	Moisture Std Dev. (%v/v)	Moisture C.V. (%)
S2	11.55	9201	2.67	0.73	27.3	11.40	0.58	5.1
Silo	17.13	10611	1.60	0.93	58.1	12.67	1.66	13.1
W80	41.17	40868	4.21	1.02	24.2	12.18	1.85	15.2
Well	33.01	26322	3.04	1.62	53.3	19.72	8.66	43.9
Pine	65.95	60529	2.66	1.11	41.7	12.75	1.61	12.6
Season Summary (all fields)	168.81	147531	3.08	1.40	45.4	13.88	4.98	35.9

Table 4-4. 1997 trimmed sorghum yield data for monitored fields.

Year & Crop	Farm	Area (ha)	N	Yield Mean (t/ha)	Yield Std Dev. (kg/ha)	Yield C.V. (%)	Moisture Mean (%v/v)	Moisture Std Dev. (%v/v)	Moisture C.V. (%)
1995 Wheat	Marinya	49.00	38799	2.06	0.97	47.1	10.05	1.33	13.2
	Maidens	77.29	32082	0.96	0.78	81.3	8.81	0.44	5.0
1996 Sorghum	Marinya	76.35	109682	6.43	0.74	11.5	12.73	1.16	9.1
	Romaka	138.09	189049	6.22	1.33	21.4	13.15	1.28	9.7
	Cabro	90.92	136073	5.88	1.11	18.9	12.72	1.05	8.3
1996 Wheat	Marinya	221.86	257881	3.87	0.78	20.2	10.36	1.69	16.3
	Romaka	202.11	226145	5.50	0.79	14.4	11.16	1.51	13.5
	Maidens	77.29	110942	4.54	0.59	13.0	10.88	0.66	6.1
	Bommera	26.78	27789	2.52	0.83	32.9	10.51	0.64	6.1
	Cabro	205.14	244233	3.69	0.86	23.3	10.05	1.14	11.3
	KWee	177.17	212089	4.23	0.75	17.7	11.42	0.80	7.0
1997 Sorghum	Marinya	102.86	87002	3.38	1.50	44.4	14.66	6.21	42.4
	Romaka	65.95	60529	2.66	1.11	41.7	12.75	1.61	12.6

Table 4-5. Trimmed sorghum yield data for 2 seasons on a farm block basis.

4.3.4 Spatio -Temporal Variability in Grain Yield

While spatial yield distributions determined in one harvest may provide valuable data on small-scale variability pertaining to the individual season, gathering information with which to modify agronomic practices will require data about the temporal influence on the degree and pattern of spatial variability.

Four wheat fields and one sorghum field were monitored after being sown to the same crop over the two seasons documented here. Figures 4-12 to 4-15 and 4-18 separately display data for the five fields, and in each case: (a) = year 1 yield map, (b) = year 2 yield map, (c) = difference in yield between year 2 and year 1. Again, a 5 m radius circular moving average has been used to predict the data onto a 3.5 m grid for visual representation.

The 1995 wheat yield (Figures 4-12a to 4-15a) was significantly decreased by late frost and rainfall damage at harvest, while the 1996 season (Figures 4-12b to 4-15b) was marred slightly by rainfall late in the harvest. The 1996 sorghum growing season (Figure 4-18a) was completed under almost ideal growing conditions while the 1997 harvest (Figure 4-18b) showed signs of late moisture stress and, ironically, rainfall damage during harvest.

Wheat

The spatial variability in the trimmed yield data for both seasons is represented in the global variogram parameters shown in Table 4-6.

		Exponential Variogram Parameters			
Field Name	Year	C0	C	apparent range (m)	NR (%)
B1	1995	0.031	0.286	83.3	10
	1996	0.063	0.182	22.9	26
B2	1995	0.027	0.674	319.5	4
	1996	0.042	0.189	46.8	18
B4	1995	0.061	0.443	103.8	12
	1996	0.115	0.168	93.0	41
Horse	1995	0.080	0.190	134.7	30
	1996	0.081	0.087	66.6	48
Maidens	1995	0.029	0.286	78.0	9
	1996	0.126	0.102	74.7	55

Table 4-6. Global variogram parameters for 1995 and 1996 trimmed yield data .

The significance of spatial structure in the data (reflected in the %NR - defined in Equation 1-14) shifts from strong in 1995 to moderate in 1996 across the majority of fields. B1 and B2 remain strong in both years. A moderate to strong relationship is reconcilable with the studies reported in the literature (Table 1-13). The median range (80.6 m) is remarkably similar to the median reported in Table 1-13 (83 m) however the median total semivariance (approximately equating the data variance) is approximately one third (0.28 as compared to 1.0). While inconclusive, this analysis suggests that the yield monitoring operation may be recording a reduced yield variability to that actually occuring in the field.

Predicting onto a regularised grid using the moving mean procedure provides an expected reduction in the nugget and total semivariance within the yield data (Table 4-7). The dramatic reduction in the nugget semivariance ensures that the spatial structure component remains strong in all fields in both years. Table 4-7 also shows a reduction in the median apparent range (75.4m). Such further reduction in the data variance may be undesirable.

		Exponential Variogram Parameters			
Field Name	Year	C0	C	apparent range (m)	NR (%)
B1	1995	0	0.281	78.2	0
	1996	0	0.128	27.6	0
B2	1995	0	0.577	252.5	0
	1996	0	0.167	51.9	0
B4	1995	0	0.424	102.3	0
	1996	0.020	0.172	97.8	10
Horse	1995	0.008	0.205	114.0	4
	1996	0.007	0.095	60.0	7
Maidens	1995	0	0.243	69.6	0
	1996	0.017	0.107	72.6	14

Table 4-7. Global variogram parameters for 1995 and 1996 predicted yield data (5m moving average; 3.5m grid).

Correlation in the spatial distribution of crop yield between seasons is small yet significant at the 0.01% level in all of the wheat fields monitored. Table 4-8 displays the Pearson correlation for the grid-based yield data in each field . The prediction for each season has been performed on the same grid in each individual field to eliminate the influence of spatial variability.

Field Name	Years	Temporal Correlation (Pearsons)	Corresponding Spatial Correllogram Range (m)	Mean Corresponding Spatial Correllogram Range (m)
B1	1995	0.26	32	21
	1996		11	
B2	1995	0.10	105	91
	1996		48	
B4	1995	0.21	40	40
	1996		40	
Horse	1995	0.12	137	121
	1996		131	
Maidens	1995	-0.20	216	136
	1996		56	

Table 4-8. Pearson correlation coefficient between seasons and the spatial correllogram range that corresponds to the coefficient. Mean corresponding correllogram range is calculated using the mean yield values across seasons to estimate the corellogram (predicted yield data - 5m moving average; 3.5m grid).

These small correlations are only considered significant due to the large number of observations. A further undesirable attribute of the correlation statistic in spatial interpretation is the confounding of positively and negatively correlated areas within the data space. The negative correlation in the 'maidens' field is attributable to a dominance of negative correlation throughout the field. This is quite strikingly evident as an inversion of the yield quantity within an apparently stable pattern across most of the field in Figures 4-15a and 4-15b. More subtly (and cloaked by the correlation statistic), are areas of negative correlation in the northern half of Figure 4-13a and 4-13b where discernable patterns are repeated in both years. In Figures 4-13 and 4-15, these inversion areas yield up to 2.5 t/ha lower than the surrounds in the 1995 season, while in 1996 the yield is 0.5 t/ha to 1 t/ha higher than the surrounding areas.

Such inversion between seasons highlights the significant interaction between the climate, soil and crop yield. In this instance, the combined effect of climate and subtle differences in elevation could be responsible for frost damage in lower areas in 1995 and subsequently superior soil moisture availability in 1996. Variability in soil type may also be a factor causing variability in crop maturity, and therefore frost susceptibility, across the fields.

In Figure 4-14a a discernable 0.5 t/ha to 1 t/ha decrease in yield below the north-east/ south-west diagonal is apparent in 1995 but is not evident in the proceeding year (Figure 4-14b). Again elevation is believed to be the factor governing the incidence of frost damage as the field falls through a 0.8% slope from north-west to south-east.

Table 4-9 catalogues the descriptive statistics for the individual seasons and the difference between the two seasons in each field. The data, along with that presented in Tables 4-1 to 4-4, confirms the observation in Chapter 1 that yield variability decreases with increasing mean yield. It also shows that their is variability of a similar magnitude to be expected in the yield response within a single field to consecutive seasons.

Figures 4-12c to 4-15c show the spatial distribution of the difference in yield between the 1996 and 1995 seasons. Differences in yield generally range from 0 to 5 t/ha, with some small areas in field B2 actually yielding lower in 1996 than 1995. The inversion areas previously described are well delineated by the differencing procedure, making these maps a possible starting point for zoning the field into different management units. In Figures 4-12c to 4-14c the general areas above 2 t/ha could be segregated for investigation into landscape and soil factors that may retard crop development or increase frost susceptibility. In Figure 4-15c, the area above 4 t/ha could fulfill the same segregation criteria.

While the difference maps provide a physical tonnage comparison between the years and the associated variance is a more spatially integrative indicator of variability in physico-chemical attributes within a field than the variance from individual years, an estimate of the temporal variance could provide a indicator of seasonal or climatic influences on crop yield.

The temporal variance may be simply estimated by Equation 4-3.

$$\sigma^2_t = \frac{\sum_{i=1}^{n} 1/2(Y2_i - Y1_i)^2}{n-1} \qquad (4\text{-}3)$$

where:

σ^2_t	=	temporal variance
$Y2$	=	yield value at point i for 1996
$Y1$	=	yield value at point i for 1995

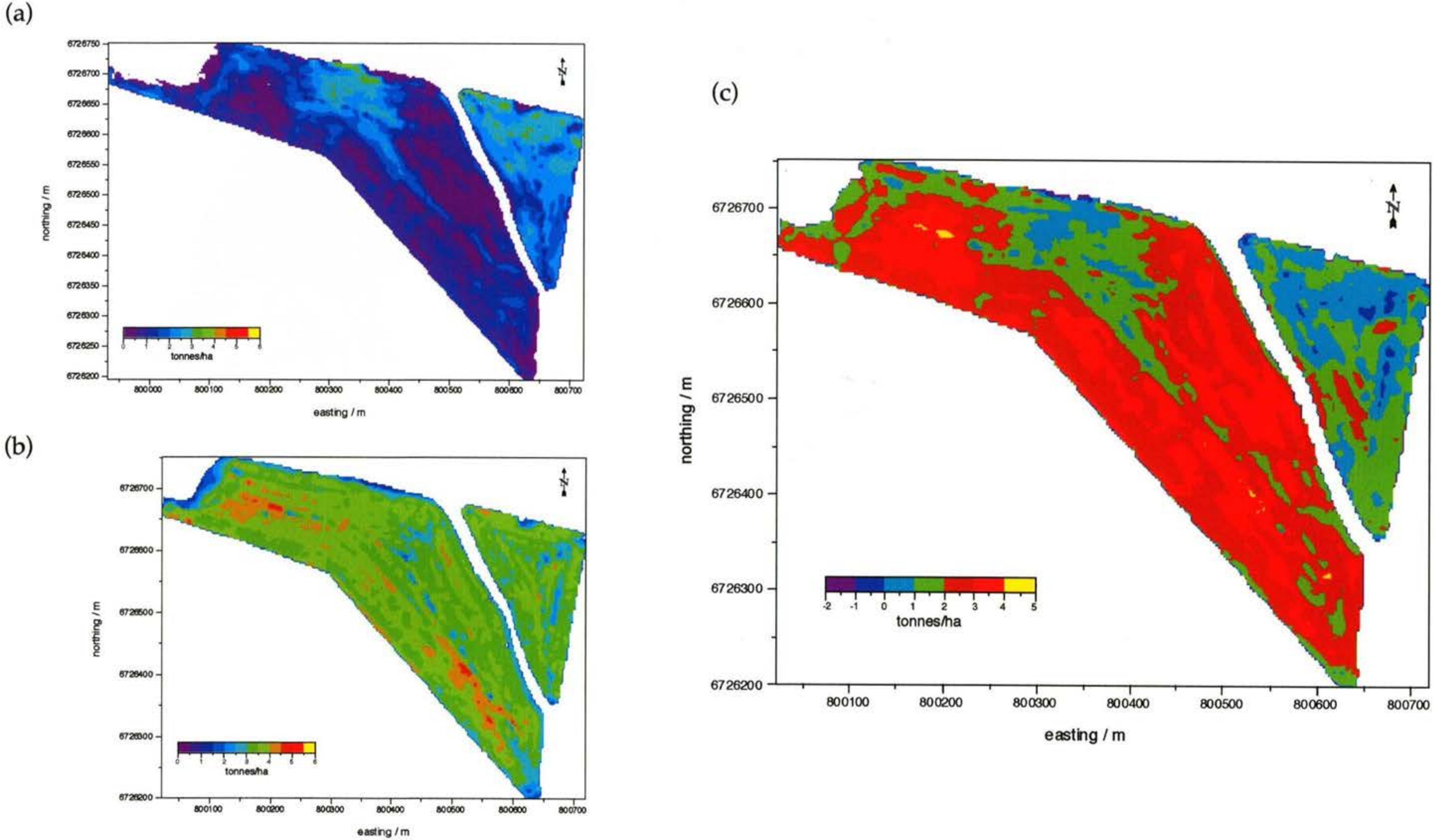


Figure 4-12. Wheat yield maps for Field B1 and B2 - (a)1995 season (b) 1996 season (c) seasonal difference.

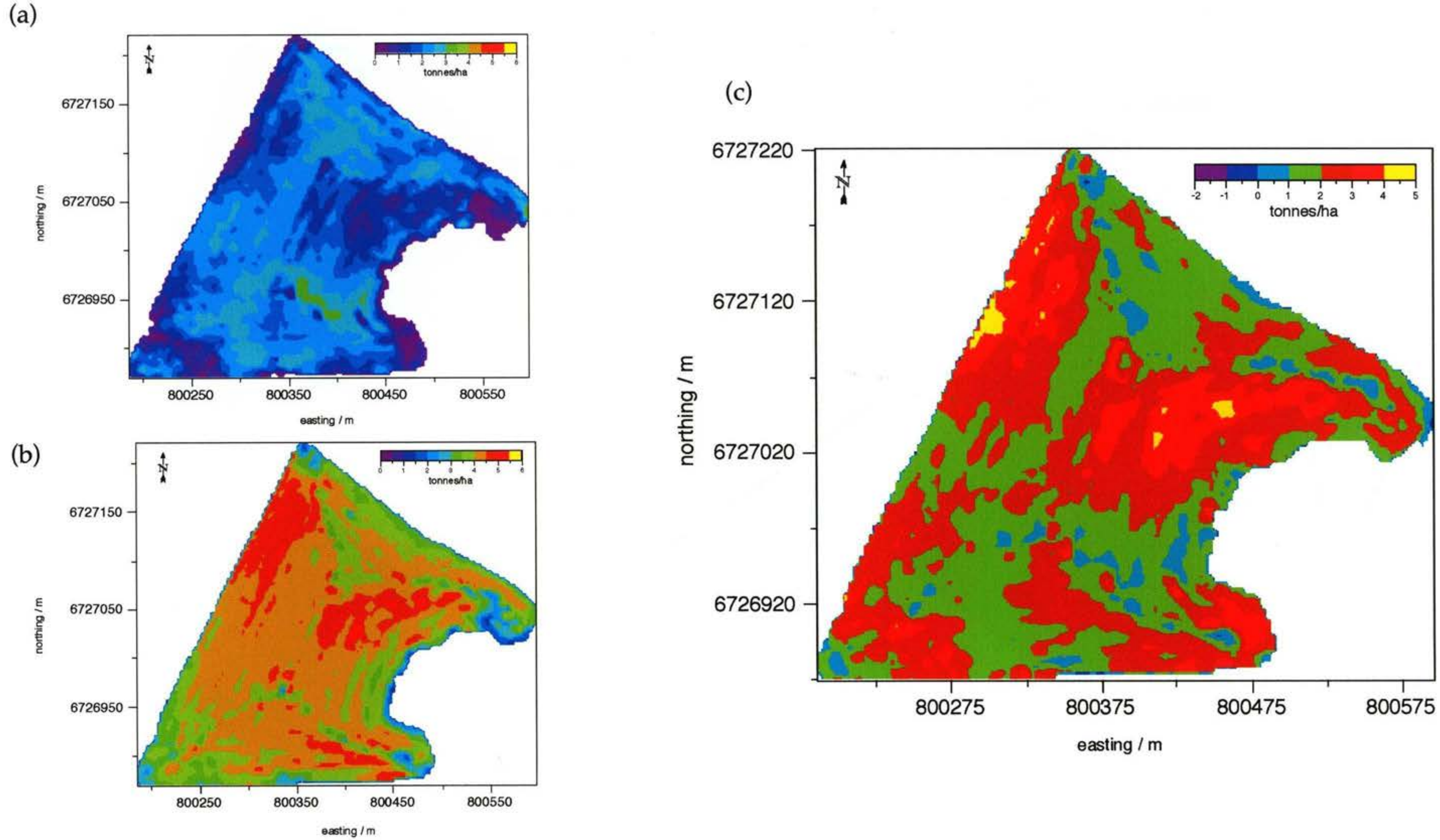


Figure 4-13. Wheat yield maps for Field B4 - (a)1995 season (b) 1996 season (c) seasonal difference.

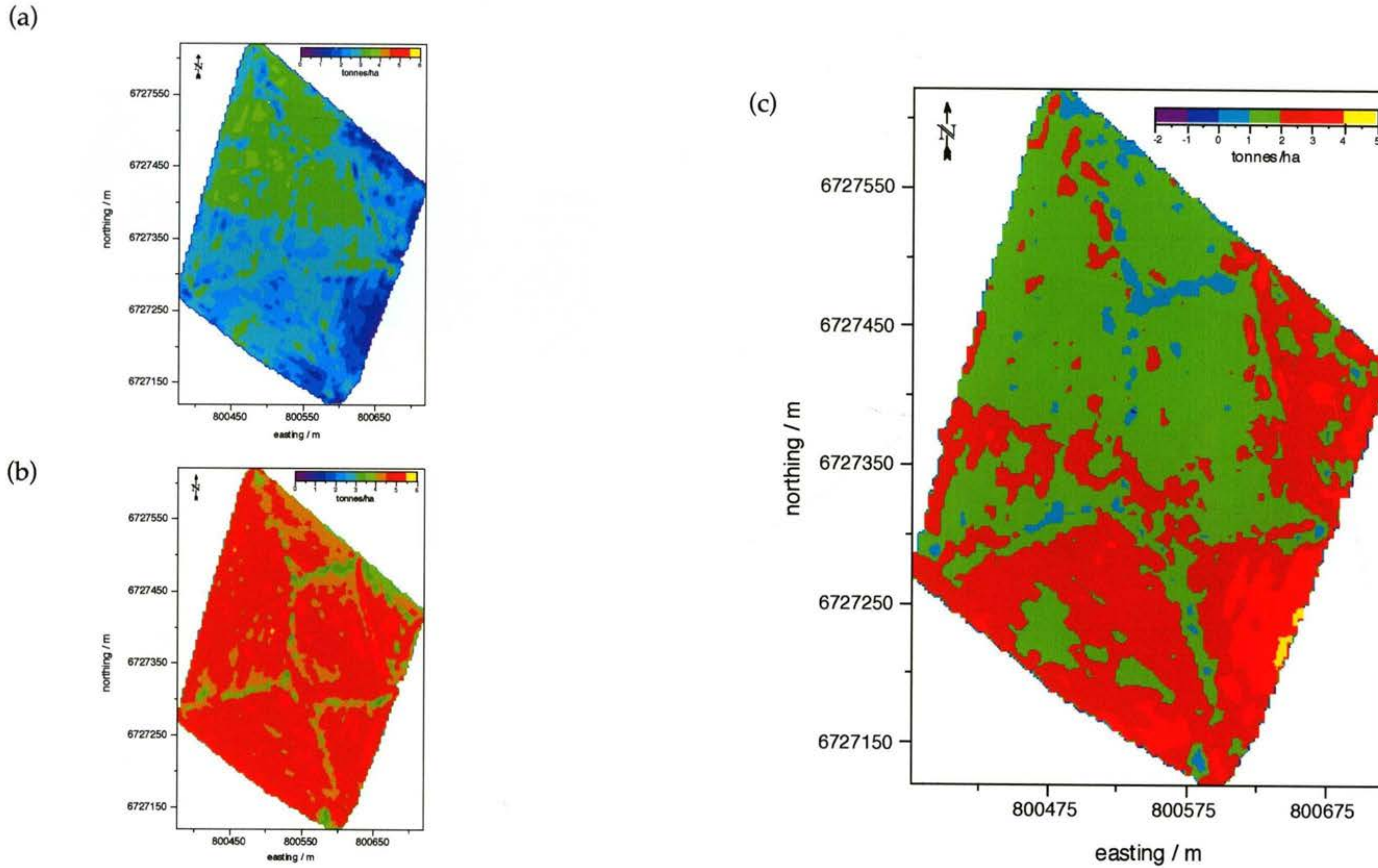


Figure 4-14. Wheat yield maps for Horse Field - (a)1995 season (b) 1996 season (c) seasonal difference.

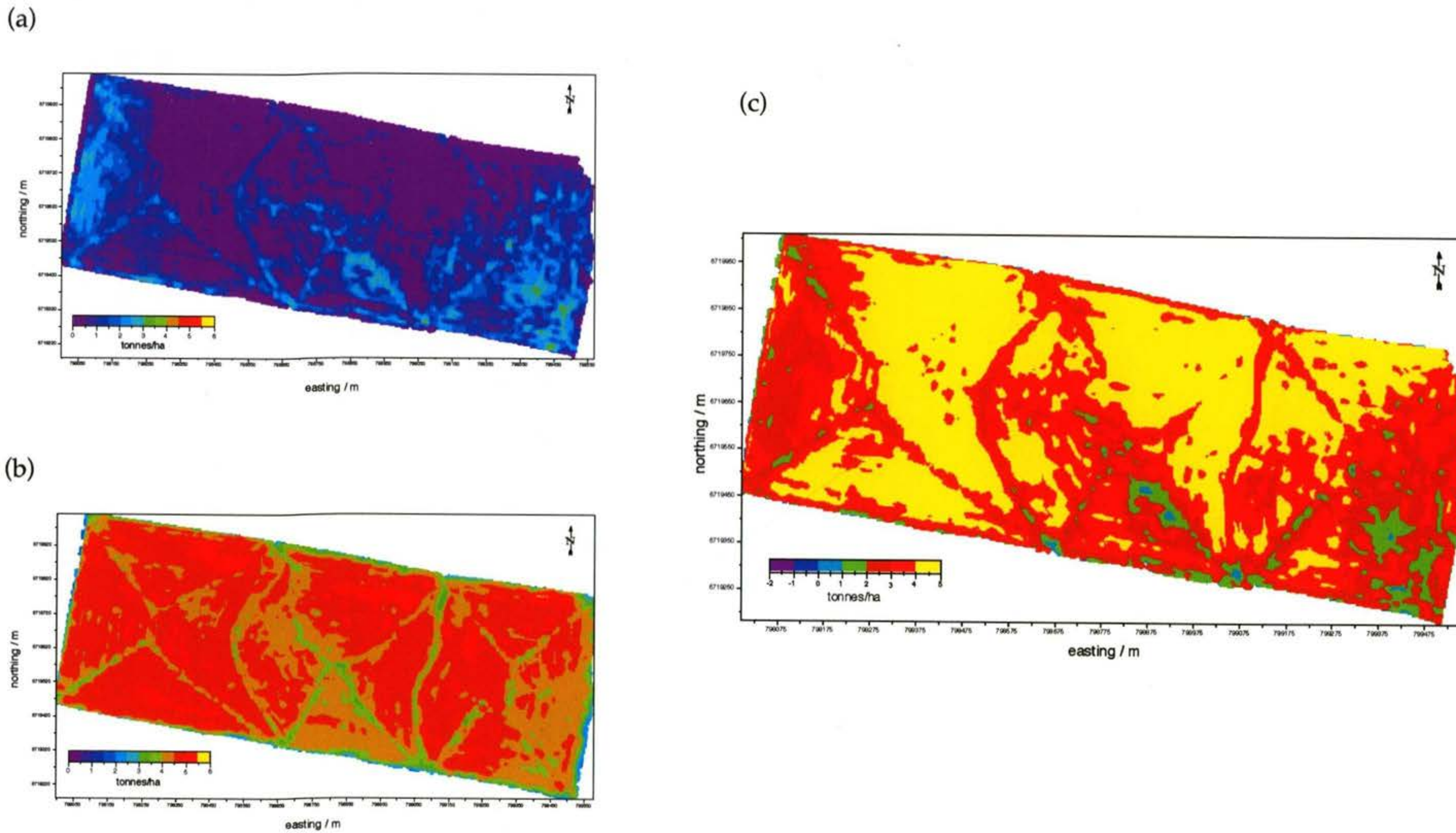


Figure 4-15. Wheat yield maps for Maidens - (a)1995 season (b) 1996 season (c) seasonal difference.

			Yield			
Field Name	Area (ha)	Year	Mean (t/ha)	Variance. $(t/ha)^2$	Std Dev. (t/ha)	C.V. (%)
B1 & B2	16.14	1995	1.31	0.66	0.81	62
		1996	3.44	0.5	0.25	7
		1996-1995	2.13	0.88	0.94	44
		Temporal		2.70	1.64	
B4	8.12	1995	1.89	0.44	0.66	35
		1996	4.03	0.34	0.58	14
		1996-1995	2.14	0.59	0.77	36
		Temporal		2.58	1.61	
Horse	10.85	1995	2.66	0.34	0.58	22
		1996	4.65	0.14	0.38	8
		1996-1995	1.99	0.43	0.66	33
		Temporal		2.20	1.48	
Maidens	77.29	1995	0.90	0.49	0.70	78
		1996	4.53	0.22	0.47	10
		1996-1995	3.63	0.79	0.89	25
		Temporal		6.98	2.64	

Table 4-9. Descriptive statistics for the wheat fields in space and time.

This estimate of temporal variance is therefore a comparison of yield values between seasons from fixed points in the field. This confers a spatial stationarity to the data sets. The estimates of temporal variance calculated for the four wheat fields are included in Table 4-9 and are substantially higher than the spatial variance in all cases. The inference being that the variation in yield attributable to spatial variability in physico-chemical attributes of the cropping system is much less than that induced by season to season climatic variability in this instance.

It may also be postulated that a high temporal variance in conjunction with a low spatial variance for the difference between years suggests a relatively uniform field on which crop yield is overwelmingly governed by climatic conditions.

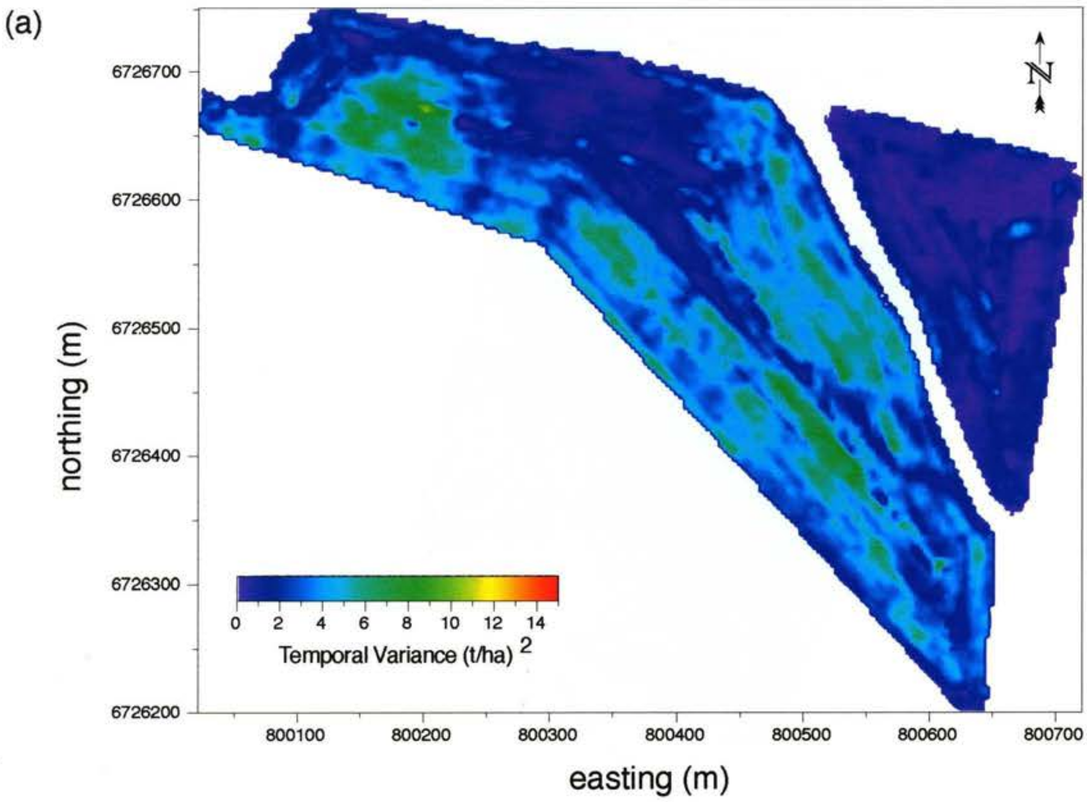
The spatial distribution of the temporal variance at each evaluated point in the fields is mapped in Figures 4-16 and 4-17. These maps may prove to be a very useful adjunct to the physical difference maps (Figures 4-12c to 4-15c) for discriminating management zones within a field, especially when constructed for a number of years. Stable areas of temporal variance for a number of years would suggest that some form of differential management may be feasible. Areas of low temporal variability would prove the easiest to determine management regimes, with areas expressing high temporal variability more likely to be identified as high risk zones and treated accordingly. As low temporal variability does not indicate the yield quantity, but rather little change in yield quantity over time, correlation with the physical difference map could be used to determine a yield potential class.

Sorghum

Only one field was sown to continuous sorghum over the experimental period. The maps of individual years, and the spatial distribution of the difference in yield between 1996 and 1997 are shown in Figure 4-18. Unlike the wheat fields, this sorghum field shows a generally random spatial pattern in both years despite the substantial decrease in yield in 1997. The observed spatial distribution suggests that the field would be difficult to segregate into management zones on the basis of yield.

			Yield			
Field Name	Area (ha)	Year	Mean (t/ha)	Variance. $(t/ha)^2$	Std Dev. (t/ha)	C.V. (%)
S2	77.29	1996	6.12	0.24	0.49	8
		1997	2.63	0.37	0.61	23
		1997-1996	-3.49	0.44	0.67	19
		Temporal Variance		6.30	2.51	

Table 4-10. Descriptive statistics for the sorghum field S2 in space and time.



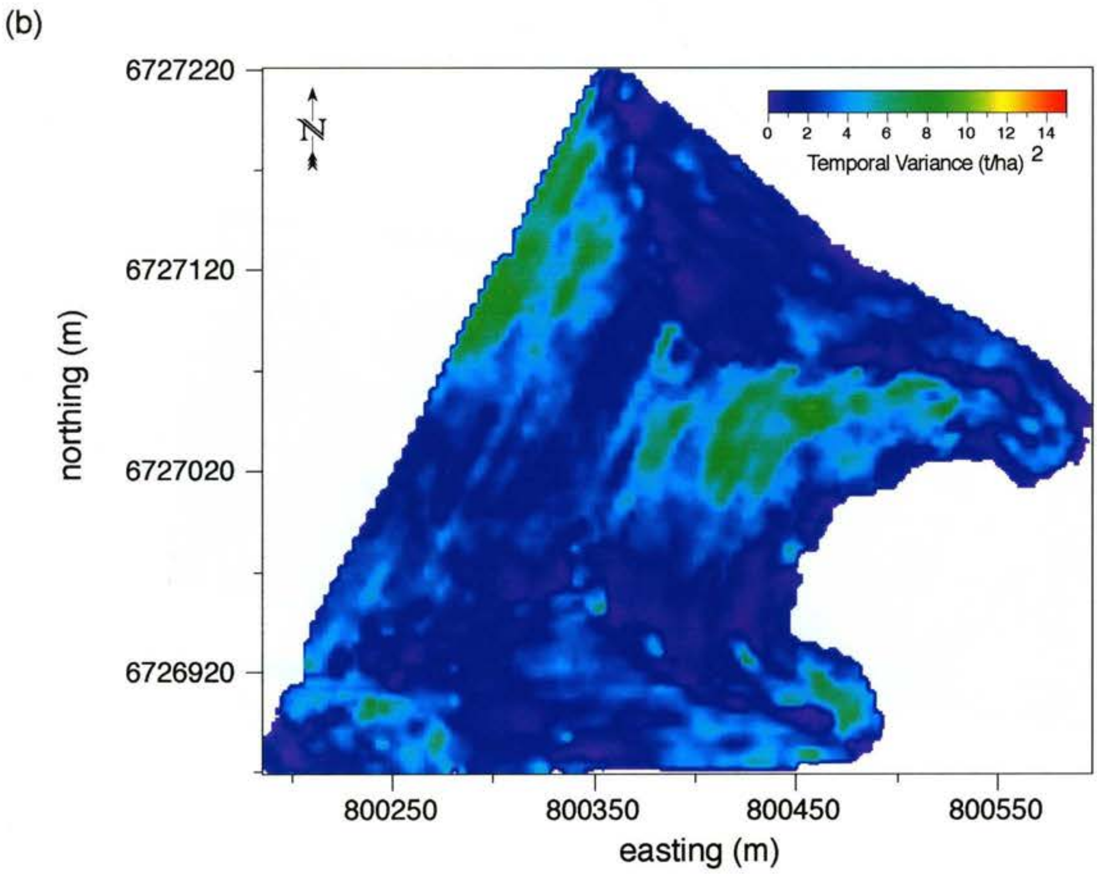


Figure 4-16. Yield temporal variance maps - (a) Fields B1 & B2 (b) Field B4.

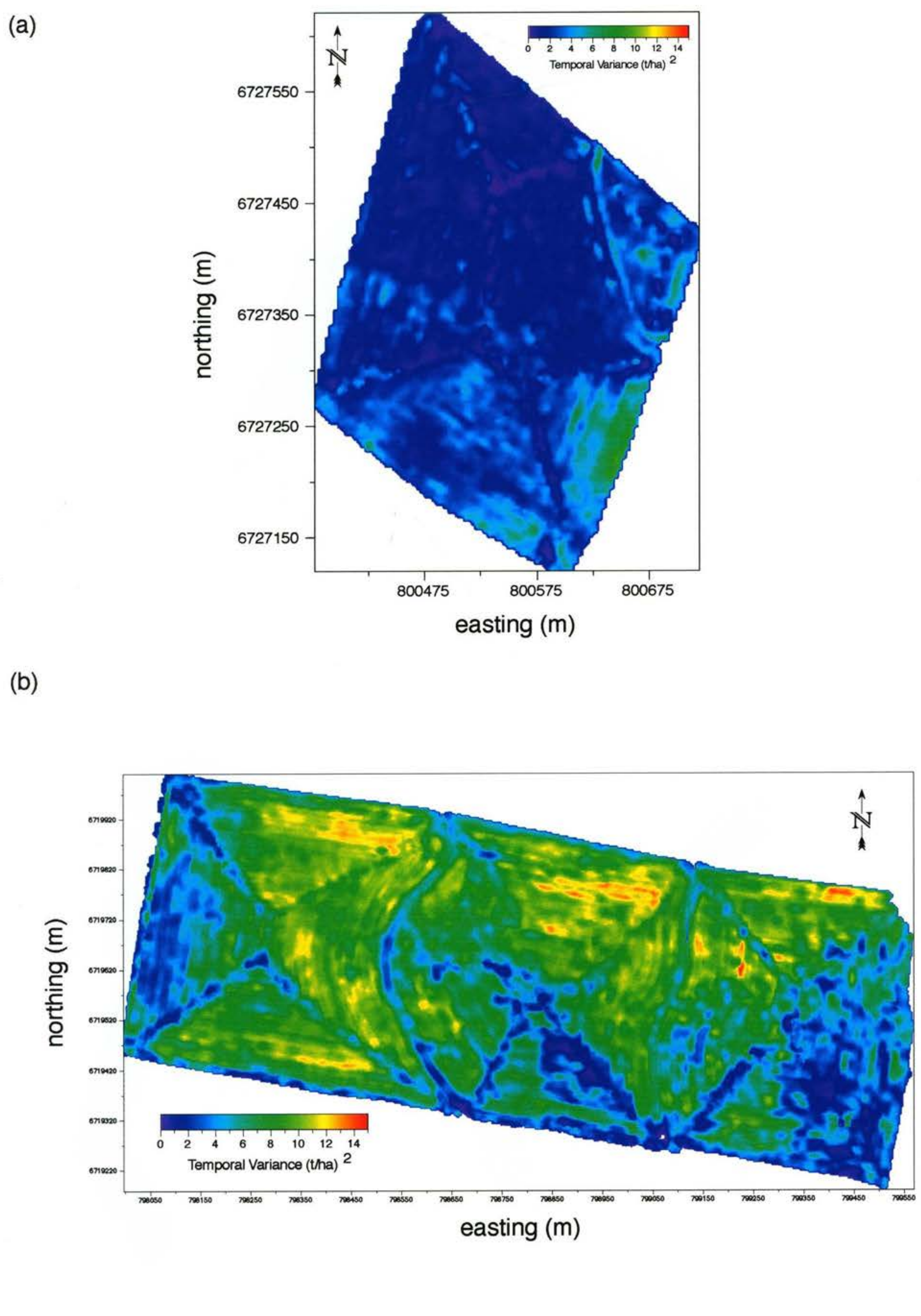


Figure 4-17. Yield temporal variance maps - (a) Horse Field (b) Maidens.

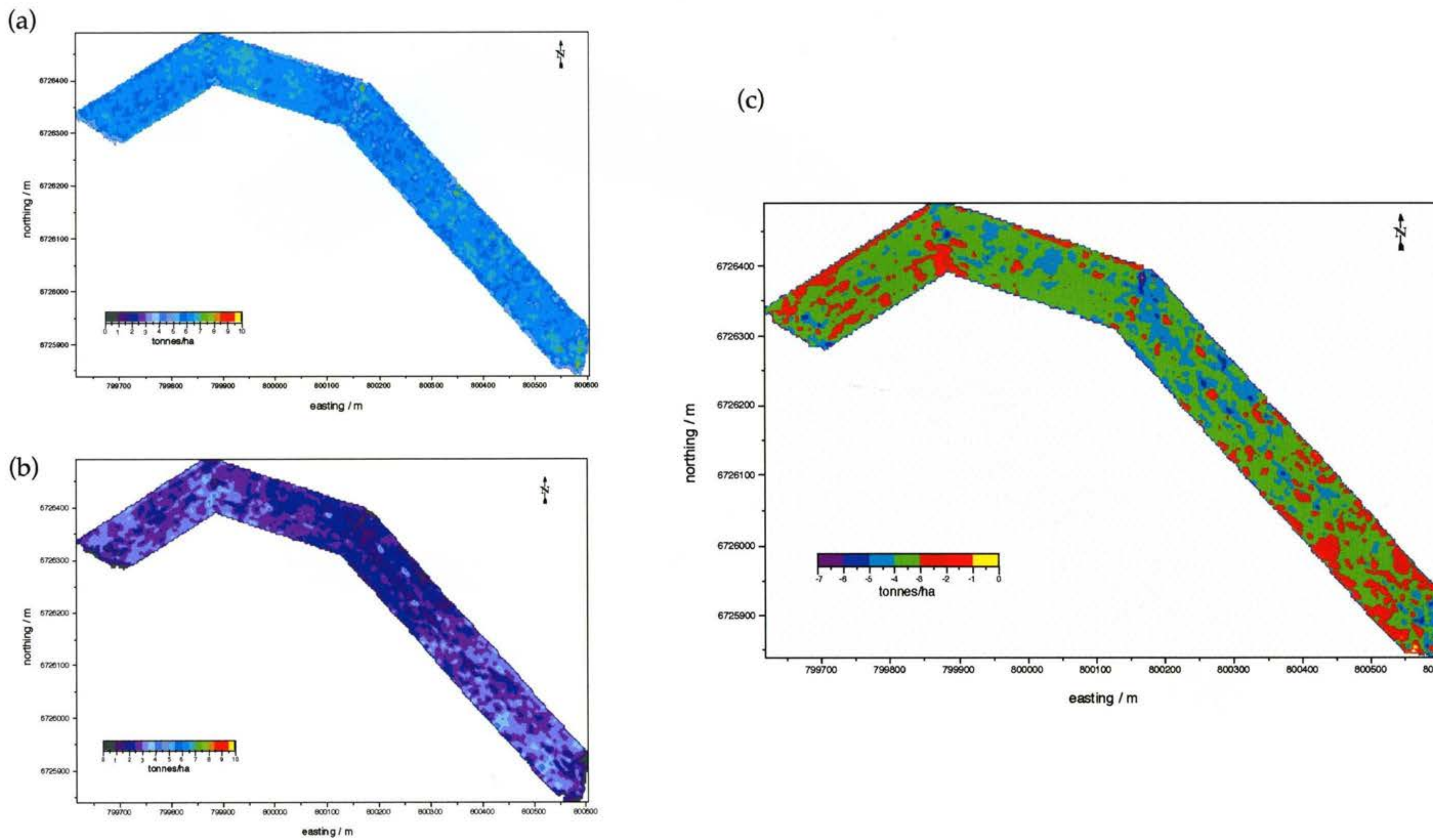


Figure 4-18. Sorghum yield maps for Field S2 - (a)1996 season (b) 1997 season (c) seasonal difference.

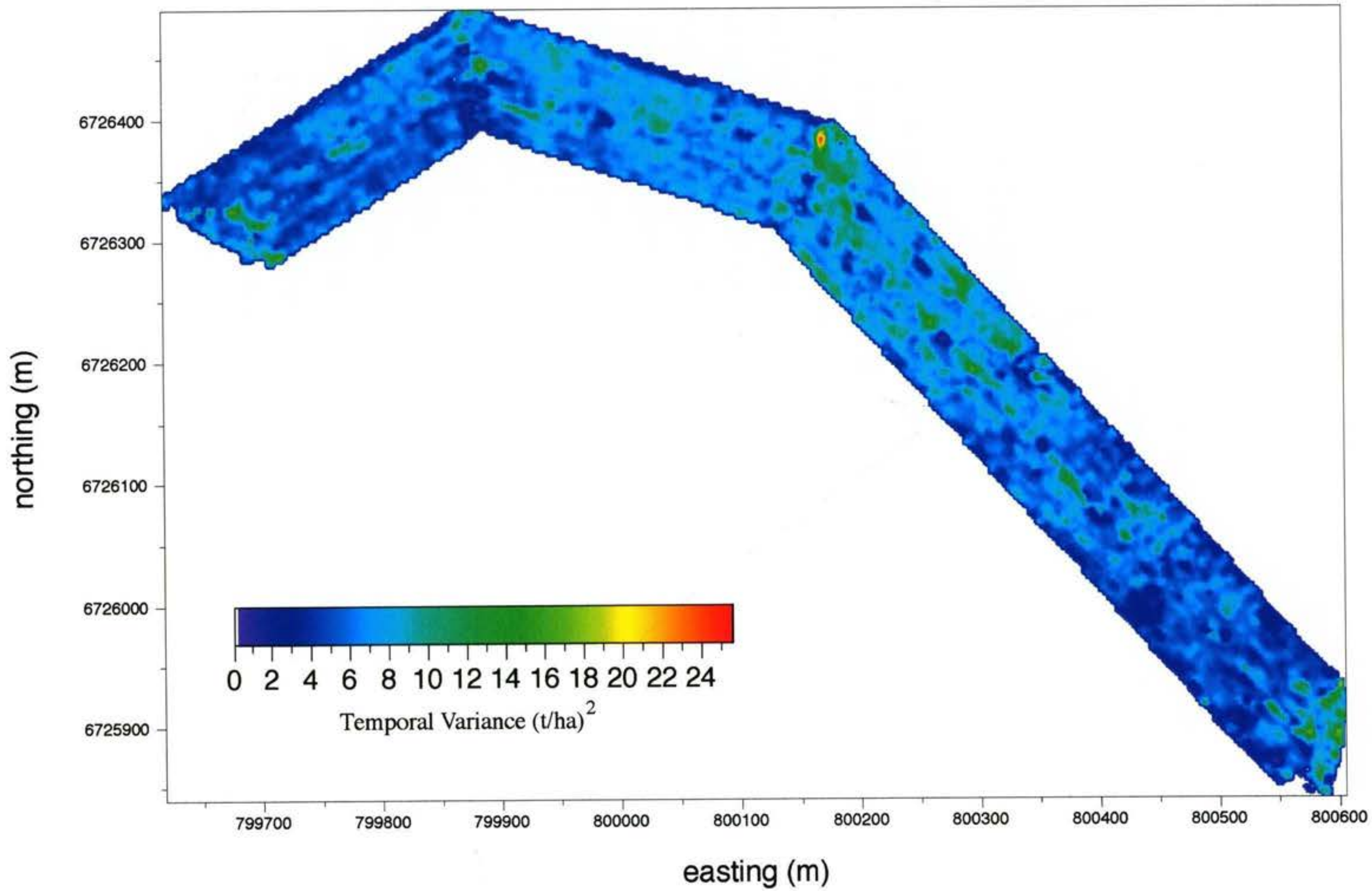


Figure 4-19. Yield temporal variance map for Field S2.

Table 4-10 records an increase in variability (variance and C.V.) with decreasing yield values as noted in the wheat fields. The C.V. of the difference between years is lower than those calculated for the wheat fields, reinforcing the suggestion that the field offers little potential for differentiating management zones. The temporal variance is again much larger than the spatial variance of the difference between years which suggests that the influence of climatic conditions is dominating the crop yield. This also leads to the belief that this field would be best treated as a homogeneous unit.

Further strengthening this hypothesis is the even spatial distribution of the temporal variance as seen in Figure 4-19. Unlike the wheat fields, little spatial pattern is evident.

4.4 GENERAL DISCUSSION

Farm managers delivering grain directly from the field to point of sale or commercial storage have traditionally been able to monitor the total yield in each field by collating truck load weights. This data would provide information on variability between fields and could be used to analyse the variability at the larger farm block and whole farm scales. This information would no doubt prove valuable to variable management on a coarse scale, but provide no insight into the possibility of changing management requirements within individual fields. The data presented here provides evidence of considerable variation in wheat and sorghum grain yield at all scales appropriate to farm management.

The relevance of the within-field scale to farm management can be inferred from the spatial variability exhibited in the yield data maps, but a more impressive depiction results from the extrapolation of yield to gross margin. In Figure 4-20, uniform field treatment costs have been deducted from variable gross profit (yield × price). In 1995 the field lost an average of $A53/ha with only 32% of the field returning a gross profit. The 1996 harvest produced a gross profit range between $A25/ha and $A540/ha at a mean of $A295/ha. The potential for an increase in gross profit in both years is obvious. In the simplest case, the identification of zones at risk of low production or with inherent lower yield potential, may be used to reduce fertiliser rates and therefore variable costs.

As discussed in Chapter 2, the technology to apply inputs such as fertiliser at variable rates is commercially available. Hindering the widespread adoption of such practices is the present lack of a relatively inexpensive method for determining management zones that have some robust agronomic rationale. Cluster analysis of multi-season crop yield data has been suggested by Lark & Stafford (1997) and this approach could also be applied to the crop yield difference and temporal variance information gleaned from the experimental data presented herein. Clustering analysis is a multivariate technique which may be applied to any number of variables, making it suitable for single and multi-season analysis. For this discussion, a process of K-means clustering is utilised that employs hard-set classification to assign observations as members of one cluster only.

Table 4-11 records the descriptive statistical results of the analysis and Figures 4-21 to 4-29 present the spatial distribution.

Data Type			Number of Clusters in Analysis								
			4 Clusters				3 Clusters			2 Clusters	
			1	2	3	4	1	2	3	1	2
Crop Yield											
	1995	μ	0.69	2.14	2.20	1.04	1.04	2.36	1.40	1.07	2.05
		σ	0.37	0.41	0.39	0.31	0.57	0.29	0.40	0.58	0.55
	1996	μ	2.62	2.98	4.15	4.23	3.01	4.07	4.40	3.15	4.20
		σ	0.55	0.32	0.34	0.48	0.57	0.34	0.33	0.62	0.36
		N	370	252	4470	1218	844	3518	1948	1040	5270
		% Area of field	6	4	71	19	13	56	31	16	84
Yield Difference		μ	1.06	1.82	2.54	3.48	1.35	2.22	3.26	1.64	2.89
		σ	0.32	0.21	0.23	0.34	0.37	0.27	0.41	0.44	0.49
		N	1036	2444	1930	843	2162	2773	1318	3763	2490
		% Area of field	17	39	31	13	35	44	21	60	40
Temporal Variance		μ	1.09	2.49	4.22	6.89	1.36	3.39	6.49	1.74	5.09
		σ	0.47	0.45	0.59	0.97	0.60	0.70	1.10	0.85	1.43
		N	2532	2111	1109	501	3508	2083	662	4680	1573
		% Area of field	40	34	18	8	56	33	11	75	25

Table 4-11. Descriptive statistics for cluster analysis of field B4 based on crop yield over two seasons (1995 & 1996), yield difference (1996 – 1995) and the temporal variance between 1995 & 1996.

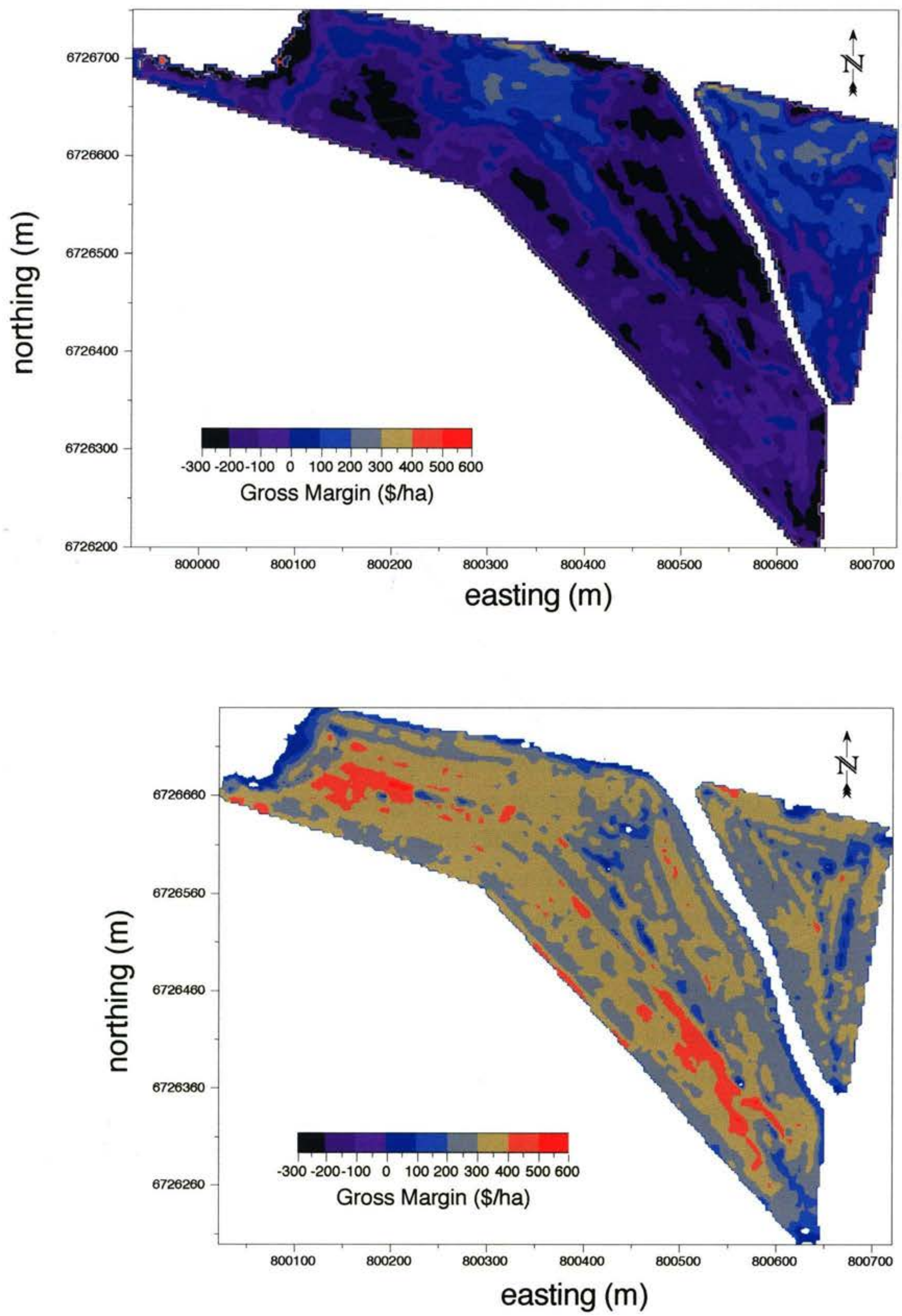


Figure 4-20. Gross margin maps for Fields B1 & B2 - (a) season 1995 (b) season 1996.

It is important that each cluster be founded on an agronomically rational differentiation, and for this reason a maximum of 4 clusters was chosen for the basic two season analysis. Four clusters, as shown in Figure 21b segregates on high yields in both years, low yields in both years and the two possibilities of inverse response between the years. More clusters may be useful with an increase in the number of seasons incorporated in an analysis. For the yield difference and temporal variance examples a maximum of 4 clusters was assessed for comparison purposes.

An agronomic interpretation of the results is also probably of more importance than a statistical approach. In each analysis in Table 4-11, there is a significant difference between each relevant cluster mean due to the substantial number of observations. However, the spatial aggregation of observations allocated to a cluster may prove diffuse or of small total physical dimension. Such a result would offer little beneficial information to farm management.

A four-cluster analysis of crop yield in 1995 and 1996 (Figure 21a) shows a spatial predominance of cluster 3, with coherent inclusions of cluster 4. Clusters 1 and 2 are basically restricted to the field boundary, representing a combined 10% of the field area and would be difficult to manage as separate units. The three-cluster analysis in Figure 22 results in the general summation of the previous clusters 1 and 2 into the new cluster 1 (Figure 22b). Cluster 2, representing areas in the field that respond with relatively high yield in both seasons, remains dominant (56% of field area). Areas which responded poorly in 1995 but relatively well in 1996 (cluster 3) remain as coherent inclusions (31% of field area). The areal dimensions of cluster 1 (basically reflecting the areas of low yield response in 1996 and 1995) may now be physically manageable, but may remain too small to be economically viable (13% of field area). Clustering on the premise of two clusters produces Figure 23. Here, the ability to define areas with inverse response over time has been relinquished and a field dominated by the high results of 1996 is displayed. This clearly dismisses the information provided by the 1995 season results and would be useless to management unless the 1995 yield response was considered an unrepeatable artefact.

Given the yield data on these two seasons, this clustering approach may be best interpreted for management as 3 zones. This can be achieved by combining clusters 1 and 2 from the 4 cluster analysis or by accepting the three cluster analysis boundaries. The delineation between the means of the remaining two clusters is slightly increased (~ 0.3 t/ha in 1996) in the 3 cluster analysis (refer Table 4-11) and may be preferrable. The choice of absorbing cluster 1 into the management regime of the dominant cluster 2 is then a matter of economic and risk analysis.

The interpretation of the cluster analysis based on seasonal yield difference and temporal variance is more straightforward. As can be seen from Figures 24b to 29b, the clustering process provides segregation regions that may be interpreted as quantifiable cuttoff zones. The means and standard deviations of the clusters are recorded in table 4-11.

In the 4 cluster analysis based on yield difference, the separation between the cluster means increases from an average of 0.7 t/ha for 4 clusters to 0.9 t/ha for 3 clusters and 1.2 t/ha for 2 clusters. Given such information the acceptance of cluster delineation may eventually include an assessment of the economic significance of the yield difference (given the possible increased cost of variable application) as well as considering the spatial dimension and aggregation of each cluster. In Table 4-11, cluster 4 is smaller in overall field area than cluster 1 (13% compared with 17%), but appears in Figure 24a to be more aggregated and ameniable to zone management. The subsequent consideration of only 3 clusters in the analysis provides a more suitable zonal delineation (Figure 25a) however the areas allocated to cluster 1 may still be considered as mostly disaggregated. The smaller areas could be absorbed into the management regime of cluster 2, leaving a small number of cluster 1 regions. Alternatively, Figure 26 shows the results of a 2 cluster analysis which provides a greater separation of the cluster means and similar delineation of the significant yield inversion zones as depicted in Figure 22a.

While all three data sets provide evidence of gradational changes throughout the field (i.e. very few occurrences of spatially adjacent clusters not being numerically adjacent), the cluster analysis of temporal variance provides the smoothest, most contiguous representation of the variation. In the 4 cluster analysis, while cluster 4 is smaller than cluster 1, there is little discrepancy in the observable aggregation (Figure 27a). The size of cluster 4 (8% of the field area) may however be considered insignificant. Consideration of only 3 clusters (Figure 28a) appears to produce an increased aggregation in clusters 1 and 2 but little increase in the areal dimensions of the cluster based on the highest temporal variance (8% to 11%). This map provides a more spatially contiguous display of a three cluster analysis than presented in Figure 25a and could be utilised as a base map for three management zones if the size of cluster 3 could be considered economically significant. Figure 29 shows that the results of a 2 cluster analysis provides strong identification of the areas of response inversion with boundaries more comparable to the crop yield map (Figure 22a) than the 2 cluster analysis of the crop yield difference data (Figure 25a).

It must be remembered that the temporal variance does not discriminate between similarly high and similarly low response or between the yield response inversion possibilities across seasons. The temporal variability maps must be interpreted in conjunction with the crop yield or yield difference maps. In this instance, the temporal variance maps can be

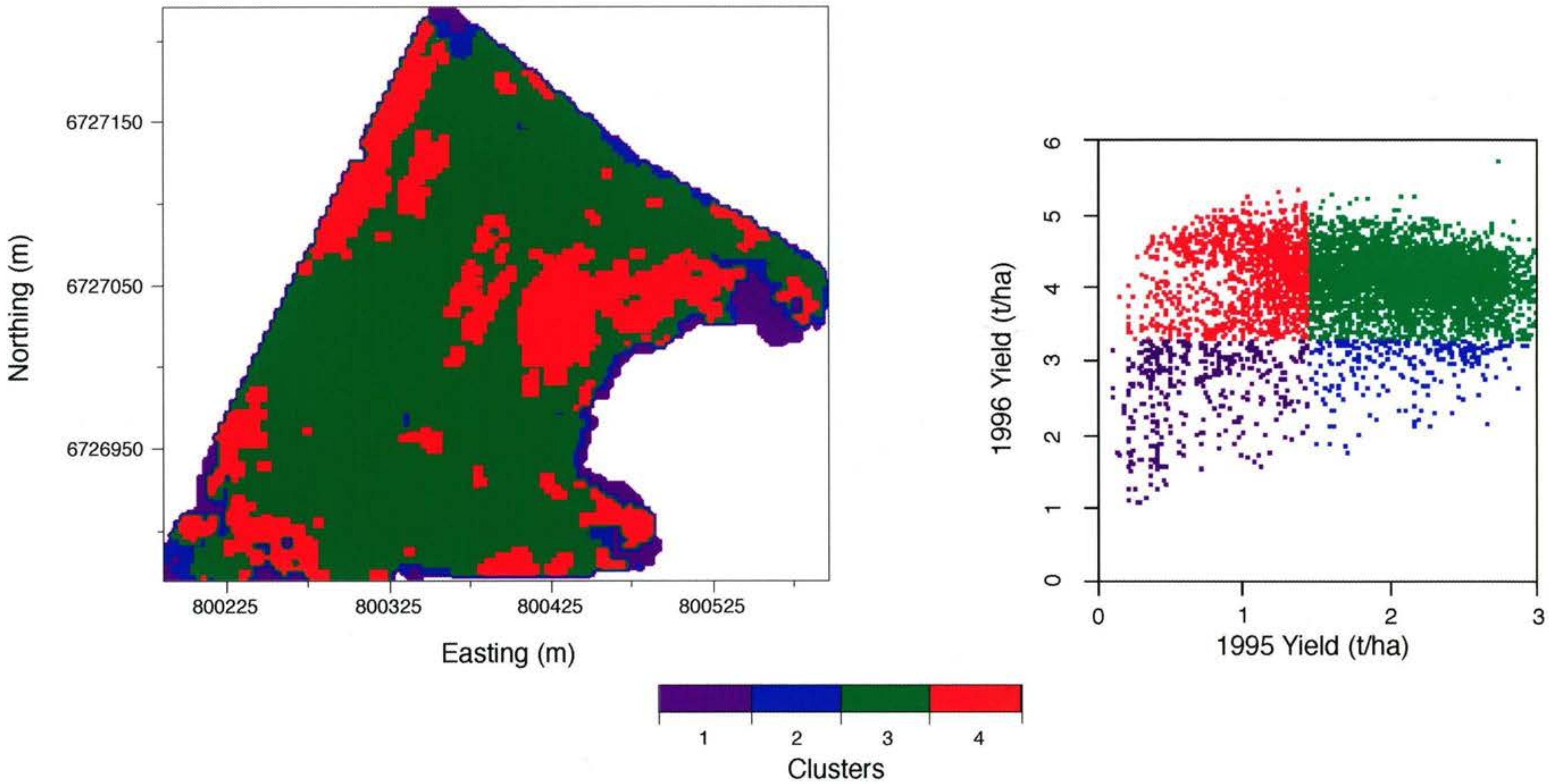


Figure 4-21. **Four cluster analysis on crop yield - (a) spatial representation (b) data demarkation.**

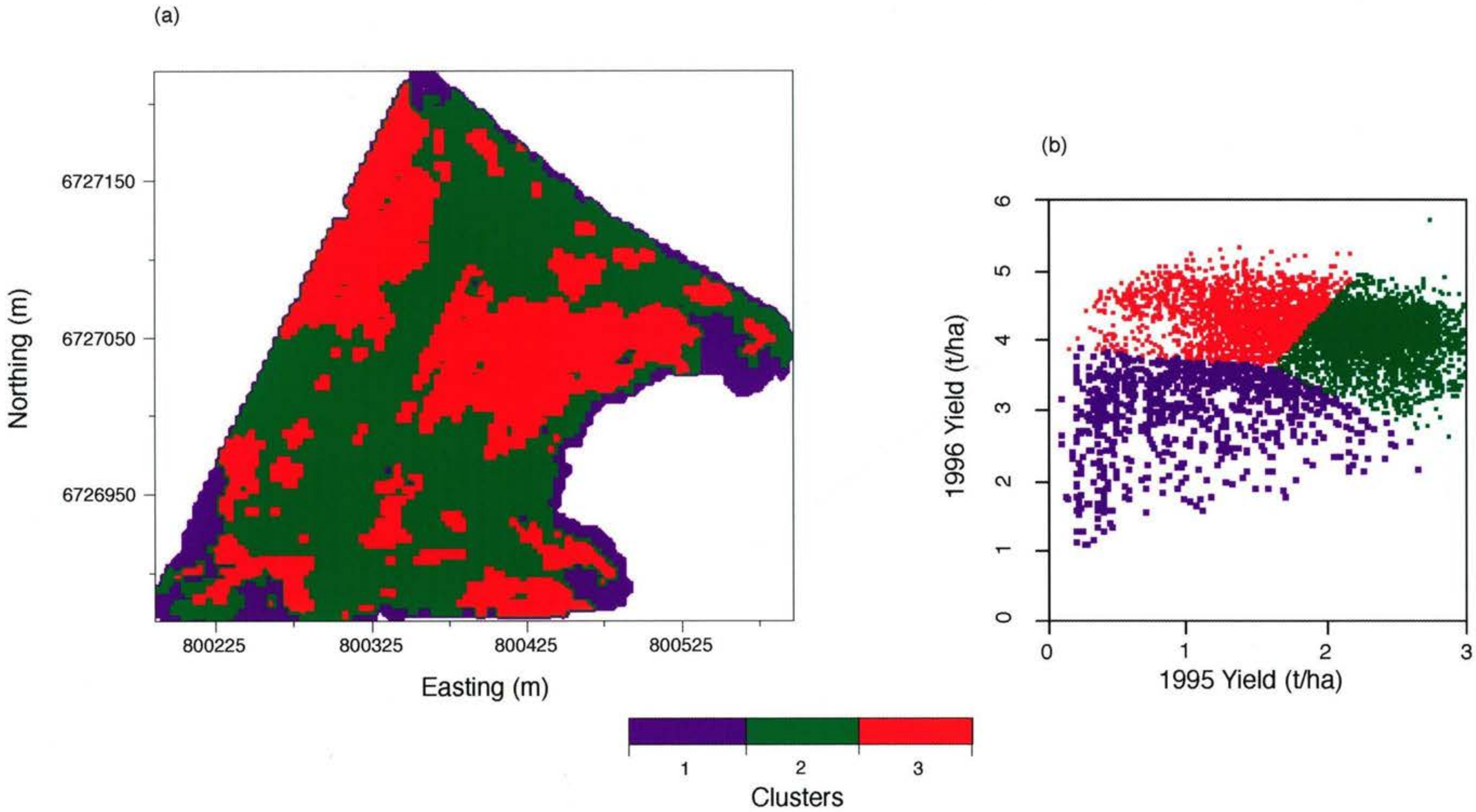


Figure 4-22. **Three cluster analysis on crop yield - (a) spatial representation (b) data demarkation.**

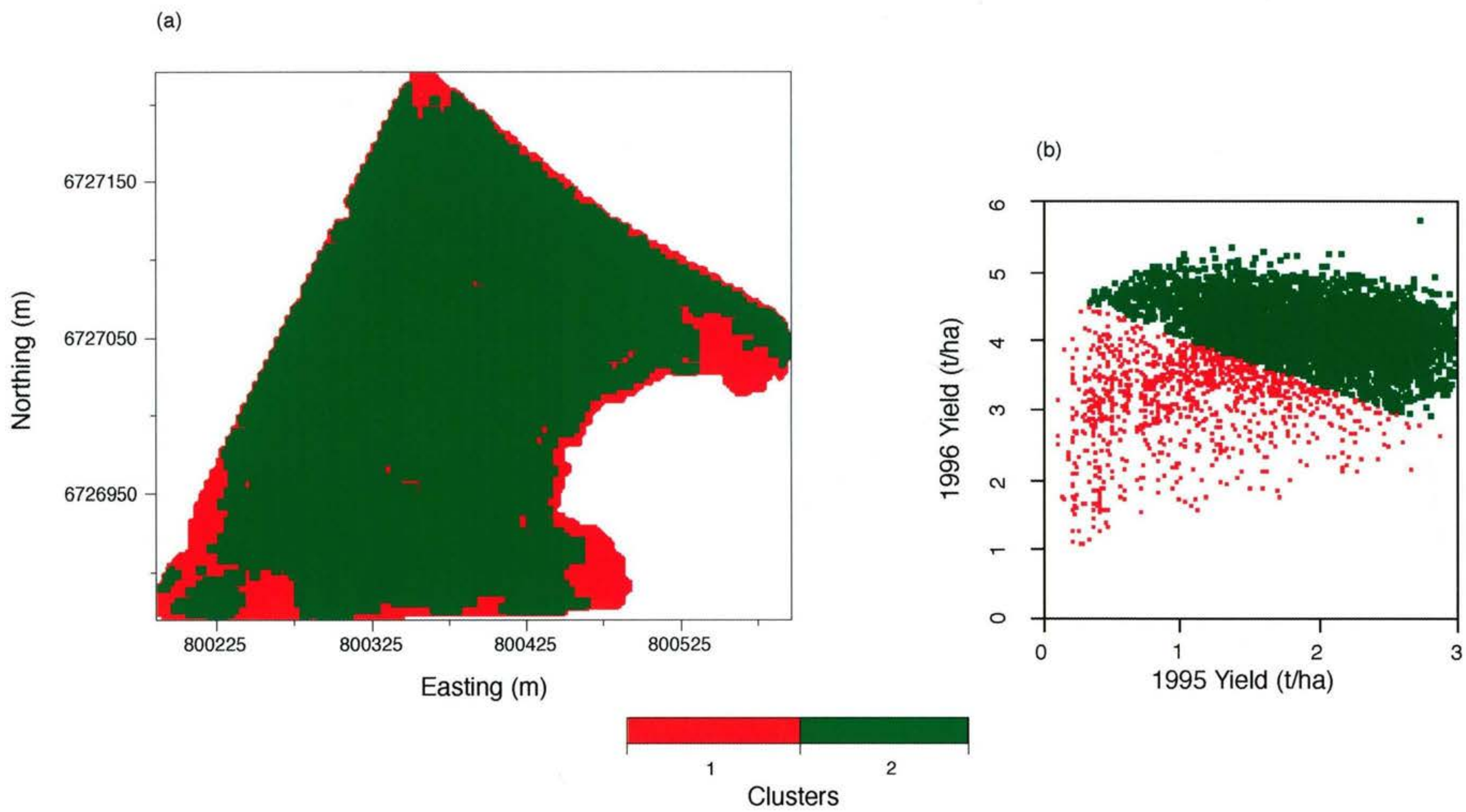


Figure 4-23. Two cluster analysis on crop yield - (a) spatial representation (b) data demarkation.

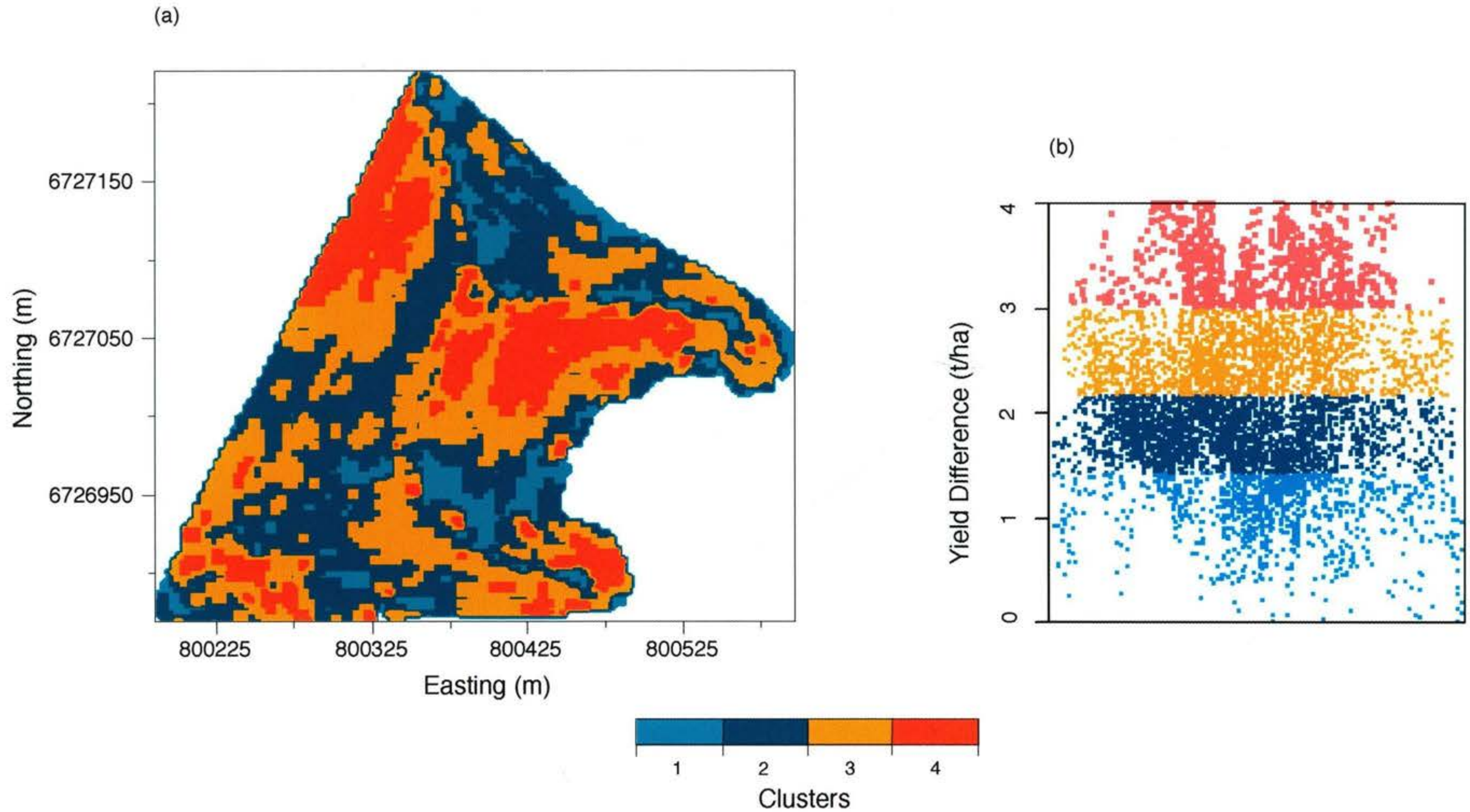


Figure 4-24. Four cluster analysis on difference in crop yield - (a) spatial representation (b) data demarkation.

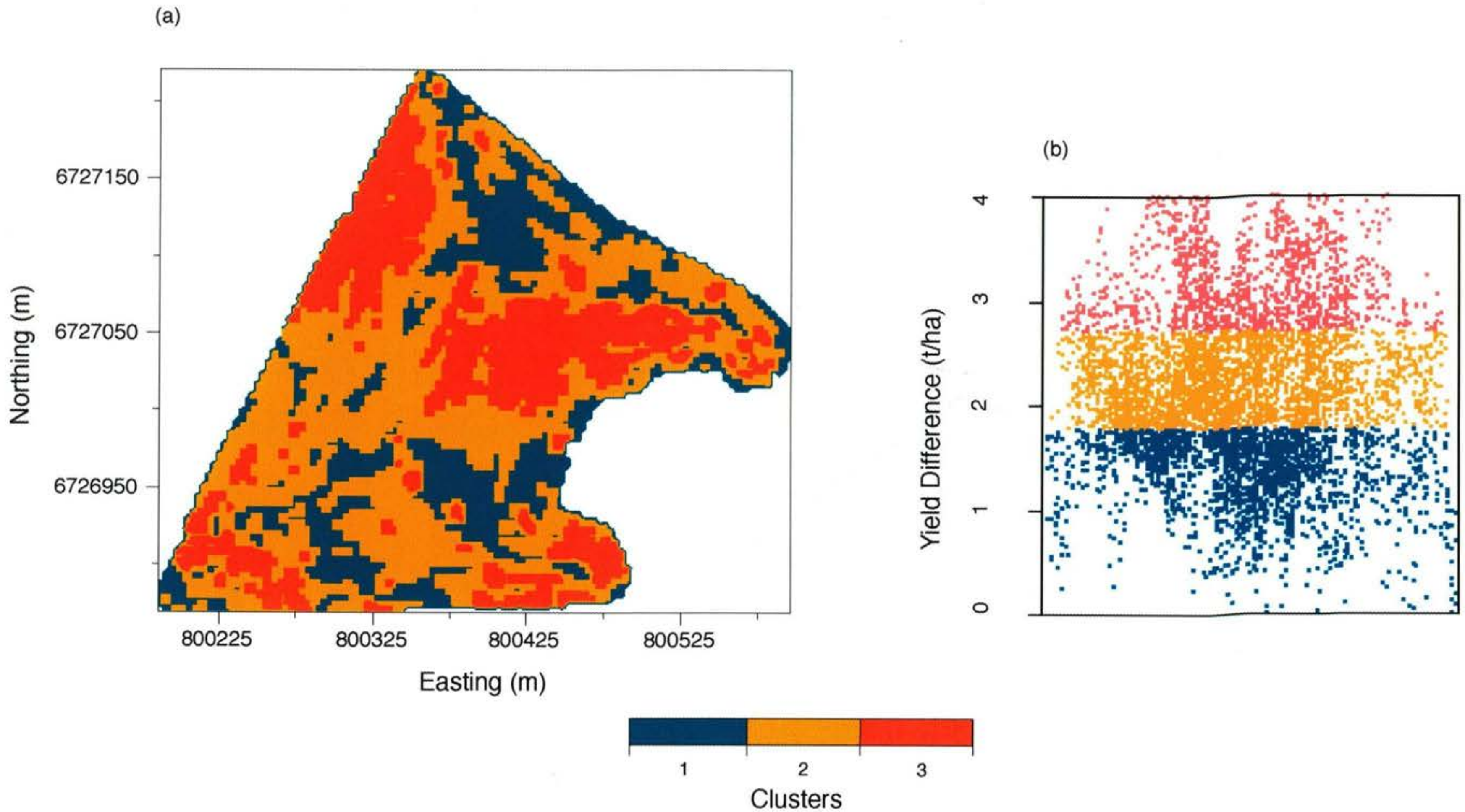


Figure 4-25. Three cluster analysis on difference in crop yield - (a) spatial representation (b) data demarkation.

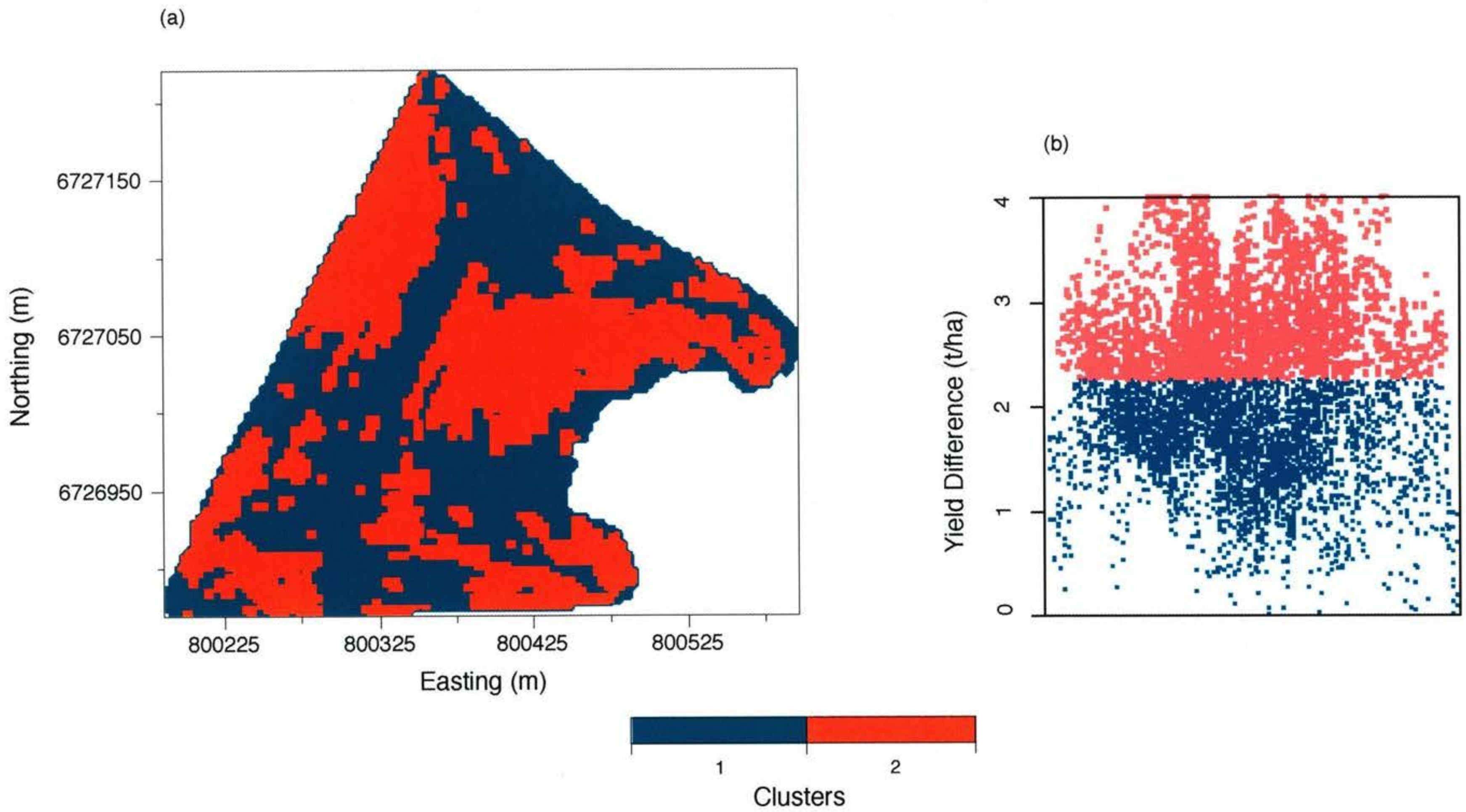


Figure 4-26. Two cluster analysis on difference in crop yield - (a) spatial representation (b) data demarkation.

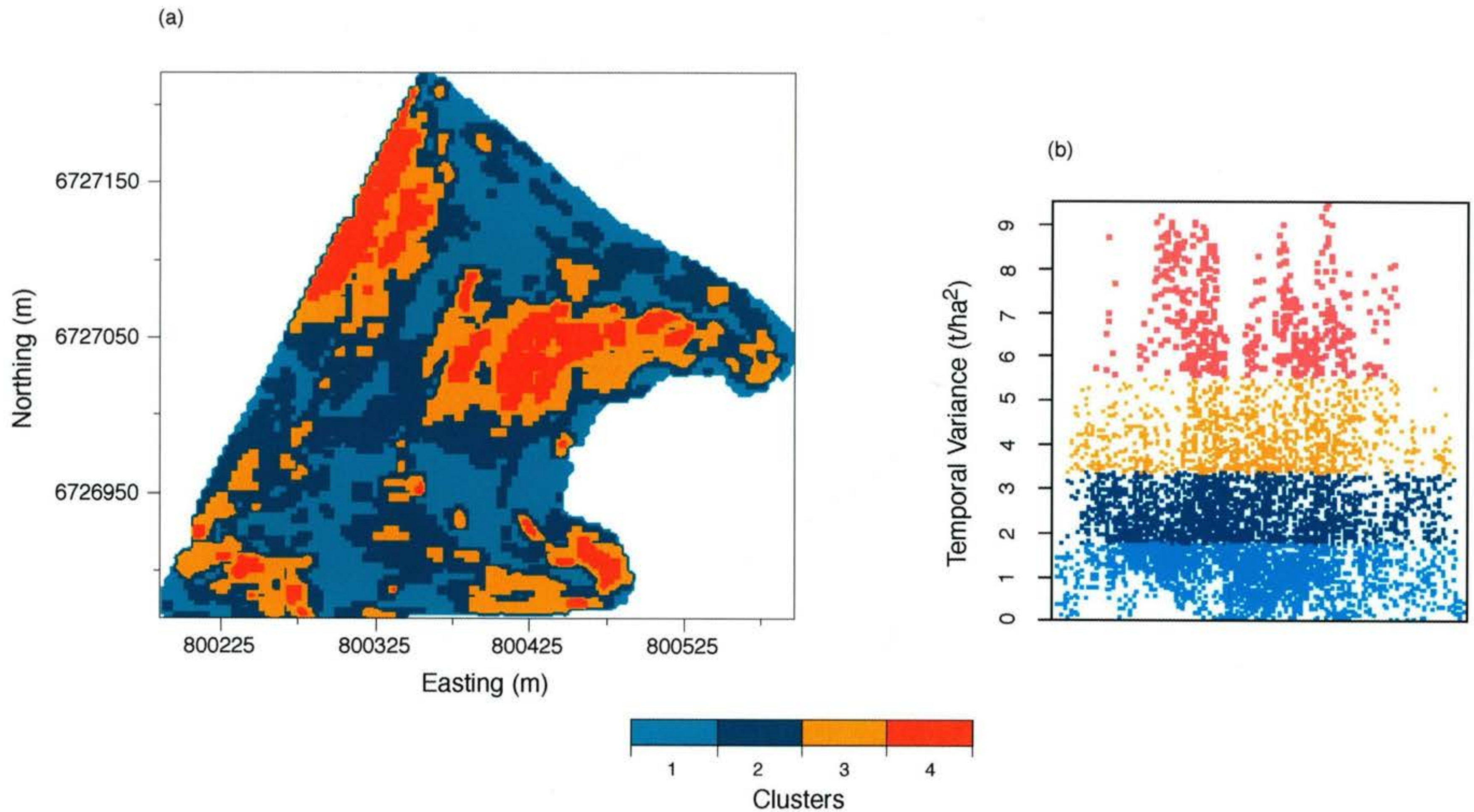


Figure 4-27. Four cluster analysis on temporal variance in crop yield - (a) spatial representation (b) data demarkation.

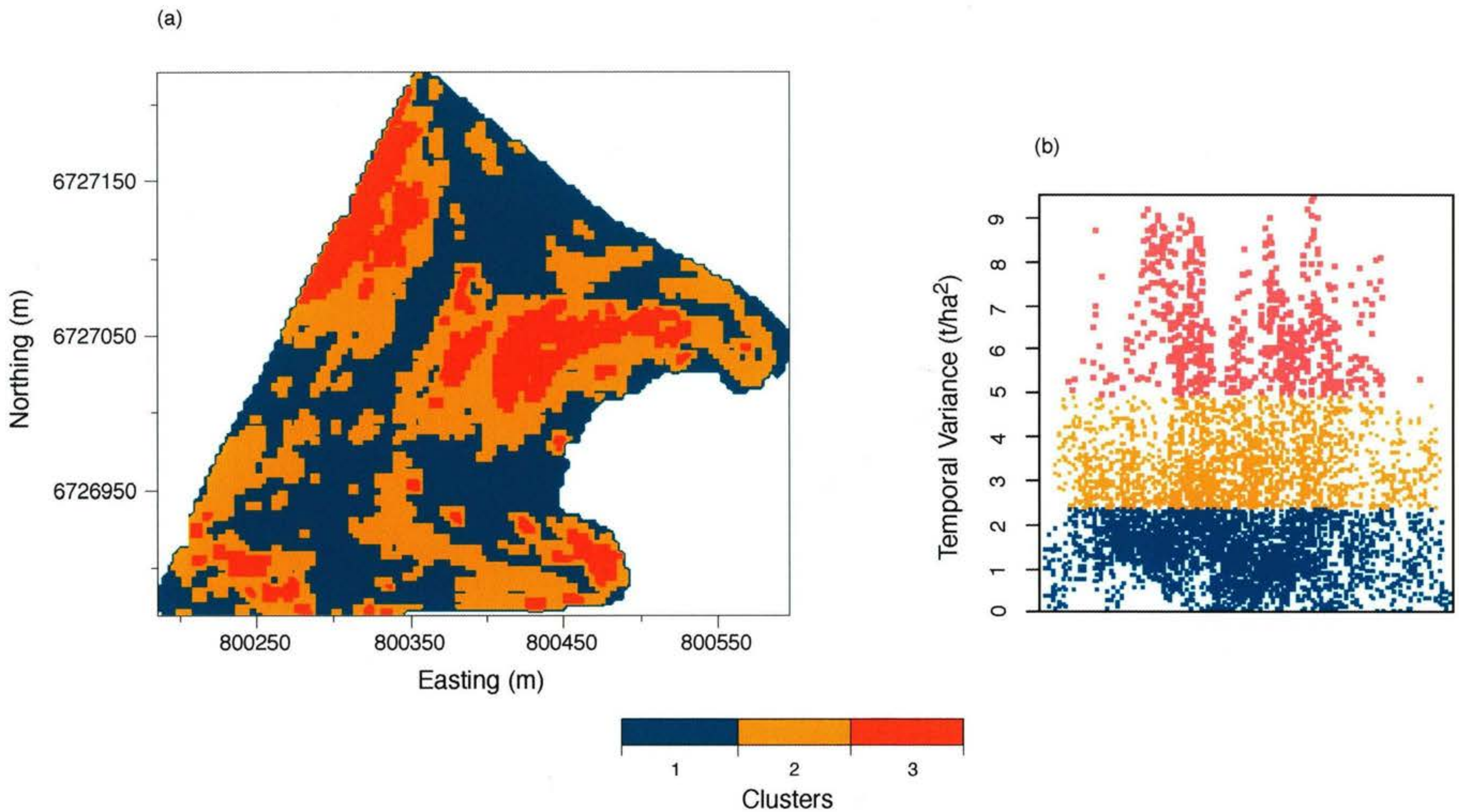


Figure 4-28. **Three cluster analysis on temporal variance in crop yield - (a) spatial representation (b) data demarkation.**

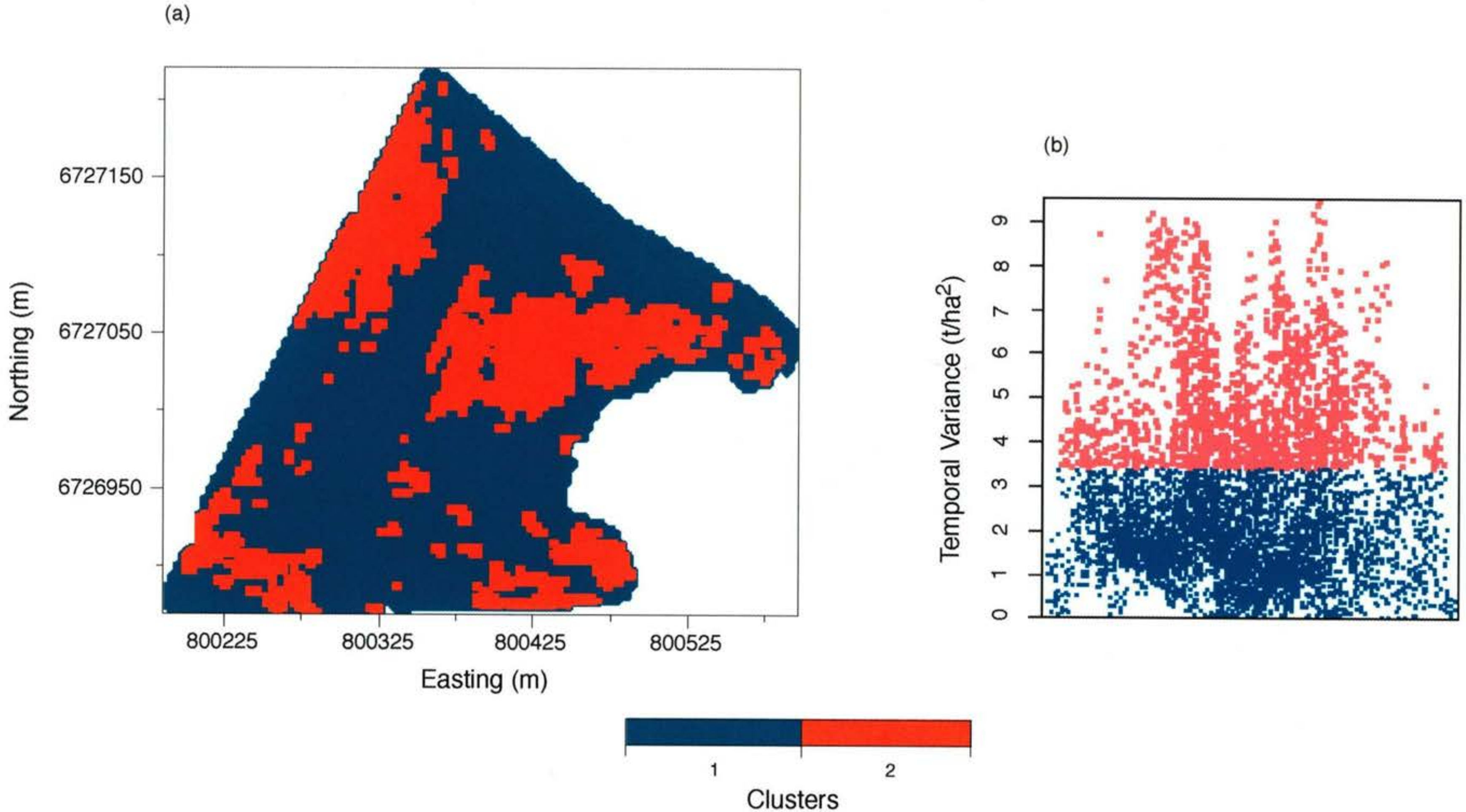


Figure 4-29. **Two cluster analysis on temporal variance in crop yield - (a) spatial representation (b) data demarkation.**

confidently interpreted as reflecting observed spatial variability in crop yield. The segregation of clusters based on defineable and easily understood variance levels provides useful information for assessing the economic impact of each cluster analysis. It also offers the opportunity to asses the risk associated with cluster scenarios based on the accuracy (expressed as variance) that is associated with the original yield data. These points suggest that the temporal variance maps for 3 and 2 clusters may be most useful in the search for techniques to define management zones within this field.

Fuzzy-set classification (McBratney et al., 1992) may also be used to partition membership of an observation between defined clusters as an alternative to the hard-set process. However, unless a continuously variable surface is the desired outcome, some form of hard-set classification must be eventually employed in the final mapping procedure to define management zones. Lark & Stafford 1997 employed a fuzzy-set clustering analysis of three years yield data to define regions of a field that may have similar factors limiting yield. They settled on 4 clusters as optimum and found reasonable continuity in management zones determined on the hard-set classification of maximum class membership. The technique proposed by Burrough & Swindell (1997) (refer section 2.4.2) for delineation of unit boundaries using a confusion index based on fuzzy-set cluster membership may offer an alternative to this final hard-set operation, but the process requires further experimentation.

The hypothesis underlying this discussion, namely, that management units may be delineated from the yield maps, is based on the assumption that the underlying soil variability will be reflected sufficiently in these maps (other methods for delineation management units have been discussed in section 2.4.2). The study by Lark & Stafford (1997) provides some evidence for accepting this assumption. The authors found that a significant proportion of the variation in soil moisture content could be explained by the regions defined by the yield clustering process. Unfortunately, obtaining soil variability information at the same scale as the yield data has restrained the ability to repeatedly test this assumption at all but coarse scales. Soil sampling and analysis is prohibitively laborious and expensive to undertake at the metre or tens-of-metre scale that is required. The development of intrusive or remote methods of soil attribute sensing will eventually overcome this restriction.

At present, aerial or satellite platform remote imagery offers the most suitable sampling method. Some preliminary aerial photography of the "Romaka" Lease field following a stubble burn in 1997 is presented in Figure 4-30 along with the corresponding yield map from the previous wheat harvest.

There is a striking correlation between soil colour and crop yield in the highlighted area of the field where a yield reduction of up to 4.5 t is registered by the yield monitor in the lighter coloured soil. This soil is lighter in texture than the rest of the field. Such remarkable correlation qualitatively validates the assumption discussed above and also confirms that the yield monitoring process described in these experiments can be relied on to distinguish relative yield changes.

The results presented herein also highlight the accuracy of grain mass flow measurement using the impact-based sensor. The maximum mean load error of 1.37% and maximum individual load error of 3.2% for the calibration runs agrees with the results from recent literature presented in Section 2.2.2. Contributing to these errors are variations in grain density, foreign material, ground slope, machine vibration and electrical noise, and ambient dust and humidity levels.

What cannot be assessed from these experiments is the accuracy of the yield value calculated from each mass-flow observation. It can be seen from Equation 4-1 that a yield estimate requires a distance travelled and swath width measurement (to calculate area harvested) in conjunction with the mass flow observation. The system employed here, like all such systems now commercially available, gathers speed information from the vehicle speed monitoring system to determine distance travelled per unit time. Cutting width is fixed but may be manually altered during harvest. Error is introduced to the area measurement from inherent speed sensor error and when the cutting table is not harvesting at the determined swath width. Missotten et al.(1996) have estimated the error associated with one commercially available speed sensor to be 2.5%. The error introduced by the assumption of a 'full' cutting-table during harvest has been estimated at 7% (Vansichen & De Baerdemaeker, 1991) and 10% (Stafford et al., 1997). However it is difficult to generalise as the magnitude will depend on harvester operator, harvest pattern, field shape and terrain. Missotten et al.(1996) attempted to remove this error by installing a sensor to detect changes in the width of crop entering the harvester. Even with the addition of the sensor, the crop width measurement was reported to include a 5% error. These errors will be difficult to remove but should be quantified.

Further errors can be expected to impact on the integrity of the estimates of crop yield per unit area. In these experiments, yield estimates were produced for every second of harvester operation. This obviously requires an area estimate to be allocated to each mass measurement. With the grain mass sensor located towards the end of the clean grain transport process there is a delay between cutting the crop and the relevant grain mass reaching the sensor. This delay means that harvester speed and grain mass observations

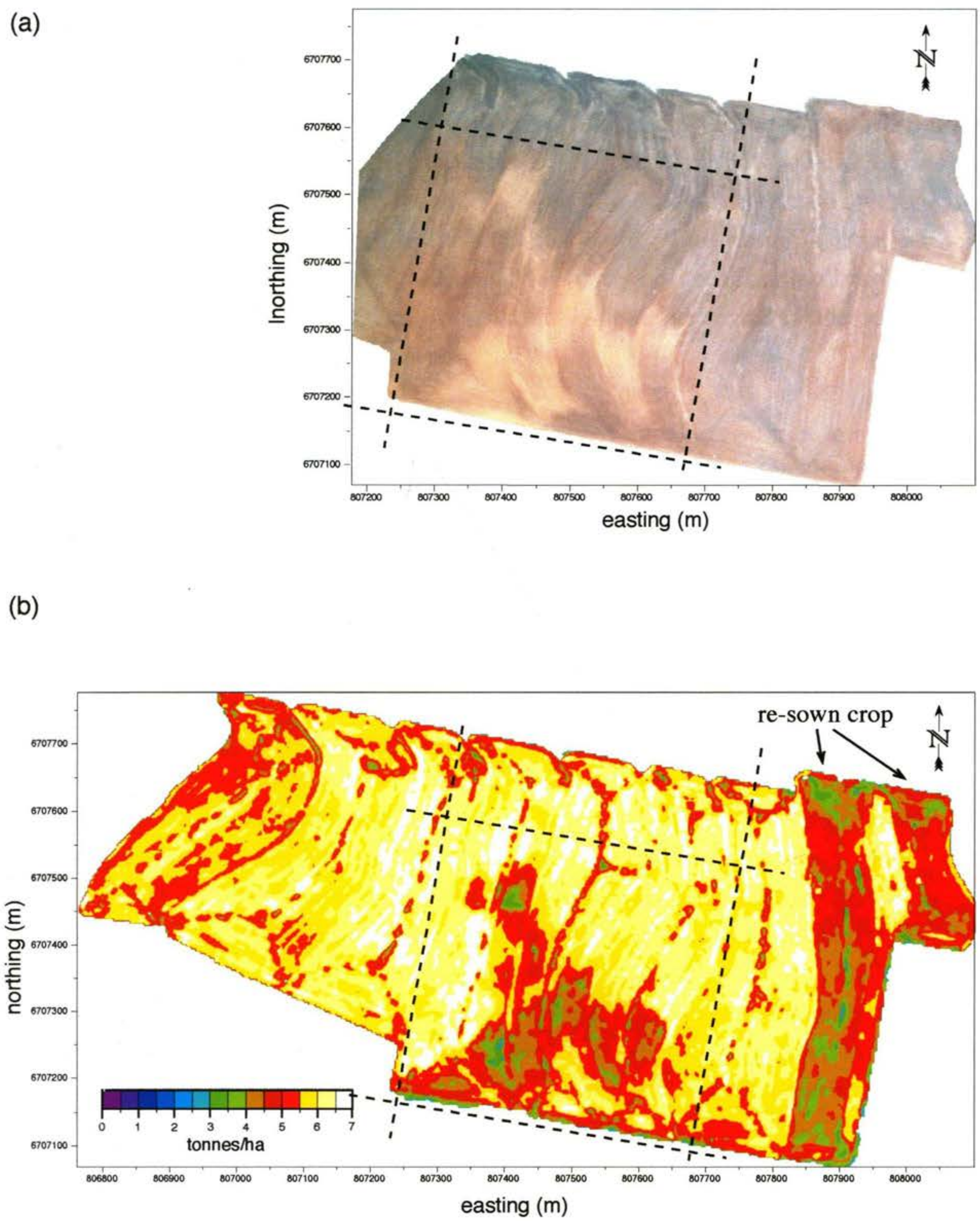


Figure 4-30. Lease Field - (a) aerial photograph of bare soil (b) the subsequent wheat yield map showing strong pattern correlation.

recorded at the same time will not relate to the same area in the field. By the time grain mass from a section of field reaches the sensor, the harvester has moved forward and the speed recorded is from this distant section of field. Error in estimating the delay will result in the mismatching of grain mass observations with the distance travelled to harvest the grain and therefore error in individual yield per unit area estimates. Adding further to this dislocation problem is the actual flow path dynamics within a combine harvester. The threshing process, grain returns and the auger transport mechanism should theoretically act to blend grain harvested at a certain time with grain harvested over a limited preceeding and proceeding time frame. If this time frame is greater than the observation frequency then the individual grain mass observations will not be directly relateable to an individual distance observation. Again, error will be introduced to the individual yield per unit area estimates.

The effect of flow dynamics must also be considered as a harvester enters and leaves a standing crop. Upon entering a crop the internal grain pathways of the harvester fill from empty and when leaving a crop these pathways empty. The impact of these dramatically changing flow rates on the mass measurement errors appears to be different (Klemme et al., 1992). At present the problem is dealt with by discarding data from the beginning and ends of harvester runs.

Another area calculation problem is introduced by sudden halts in harvester forward movement. Grain mass is subsequently allocated to an inordinately small area and the yield per unit area appears as a high spike. These data points are usually associated with low values as the harvester restarts and should be randomly distributed through the field (Murphy et al., 1995). Again, these data points are regarded as erroneous and discarded when identified. In both these cases, the removal of data points is justified on the basis that the overall data density is high and that removal will be accomodated to some degree in the subsequent interpolation process required for map construction. However, some form of quality control is required for the identification of these points, either subjectively based on expert knowledge or an objective method based on operational measurements. The process employed on the data sets presented here (Section 4.3.3; Equation 4-2) is based on a combination of the two techniques.

A final source of error is introduced in the standardisation of the yield estimate to a constant moisture content (refer Equation 4-1). Error in the moisture observations will be propogated through the yield calculation along with the other observation errors.

The errors identified will combine to impart an uncertainty in the individual yield observations as represented in Figure 4-7. The interpolation or prediction technique used to produce a continuous surface map from these non-aligned data points will add further uncertainty to the resulting yield map.

4.5 CONCLUDING REMARKS

The results of these experiments confirms the observation in Chapter 1 that whole field yield variability decreases with increasing mean crop yield and provides evidence that the spatial component of the yield variability also decreases as mean crop yield rises. Certainly, if the impact of a yield limiting factor is spatially dependent then it follows that as the severity of the effect increases, the spatial variability will also increase.

In the progression of a SSCM system, it is not sufficient to merely identify and quantify crop yield variability in space. Spatially-variable management decisions that influence crop yield must be guided. The clustering process presented offers a promising method of identifying management units. The temporal variance cluster maps offer a quantitative methodology for the stratification process but one which will require further research to determine the levels at which zoning should occur. However, the use of temporal variance clusters in conjunction with crop yield clusters should offer farm management the opportunity to incorporate economic and risk assessment in the determination of the optimum number of management units for each field.

It is vital, however, that the accuracy of the yield estimates used in any analysis be determined, the causes identified and the effect hopefully reduced. At present the true accuracy of the yield per unit area estimates provided by real-time crop monitoring systems is unknown. From the contributing errors identified, the delay parameter and associated combine harvester dynamics probably provides the greatest source of uncertainty. It is also important that the uncertainty incorporated in the individual yield estimates is not excessively increased by any subsequent prediction process. These two areas will be examined in the Chapters 5 and 6.

SECTION III

IMPROVING THE MONITORING AND MAPPING OF CROP YIELD USING REAL-TIME CROP YIELD SENSORS

CHAPTER 5

CHAPTER 5

An Examination of Combine Harvester Grain-Flow Dynamics

5.1 INTRODUCTION

The advent of real-time crop yield sensors has necessitated a more detailed understanding be established of the effects of internal threshing and transport processes on grain movement through harvesters. Commercially-available grain yield monitoring systems measure grain flow per unit time using a variety of techniques. In the majority of systems, the yield sensors are mounted in the clean-grain elevator flow or further along the grain bin delivery mechanism (refer Figure 2-4). Borgelt (1993) provides a comprehensive list of the major methodologies and sensor locations utilised. These systems register and tag yield quantities with GPS-determined locations by implementing a user-specified or manufacturer-governed single time delay between cutting a swath width and measuring the resultant grain yield at the sensor. This may be simply expressed for observations at 1 s intervals as Equation 5-1.

$$Y_{(i)} = \frac{f_{(i+p)} \times 10}{\sum_{k=i+(p-1)}^{i+p} d(k) \times w} \tag{5-1}$$

where:

$Y_{(i)}$	=	calculated yield (t/ha) for the time of position recording (i)
$f_{(i)}$	=	measured mass grain flow (kg)
p	=	time delay (s)
$d_{(i)}$	=	distance travelled since previous measurement (m)
w	=	cutting width (m)

This calculation assumes a linear, non-mixing grain flow from the cutting platform to the clean grain bin. A mechanistic evaluation of the cutting, threshing and grain-transport operations performed within a conventional harvester would suggest that a more complex mixing or convolution would be imparted on grain movement. This would imply that a non-linear delay may be more applicable in the yield/ground position tagging process. Searcy et al. (1989) proposed the use of a first-order decay model with time delay to account for such grain-flow dynamics between the cutting platform and yield sensor. The model they utilised (Equation 5-2) treated the grain entering the combine as a step input.

$$v_{(t)} = r(1 - e^{-(t-p-t_0)/q}) \tag{5-2}$$

where:

$v_{(t)}$	=	grain flow rate at the sensor
r	=	magnitude of flow rate step input (at the cutting table)
p	=	transportation delay between cutting table and sensor
t_0	=	time of step input
q	=	time constant of first order lag.

The parameters for this simple model were estimated from yield sensor data gathered as an empty combine entered a crop at constant velocity. An average time constant (q) of 2 s was calculated to be independent of grain flow rate, however they believed the transportation delay (p) ranged from 13.5 s to 17.5 s as flow rates increased.

Vansichen and De Baerdemaeker (1991) also applied a first-order model to compensate for the 'dynamic distortion' of grain flow between intake and sensor. They estimated the time delay parameter (p) as between 13.25 s and 14.25 s and between 3.5 s and 3.9 s for the time constant (q).

More recent studies (Klemme et al., 1992; Eliason et al., 1995; Murphy et al., 1995) have also acknowledged the importance of grain flow dynamics on the precision of point allocation of yields while continuing to apply single time delays ranging from 12 s to 22 s, albeit derived for the individual harvester. Birrell et al. (1995) compared a first-order model (with 12 s time delay, 0.5 s time constant and various low-pass filters) to a simple 12 s time delay model and suggested that both provide a reasonable estimate of combine flow dynamics, but preferred the simpler model, perhaps through application of the Ockham principle.

In a more thoughtful examination of the process, Lark et al. (1997) assumed the measured yield at the sensor to be a convolution of the rate of flow with respect to time at the cutterbar and an impulse response function characteristic to the harvester. They suggest that the impulse may be experimentally approximated by the sharply defined edges encountered on entering and leaving a standing crop. A Gompertz function was fitted to the flow data observed for 30s following these points and the first derivative with respect to time calculated as the impulse response function.

Taking the convolution approach appears mechanistically sensible and also allows the complex analysis to be simplified as the convolution of two functions in the time domain can be equated to the product of the respective Fourier transforms in the frequency domain.

The impulse response functions obtained by Lark et al. (1997) were quite different for entering and leaving the crop, which they point out suggests that the results might not represent the typical response during normal harvest operation.

Obviously, without directly measuring the convolution effected on grain transport during normal (or 'steady-state') operation of the harvester, the assessment of more complex models will continue to be ambiguous. However, applying the simplistic linear approach may result in the allocation of incorrect yield values to the spatial units within a field. This has obvious implications for the resolution at which accurate depiction of spatial yield variation can be made. Consequently, the determination of yield response to differential fertilisation and realistic calculations of the economic outcomes of all differential treatments will be restricted.

While errors are also present in the ground positioning and physical sensing aspects of these systems, by accounting for the true grain transport convolution the yield allocated to field spatial units should more truly represent the real field variation. An understanding of the convolution involved in the harvesting process may also be used to quantify the error associated with non deconvolved yield maps.

5.2 MATERIALS & METHODS

A John Deere 7720 (JD 7720) conventional process combine harvester with a 7 m wide cutting platform, operating at the season harvest speed of 3.24 kph (2 mph), was used to harvest the 1996 sorghum crop.

To initially define the spatial sensitivity of the monitoring system and the extent of smoothing and delay imparted on the grain during harvest, two adjacent 450m long × 7m wide header runs were delineated and the grain removed from 4 segments along the runs. The experimental setup is shown in Figure 5-3 where the grain has been removed across the two runs normal to the harvest direction in widths of 7 metres (a), 14 metres (b), 21 metres (c) and 28 metres (d). The runs were then harvested and the effect of the zero yield segments observed.

For a more detailed examination of the grain travel process within the harvester, a 50 m long sorghum strip that included a 1.5 m long by 7 m wide coloured band of grain was established in the field. The coloured grain, externally treated using enamel spray paint, was located 20 m along the sorghum strip to ensure the harvester was operating at 'steady-state' when the band was encountered.

The coloured band was devised to quantify the hypothesised grain mixing and delivery delay observed at the yield sensor caused by the movement of grain through the harvester following stem cutting and the effect on these processes of crop spatial position along the cutterbar.

With a 1 m plant row spacing, there were seven rows of sorghum in the swath width. The cutting platform was assumed to represent two reflective halves separated by the middle crop row due to the operation of the centre delivering auger system. Based on this, grain in the sorghum heads was marked using four distinct colours in the following spatial pattern: central row, the rows 1m on either side, the rows 2m on either side, and the outer row on either side (refer Figure 5-1).

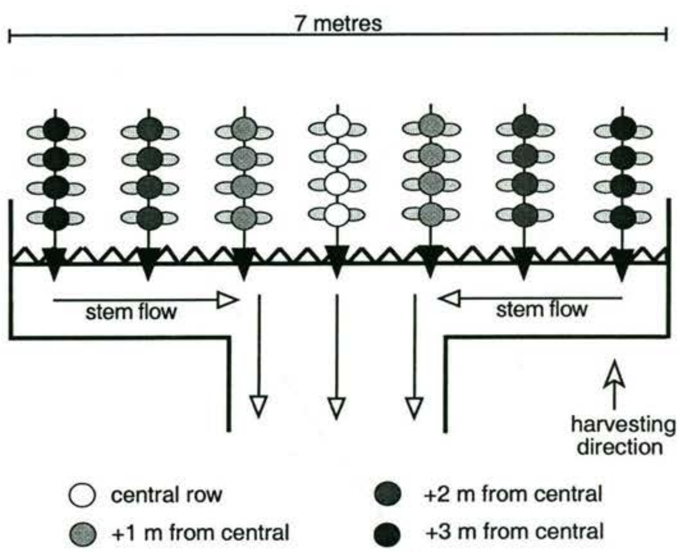


Figure 5–1. Plan view of experimental setup detailing the cutting platform, coloured grain pattern and cutting platform delivery process.

The grain for sampling was accessed by depositing the clean-grain flow from the cross-auger in a controlled strip into the inter-row space beneath the clean-grain elevator. All paddles from the clean-grain elevator were removed to prevent grain transport up the elevator, the door at the base removed, and a purpose-built rubber skirt was fitted to control the grain flow to the soil surface. The skirt was constructed to be as wide as the clean grain elevator so as not to interfere with grain flow rates.

Sampling 10 cm sections at 50 cm intervals along the flow resulted in 42 samples representing a 0.11 second sampling window each 0.45 seconds of flow. The mass of coloured and clean grain in each sample was manually determined. Figure 5-2 shows the coloured grain band, the harvest operation and the resultant mixed grain flow.

(a)

(b)

(c)

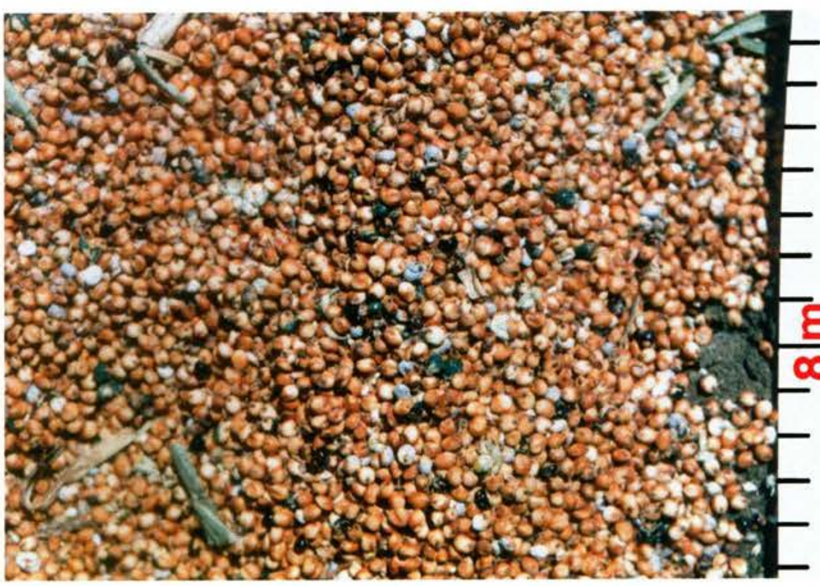


Figure 5–2. An example of coloured sorghum band (a) harvest operation (b) and grain flow strip for sampling 8m past interception of the coloured band (note coloured grain mixed with clean grain).

5.3 RESULTS & DISCUSSION

5.3.1 Spatial Sensitivity and Displacement

Harvesting the two adjacent sorghum runs with the known zero yield segments coarsely confirms and demonstrates the mixing and displacement of the grain when observed at the yield sensor. Figure 5-3 shows the yield recorded and tagged with the location of the harvester at the time of yield measurement. Immediately evident is the lack of a zero yield registration following the 7 metre cutout. Only after a zero yield gap of 14 metres does the monitoring system register the lack of grain in the run. Some smoothing of the true yield variability in the field is obviously occurring within the system. The recorded beginning of the zero yield (black points) are also displaced forward approximately 19 metres from the true origins of segments 'c' and 'd'. Zero yields only just register in one run from segment 'b' (14m cutout).

Figure 5-4 displays the yield trace for the lower header run and shows an approximately 10 metre displacement for the yield signal to fall to almost zero followed by a small fluctuation as the harvester empties of grain. This perturbation extends the displacement for the zero yield signal out to the observed 19 metres.

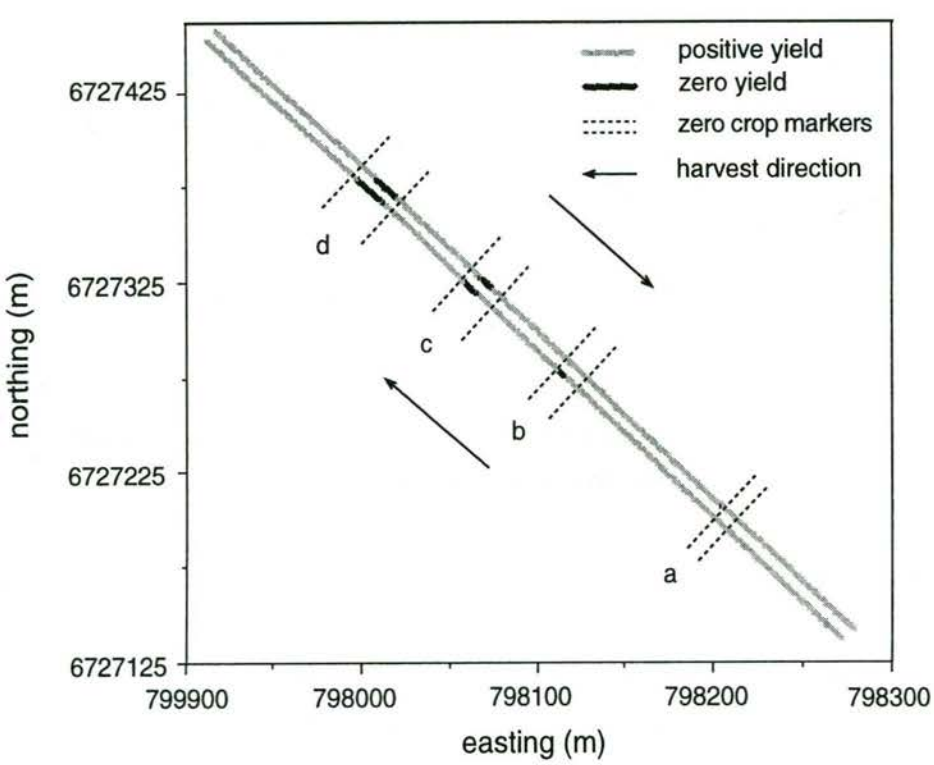


Figure 5–3. Zero yield smoothing and displacement in two adjacent header runs.

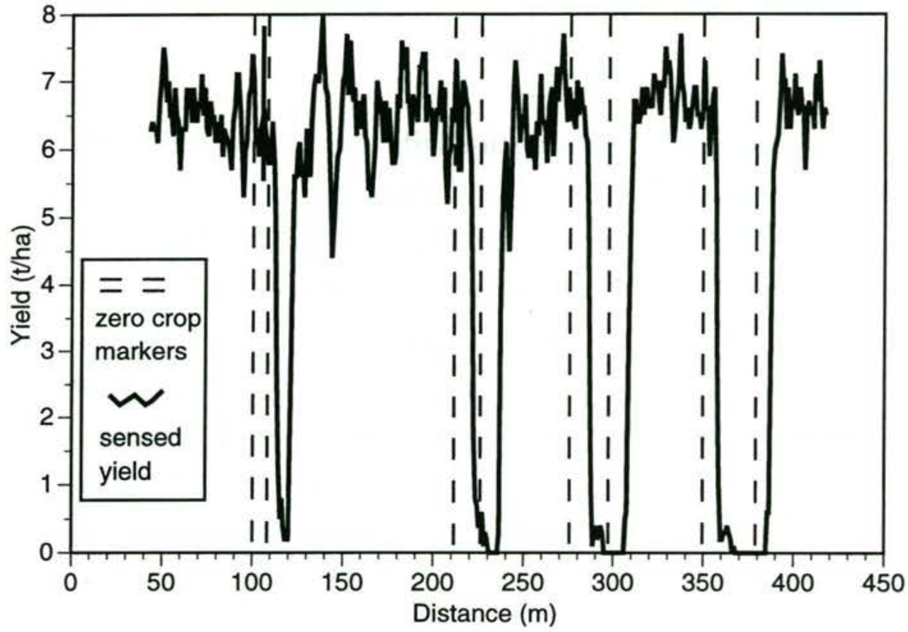


Figure 5–4. Grain yield trace and zero yield cutout positions for the lower header run in Figure 5-3.

No such fluctuation is evident as the harvester begins to fill with grain on exiting the cutout zones, suggesting that the grain flow exhibits differing patterns for grain filling and grain emptying within the harvester transport system. These results confirm that the harvesting mechanics impart a more complex effect on grain movement between the cutterbar and yield sensor than the simple linear model commonly utilised.

5.3.2 Grain-Flow Convolution and Transport Delay

While the grain transport delay appears to be non-linear in effect, it comprises two components: a linear component relating to crop position along the cutting platform and a non-linear component from the threshing and delivery process.

Platform Transport

In conventional harvesters, inflorescences are cut simultaneously along the length of the cutter bar and delivered to the throat elevator by a central delivering platform auger. The distance from the point of cutting to the throat will influence the transport time to a yield sensor mounted at the exit from the clean grain elevator. The magnitude of this effect will be governed by the platform width, and to some degree the delivery mechanism. The JD

7720 displayed a platform-position delay for sorghum delivery through the harvester as depicted in Figure 5-5.

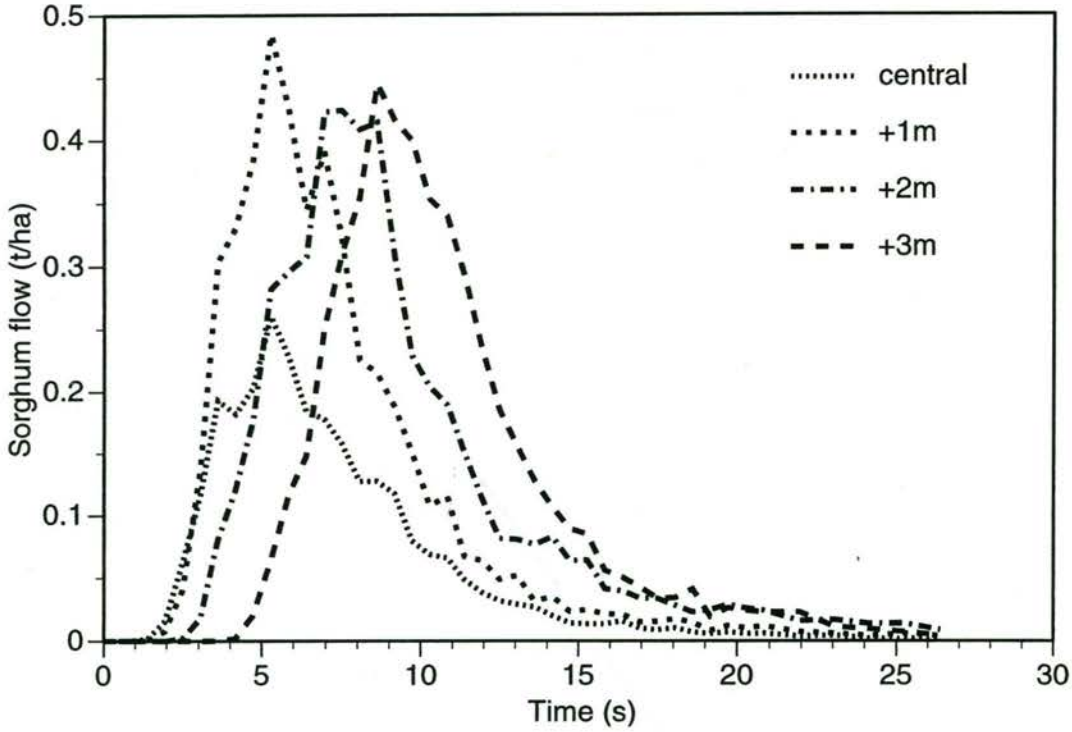


Figure 5-5. Flow of grain through the harvester based on row position relative to the centre of the cutting platform at time of crop severance.

The throat elevator width of 2 m accommodated the middle three rows directly and this is evident in the identical delivery times for the central and +1 m grain. The magnitude of the central peak is halved as it represents only one row. Rows 2 m from the platform centre have their peak flow delayed by a further 2.2 seconds, while the outer rows (3 m from the platform centre) have a peak delay of a further 1.1 seconds.

Threshing & Clean-Grain Delivery Processes

The mechanical processes that are applied to move threshed grain through the combine result in flow convolution. In the full threshing process, grain separated as it passes through the concave is collected and mixed with grain returns scavenged from within the material other than grain (MOG) passing along the straw walkers. Delivery to the base of the clean grain elevator is by the cross-delivery auger.

Total Grain Convolution

The overall effect of these processes on grain transport is shown in Figure 5-6, where the coloured grain is not delivered as a unit to the base of the clean grain elevator, but with a distinctive delivery time distribution. The peak arrives approximately 7 seconds after the cutterbar encounters the centre of the band and at a maximum of 20% of the total grain in the band. However, the distribution covers approximately 25 seconds.

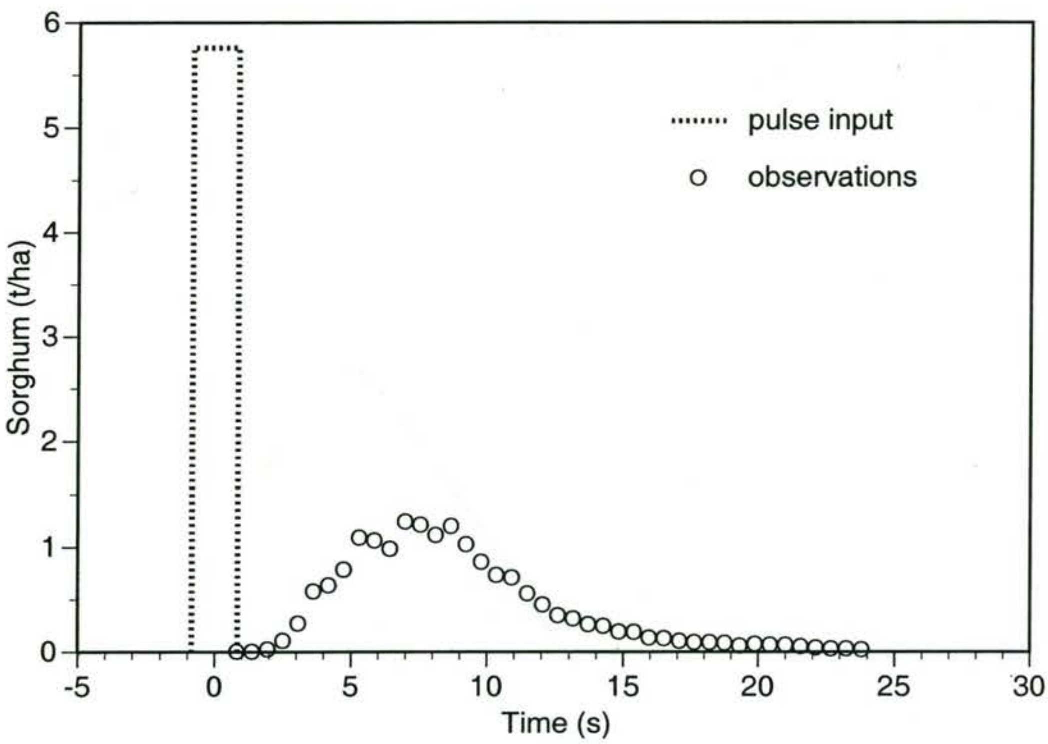


Figure 5-6. Delivery time distribution for the coloured grain pulse through the harvester. §

The distribution is relatively smooth but does display some irregularities. These may be explained by the combination of yield variability within the short coloured band affecting the peak of the coloured distribution and variability in total grain flow during the experiment caused by yield variability in crop harvested before and after the coloured band. Figure 5-7 shows the coloured grain flow compared with total grain flow during the experiment. The troughs and peaks in the two traces occur simultaneously which highlights the correspondence of total coloured output with total grain fluctuation.

§ The flow rates for these experiments were recorded an analysed in grams/second(gs^{-1}), however the graphs present the data converted to tonnes/ha (t/ha) for ease of comprehension.

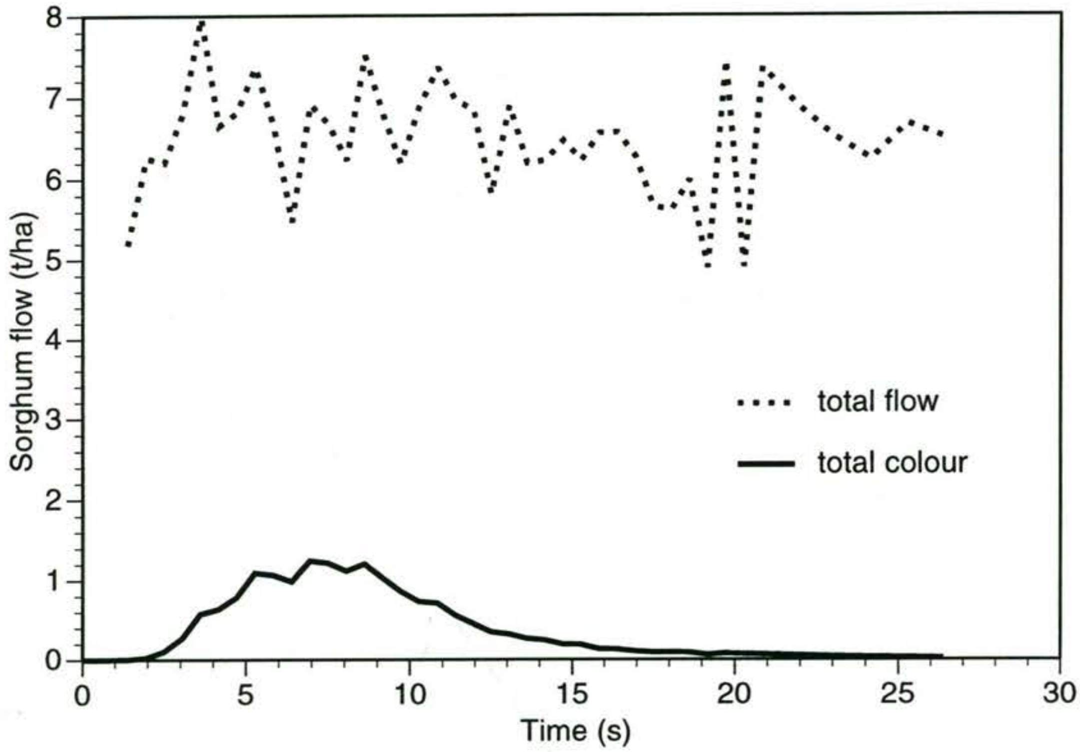


Figure 5-7. Comparison of observed coloured flow with total grain flow during the experiment.

5.3.3 Modelling Total Grain Convolution

Figure 5-6 confirms that a simple time delay would provide a poor approximation for the transfer function describing grain transport within the harvester. Similarly, a first-order exponential decay model as proposed by Searcy et al. (1989) will not adequately describe the process.

Non-Parametric

The data could be more accurately described using a cubic smoothing spline which minimises the compromise between the model fit and the degree of smoothing using Equation 5-3. (Silverman, 1985).

$$\min \sum_{i=1}^{n}[y_i - f(t_i)]^2 + \lambda \int (f''(t))^2 dt = z \tag{5-3}$$

where (in this example):

y	=	grain flow (t/ha)
t	=	time(s)
$f(t)$	=	spline
l	=	0.00003 (smoothing operator)
z	=	0.0042 (generalised cross validation)

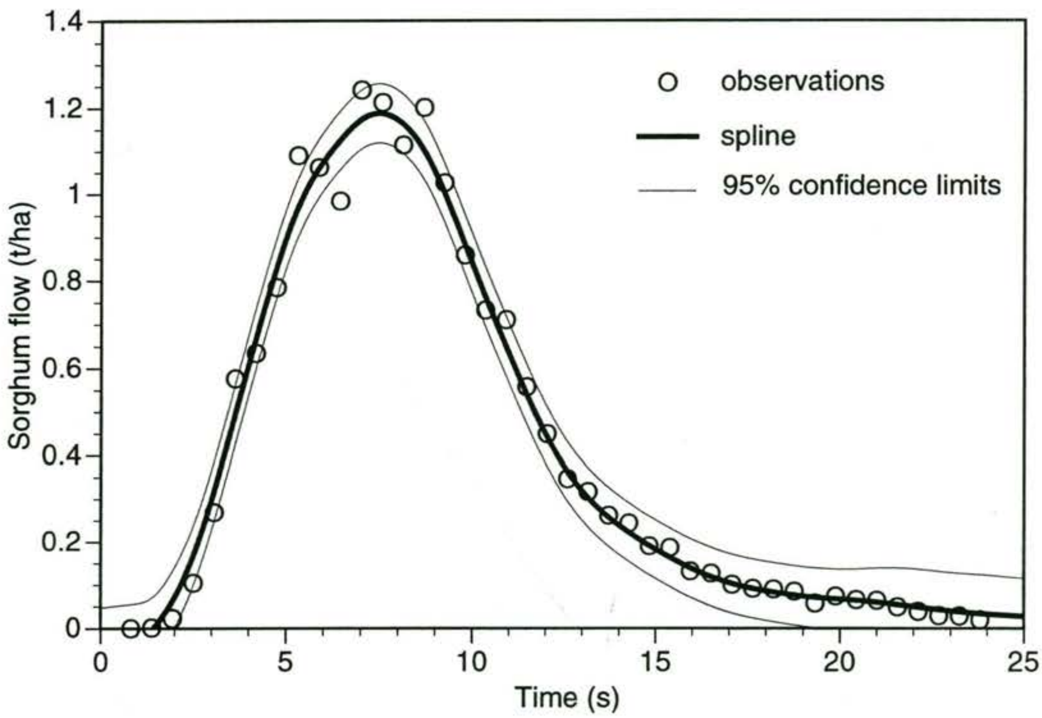


Figure 5-8. Modelled time distribution for the coloured grain pulse using a cubic smoothing spline.

In Figure 5-8, the smoothing spline fit to the experimental data is displayed along with 95% confidence limits. The spline describes the data well, providing a numerical model for the transfer function relating grain flow across the cutting platform to grain flow observed at the base of the clean grain elevator. This transfer function will only apply when the harvester is within a 'steady-state' operating range. Such conditions will not be met with the very low grain flows that occur at the beginning of runs and high harvest speeds that may result in choking of the internal pathways.

Parametric

The pulse of coloured grain through the harvester can be considered analogous to the flow of a narrow pulse of solute through a soil column. The exit concentration over time for such a solute pulse will be governed by the initial concentration, the length of the transport pathway, the velocity of solute flow and the dispersion processes imparted in the flow. For a medium with a homogeneous dispersion characteristic, Jury & Sposito (1985) provide a model that includes such parameters (Equation 5-4).

$$C(L,t) = \frac{C_0 L}{2\sqrt{\pi D t^3}} \exp\left(-\frac{(L-Vt)^2}{4Dt}\right) \qquad (5\text{-}4)$$

where:

$C(L,t)$	=	Breakthrough concentration at time t and column length L
C_0	=	Integrated initial pulse concentration with respect to pulse duration
D	=	Dispersion co-efficient
L	=	Length factor
V	=	Velocity
t	=	Time

Here, $C(L,t)$ represents the coloured grain output at each time (gs^{-1}), C_0 is the total grain in the coloured pulse (g), D equates to a characteristic grain dispersion co-efficient for the harvester (m^2s^{-1}), L is a characteristic grain pathway length (m) and V is the velocity of the harvester (ms^{-1}). The values for these attributes of the fitted model are displayed in Table 5-1 and represent physical realisations of these parameters under the experimental conditions (i.e. for this harvester at this flow rate).

V (m/s)	D	L (m)	C_0 (kg)	Mean (s)	Mode (s)
0.9	0.7	8.0	6.03	8.9	6.7

Table 5-1. Parameter values for grain flow model.

In Figure 5-9, application of the model to the experimental data confirms that the grain transport and threshing operations within a conventional harvester appear to conform to the process of dispersion described in Equation 5-4.

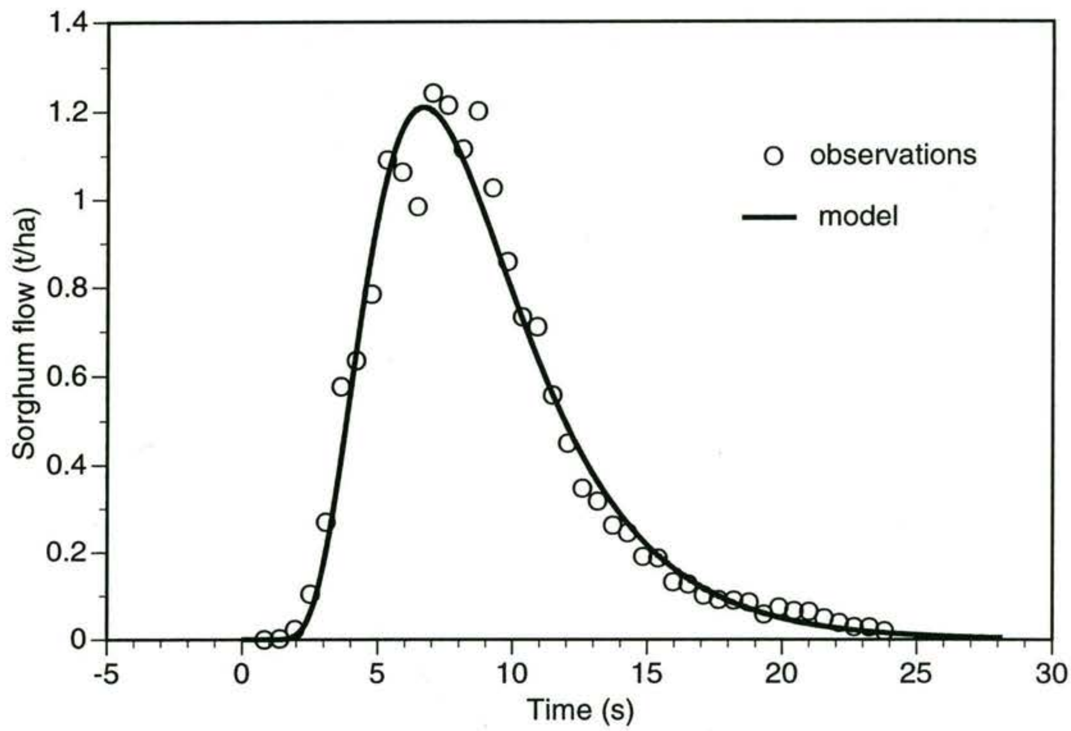


Figure 5-9. Modelled time distribution for the coloured grain pulse using the Jury & Sposito (1985) pulse input model.

In this model, the velocity, V, has been taken as the forward speed of the harvester. In the soil theory, the mean velocity of the solute front is used, which would equate to the mean grain travel speed within the harvester. This is not easily obtained and the best estimate is the harvester travel speed with the boundary conditions that the harvester is travelling at a velocity that has the machine operating at a 'steady-state' whereby the grain flow is not below the speed of the harvester. That this is a suitable velocity to utilise in the model is highlighted by Figure 5-10 where the model is shown to fit the experimental data extremely well when the centre of the coloured pulse is used as the initial time value.

This model is based on the Inverse Gaussian distribution which has its genesis in the effect Brownian motion imparts on particles moving along a linear path with constant velocity (V) (Johnson & Kotz, 1970). Under this scenario the time (t) for particles to travel a fixed distance (L) will be a random variable and follow a probability density function described by Equation 5-5.

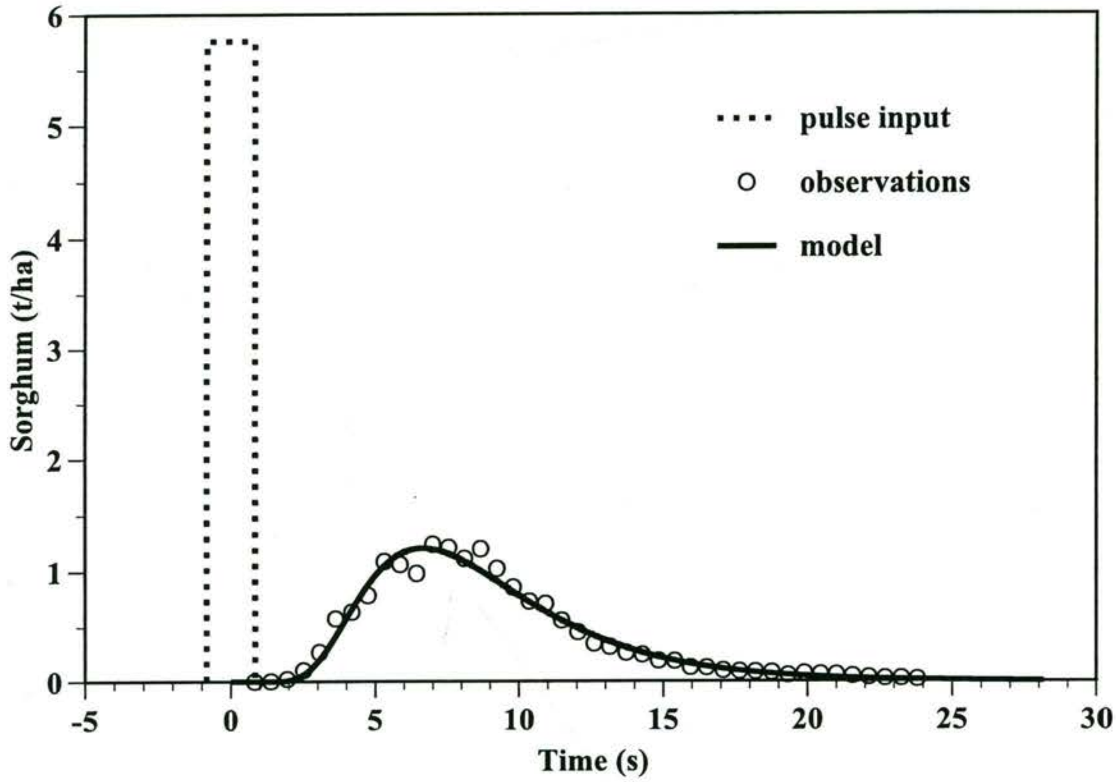


Figure 5-10. Pulse input, observed and modelled output with the centre of the pulse set as t_0 and V equal to the harvester velocity.

$$p(t) = \frac{1}{\sqrt{2\pi\beta t^3}} L \exp(-\frac{(L - Vt)^2}{2\beta t}) \qquad (5\text{-}5)$$

where:

β = diffusion constant

This process is obviously similar to the grain dispersion that occurs within the harvester. An alternative examination of the process considers that at a fixed time, i.e. at the sensor each second, the grain being measured will have covered various distances which will be random and normally distributed as Equation 5-6.

$$p(L) = \frac{1}{\sqrt{2\pi\beta t}} \exp(-\frac{(L - Vt)^2}{2\beta t}) \tag{5-6}$$

The mean and mode of the Inverse Gaussian distribution (Equation 5-5) may be estimated as by Equations 5-7 and 5-8 respectively.

$$\mu_{time} = \frac{L}{V} \tag{5-7}$$

$$t_{mode} = \mu \left\{ \left(\sqrt{\left(1 + 9/_{4\phi^2}\right)} \right) - \frac{3}{2\phi} \right\} \tag{5-8}$$

where:

$\lambda = \frac{L^2}{\beta}$ = a reciprocal measure of dispersion

$\phi = \frac{\lambda}{\mu}$

The implication of the Inverse Guassian distribution model for yield measurement is that the mass flow being registered at the sensor will contain grain that has travelled a variety of tortuous pathways through the harvester. This would suggest that for each measurement the grain had not all been harvested at the same time or from the same discrete area in the field.

5.3.4 Grain Yield Deconvolution

These results imply that the yield component of the signal recorded by the yield monitor represents a considerably smoothed depiction of the true yield. The physical threshing processes operating within the harvester impart a temporal mixing of the grain that convolves the harvest process time for each grain. The signal recorded will also possibly contain vibrational, pneumatic and instrument noise components. These will be discussed in a later section.

Continuing the analogy with soil solute transport, it can be theorised that the transfer function describing the effect of dispersion on a solute concentration entering a soil system may be used to determine the original concentration from the observed output concentrations measured over time (White, 1987). Using a description of the grain transfer function, the true yield values may be quantitatively rectified from the observed values and, due to the time based nature of the function and the harvest measurement procedure, also rectified in space.

The observed yield sensor signal when sampling at a frequency of 1Hz approximates a continuous time series of grain flow through the harvester (Birrell et al., 1995). A time series is but one realisation of the infinite suite of time series that could occur (Chatfield, 1996) and can be examined in both the time and frequency domains. With only one time scale observed, variation in such a series may best be explained by investigating the contribution to variability of a number of signal frequencies. Also, the degree of convolution shown in Figure 5-6 becomes quite computationally difficult to deal with in the time domain, but may be simplified to a basic multiplication operation in the frequency domain. Fourier analysis using the fast Fourier Transform (Cooley and Tukey, 1965) is one established method for the analysis of time series in the frequency domain.

Fourier Transformation

The complexity and magnitude of the mathematical operations required to analyse the periodicity in data series of even moderately sized data sets initially restrained development of suitable methods. In the later half of the nineteenth century there were few methods capable of handling more than small data sets. Shuster (1897) introduced the Fourier analysis procedure using the periodic components in tidal and meterological data and devised the periodogram. However, it was the advent of spectral analysis in the 1930's on the back of advances in probabilistic and statistical theory in time series, that brought rapid developments.

Progress in the theory of spectrum estimation gained momentum over the next few decades with the work of Bartlett (1948), Grenander & Rosenblatt (1953) & Blackman & Tukey (1959). Cooley & Tukey (1965) introduced the Fast Fourier Transform (FFT), that finally enabled much quicker computation and the ability to handle much larger data sets. These advancements were greatly aided by the increased application of Fourier analysis in the electrical engineering field and an ability to manipulate data sets with basic computers.

Fourier analysis requires transformation of attributes from the time domain to the Fourier domain. In generalised form, this operation creates a Fourier pair (Equation 5-9).

$$X(t) \quad \underset{InverseFourierTransform}{\overset{FourierTransformation}{\rightleftarrows}} \quad x(\omega) \qquad (5\text{-}9)$$

where:

$X(t)$	=	Observation in the Time domain
$x(\omega)$	=	Observation in the Frequency domain

For the deconvolution of grain yield observed from the yield monitor the following generalisation can be made:

$$Y_{obs} = Y_{act} * Y_{transf} \tag{5-10}$$

where:

Y_{obs}	=	yield observed from the grain yield monitor,
Y_{act}	=	actual yield that occurs in the field,
Y_{transf}	=	yield transfer function.

This generalisation is not, however, true in the time domain so the operation to distill Y_{act} from the known data must be moved into the frequency domain. This can be achieved through Fourier transformation (Equation 5-9) so that:

$Y_{obs}(t)$	with Fourier transformation becomes	$y_{obs}(\omega)$
$Y_{act}(t)$	with Fourier transformation becomes	$y_{act}(\omega)$
$Y_{transf}(t)$	with Fourier transformation becomes	$y_{transf}(\omega)$

where:

$Y_x(t)$	=	yield in the time domain,
$y_x(\omega)$	=	yield in the frequency domain.

In the Fourier domain the transfer function is the Fourier transform of the impulse response function. The impulse response function in this case is the modelled output from the coloured grain experiment.

In the frequency domain Equation 5-11 is then robust:.

$$y_{obs}(\omega) = y_{act}(\omega) * y_{transf}(\omega) \tag{5-11}$$

And when Equation 5-11 is re-expressed as Equation 5-12, the true yield (expressed in the frequency domain) can be calculated.

$$y_{act}(\omega) = y_{obs}(\omega) \,/\, y_{transf}(\omega) \tag{5-12}$$

An inverse Fourier transformation may then be applied to return y_{act} from the frequency domain to the time domain.

$y_{act}(\omega)$ with inverse Fourier transformation becomes $Y_{act}(t)$

This whole operation will result in the real yield values being restored in conjunction with harvest time rectification due to the time-based nature of the transfer function. In effect, quantities are estimated that should be more representative of the grain yield at each observation point in the field.

Variation in the original data induced by machine operation and measurement errors are likely to be amplified in the above operation and warrant removal from the raw data prior to transformation. Searcy et al. (1989) employed a 3rd-order moving weighted averaging to the yield data from a volumetric yield monitor prior to applying the first order exponential transfer function detailed in Equation 5-1. Vansichen & De Baerdemaeker (1991) incorporated a 0.5 Hz low pass filter to the sensor signal to remove vibrational force components. They then applied a 0.2 Hz filter to the speed and width signals and the yield flow time series to compensate for measurement errors and noise prior to correcting for grain flow dynamics using a first order time delay model.

Pringle et al. (1993) used a monitoring system that observed the variability in a weighed active section of grain delivery elevator and were able to determine the largest noise components at 60 and 12 Hz corresponding to the movement of chain and paddles over the active section. They then used a 0.5Hz low pass filter which they contend allowed acceptable transient response but suppressed the noise. Birrell et al. (1995) in an empirical examination of first order transfer functions also note that the inversion operation required amplifies the high frequency noise and requires some form of initial data smoothing. Lark et al. (1997) opted to average yield measurements over a 4.6m length prior to analysis which would produce such an effect.

The inversion process and the fact that the transfer function models are smooth, twice differentiable approximations of a variable process strengthen the requirement for initial data smoothing. While these smoothing operations appear necessary prior to any attempt to dynamically rectify grain yield, there is obviously a trade-off between adequately correcting the yield signal and amplifying inherent errors (Vansichen & De Baerdemaeker, 1991).

Given the above, the degree and method of smoothing to be applied to the original data obtained from grain impact yield sensors remains subjective. Measuring the contribution of machinery noise in these systems will improve this situation in the future. For this experiment, a moving process of median polishing using three observations was applied based on the Tukey (1977) method of repeated median smoothing, splitting and hanning. This method reduces the influence of very high or low values on the smoothing process and therefore acts in effect more like a low-pass filter than would a moving mean procedure while using the data to continuously determine the cutoff.

Figure 5-11 displays an example of the median polishing as applied to a 100 s time series (approximately 90m header run). The transformed data has also been shifted backward 1 s to account for transport from the base to the top of the clean-grain elevator, where the yield sensor is installed. This linear component of the transport process operates at 2.4 ms^{-1} (Nelson, 1997 personal comm.)

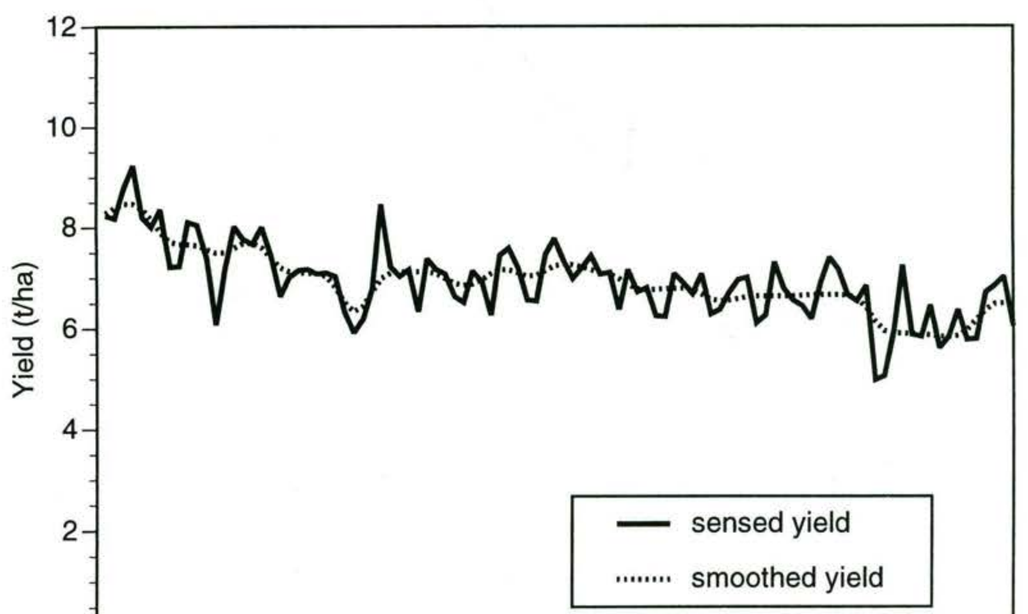


Figure 5-11. Median polishing of sensed yield data expressed as tonnes/ha.

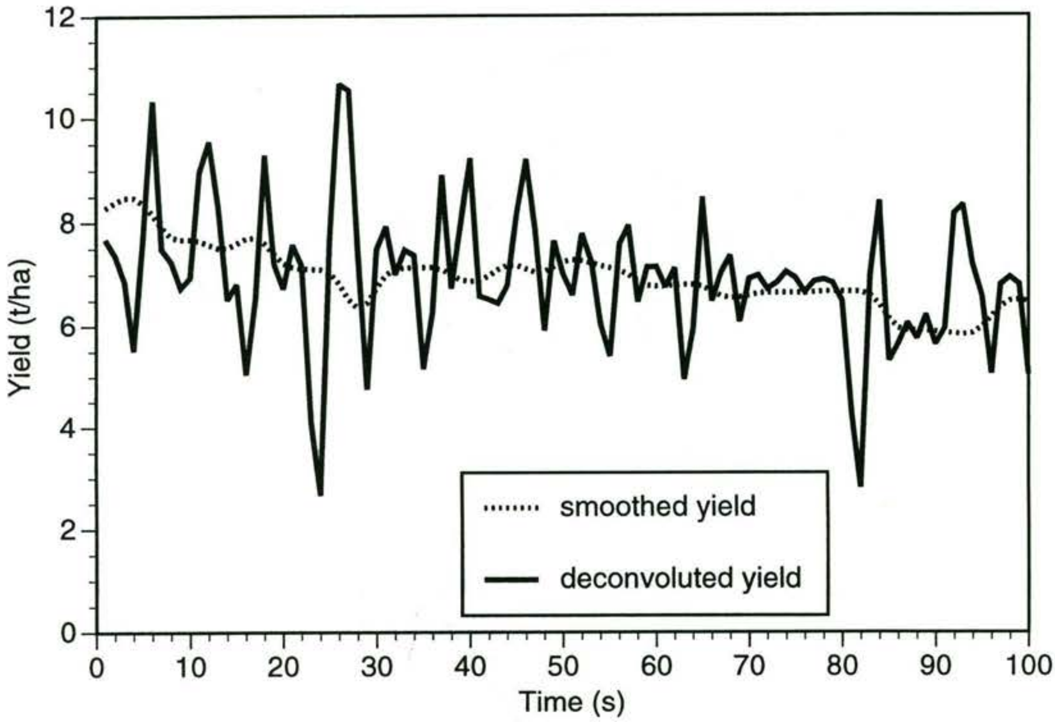


Figure 5-12. Deconvoluted yield values using the experimental transfer function as compared with the smoothed yield input.

Using this smoothed data as the input to the Fourier transformation process produces a yield output that is dynamically rectified (Figure 5-12). As would be expected, the previously demonstrated mixing occurring within the harvester has been removed and changes in the gradient of the time series trace are accentuated. The process also places the yield values at the time the crop was encountered, not the time of measurement as represented by the smoothed yield. A comparison of the deconvoluted yield with the original sensed yield data (Table 5-2 and Figure 5-13) more clearly shows the increase in variability that has occurred through deconvolution. Notably, the CV rises from 10.8% to 19.6%.

Yield	Min (t/ha)	Max (t/ha)	Mean (t/ha)	Std Dev. (t/ha)	C.V. (%)
Sensed Yield	4.97	9.23	6.93	0.75	10.8
Deconv oluted Yield	2.66	10.66	6.93	1.36	19.6

Table 5-2. Statistical moments of the sensed and deconvoluted yield.

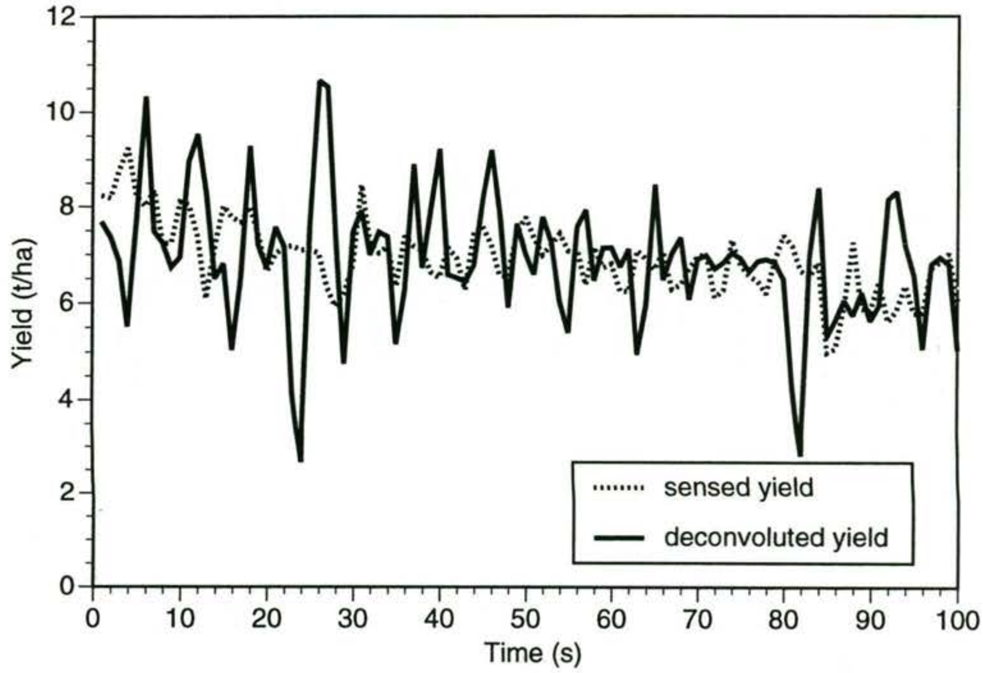


Figure 5-13. Deconvoluted yield values using the experimental transfer function as compared with the smoothed yield input.

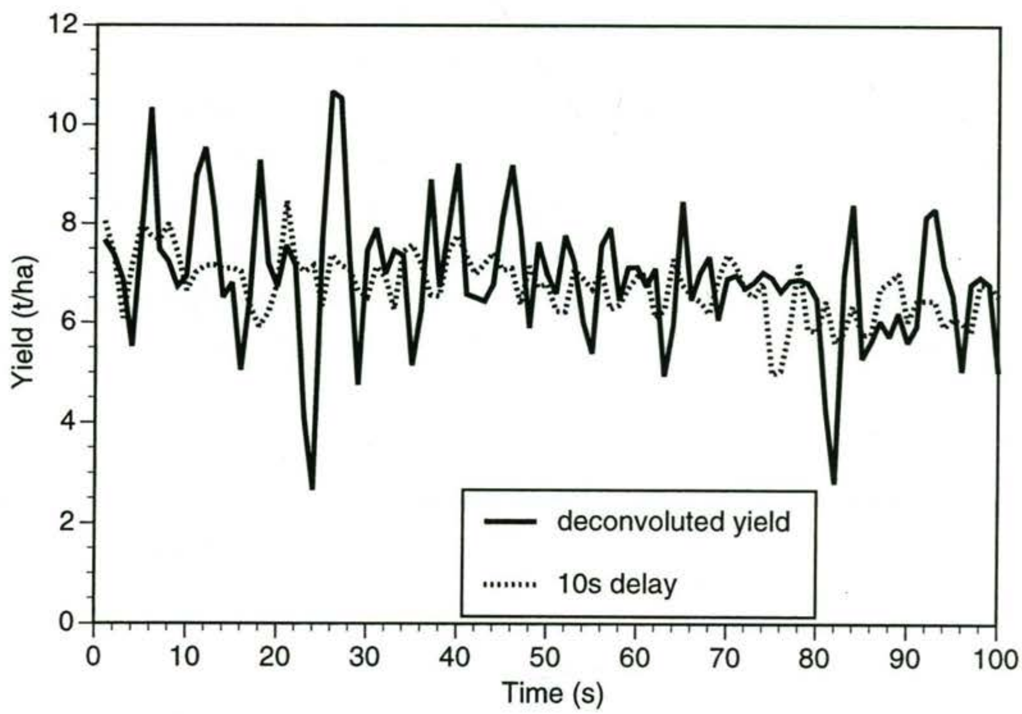


Figure 5-14. Deconvoluted yield values using the experimental transfer function as compared with a 10s linear delay.

Figure 5-14 provides an insight into the effect this dynamic adjustment has in comparison to a simple time-delay model for rectification. The travel time for 50% of the colored grain to reach the yield sensor position (8.9s + 1s = 9.9s) was applied as a linear delay. It is clear that both the time and quantity adjustments differ significantly between the two cases.

5.4 GENERAL DISCUSSION

The results documented in this chapter suggest that there is a degree of smoothing applied to the instantaneous yield measurement data that is introduced by the harvesting mechanisms. This smoothing will not be corrected by the use of a simple linear time delay.

As previously discussed, the importance of this time lag in grain flow monitoring has been acknowledged by a number of authors. Along with an accurate determination of operational cutting width, the best estimate for the time lag is necessary to ensure meaningful accuracy in the resulting yield maps. The methods previously considered for determining this component of the process have all inferred a model from other measured parameters. The most common approach being an estimate of the time to steady flow rates on the observed yield trace as an empty harvester enters a crop (Searcy et al., 1989; Murphy et al., 1995; Birrell et al., 1995; Nolan et al., 1996) or leaves the crop (Lark et al., 1997)

Internal transport of grain as a harvester fills from empty or empties from full would not undergo the same dynamics as a harvester that is encountering a fluctuating but relatively 'steady-state' grain flow rate. Figure 5-4 intimates that there are differences between the emptying and filling processes as seen at the grain flow sensor. Searcy et al. (1989) noted this in the estimate of their time constant (q) ranging from a mean of 2 s on entering the crop to 10 s leaving the crop. Lark et al. (1997) produced two different impulse response functions for these two processes that demonstrated vastly increased mixing time for crop exit. They concluded that the two models provided a "pessimistic" and "optimistic" account of the mixing influence imparted by the harvest mechanism. While there has been no justification shown for choosing the entrance over the exit transport time in previous research, Figure 5-4 does highlight the 'tailing' effect of the emptying process.

Intuitively, while the harvester is operating within the normal crop yield range, the two effects observed by previous studies may be combined to influence the transport function through the harvester. Figure 5-7 suggests that this is the case. The mixing component is apparently taking place over a greater period of time than the 0.5 s incorporated by Birrell et al. (1995) or the maximum 10 s reported by Searcy et al. (1989). Indeed, these results offer a mixing period of 17-18 s for 95% of the coloured grain to pass the sensor, which at the harvest speed of $0.9ms^{-1}$, equates to 15 -16 m of the harvest run. The maximum concentration of coloured grain (mode) arrives at the sensor at approximately 8s, or 7m of the harvest run. That the mode is only 20% of the total coloured grain accentuates the internal mixing. These figures fall within the optimistic (15m)/pessimistic (25m) mixing predictions of Lark et al. (1997).

It is also interesting to note that the deconvolution increases the CV of the yield data in the experiment from 10.8% to 19.6%. This adjusted value closely equates to the mean CV presented by Taylor et al (1997) for small-scale manual sampling of within-field crop yield variability.

Replication of the experiment presented here has not been possible as yet due to labour and time costs associated with initiating and conducting the measurements. However, deconvolution of the yield data in Figure 5-2 (experimental data not used in generating the transfer function) using the proposed model retrieves the start and end points of the zero yield bands with more accuracy than the single 10 s time delay (Figure 5-15). It must be noted however that the changing transfer functions as the harvester empties and then fills causes unrealistic yield fluctuations at these points when using the "steady-state" function.

The transfer function has also been applied to data from the most recent sorghum harvest (1998 season - data not included in this thesis). The spatial relationships between yield estimates obtained by hand harvesting and threshing, yield monitoring and deconvoluted yield monitor data were compared for a single 2.5ha area. The variograms for these three data sets are shown in Figure 5-16. The smoothing of the yield monitor data is again quite evident when compared with the hand sampled yield estimates. Yield deconvolution provides a variogram that essentially estimates the same nugget (C0) parameter of the hand sampled data. The estimate of total semivariance (C0 + C) is less accurate but more representative than that provided by the convoluted yield data.

Other studies provide corroborative evidence for the validity of the transfer function. Boydell et al. (1996) present a similar shaped transfer function for the flow of peanuts within a peanut harvester. While a peanut harvester operates similarly to a grain harvester, the process is far more direct and the results showed a maximum of approximately 90% coloured kernels at the mode. The experiment was conducted with coloured kernel bands that appear to have been too long and subsequently disguised the true mixing, however the shape of the output at the sensor is very similar overall and would follow an Inverse

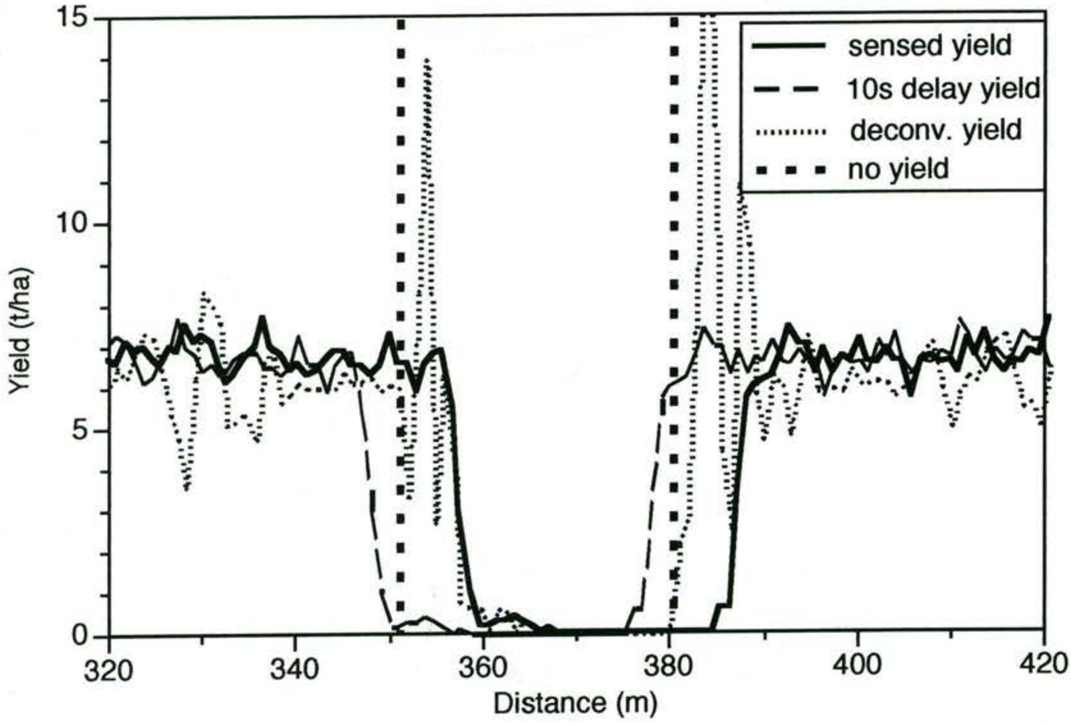


Figure 5-15. Yield data for the 24m grain gap experiment comparing the sensed yield with that deconvoluted using the experimental model and using the simple 10s delay.

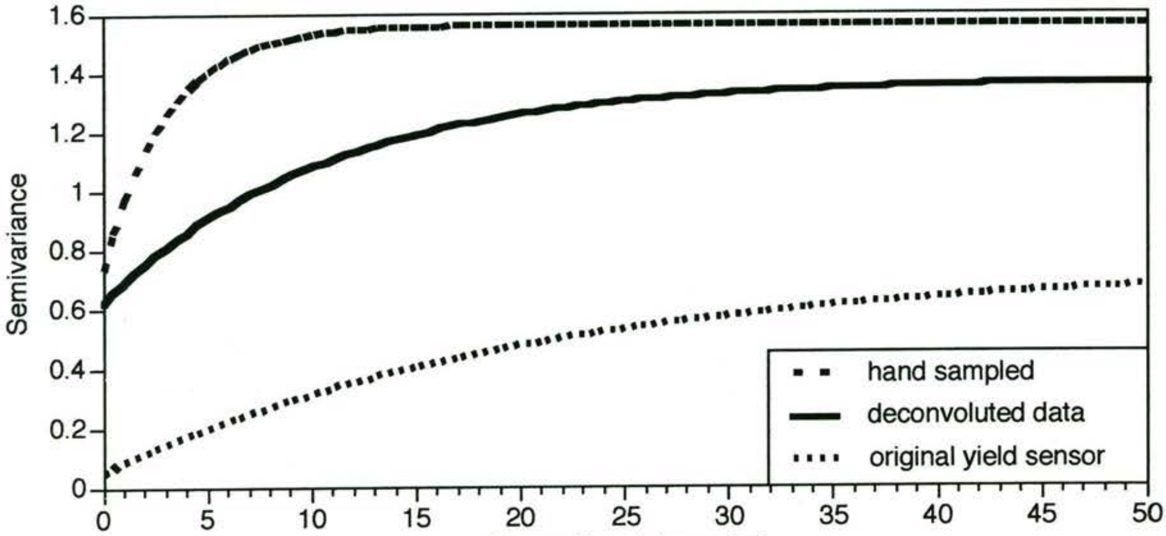


Figure 5-16. Comparison of semivariograms for sorghum yield data obtained in a 2.5ha field using hand harvesting and threshing, yield monitoring and deconvoluted yield monitor data.

Gaussian distribution. The impulse response functions derived by Lark et al. (1997) from the flow patterns at the start and end of harvester runs also display a similar form that could be approximated by the Inverse Gaussian distribution.

The model presented here is suggested as a beginning for further research into the characterisation of grain flow during the harvest process. No doubt the moments of the distribution model will be affected to some degree by flow rates and harvester operational configuration. It is envisaged that future verification of the flow model will lead to procedures for more rapid determination of the parameters L and D for various harvester configurations.

To this end it may be possible to use a substance to mark the crop in a number of locations across a field or farm that can then be sensed automatically by detectors at the output of the bubble-up auger. Skotnikov & McGrath (1996) suggest the use of metal-based paints and metal detectors, however low-dose radioactive isotopes may also be suitable. It may also be feasible to use the grain moisture sensor that is usually installed with the yield monitoring equipment to detect the passage of strategically wetted grain bands in the field. Such rapid replication of the experiment would characterise any variability in the flow model and allow greater accuracy in yield correction.

A fuller understanding of flow dynamics should be coupled with improvements in the concentration and direction of the grain flow from the exit of the clean-grain auger to an impact-type yield sensor. Strubbe et al. (1996) documented the flow pattern of free grain at the exit of the clean-grain elevator and restricted the dispersion they found by guiding the grain flow using curved plates and concentrating the flow with a small rotor mounted on the lower side of the exit to prevent grain by-passing the sensor.

Further work is also required in measuring the noise components in the sensed signal so that a more objective smoothing or filtering may be applied prior to the Fourier transformation procedure. The hand sampled data shown in Figure 5-16 will be used for this purpose. Wavelet theory and spectrum analysis will also be investigated in the future.

5.5 CONCLUDING REMARKS

A process is described for determining the flow pattern of sorghum grain through a harvester using plants systematically coloured prior to harvest. Grain movement is shown to be partially influenced by the position of the row in relation to the centre of the cutting platform leading edge. Grain from the outer rows is delayed in comparison with those more centrally located. A more significant impact is made on grain flow by internal mixing during the threshing and auger transport processes. The two effects can be combined and represented by a grain transfer function which quantifies these grain flow dynamics.

The dynamics of the grain flow within the harvester obviously results in convolution of the true yield. Yield sensors intercepting the grain flow at the end of the transport process will be registering this smoothed yield. Deconvolution is required if the correct yield is to be located within the field at a fine-scale. Fourier analysis allows the signal to be untwined and also provides the correct time adjustment.

If yield trends are the only interest then this process may not be necessary. Until it is known at what scale we can realistically manage on a site-specific basis, the author believes that accuracy (or at least qualification of errors) should be a priority. Procedures along the lines presented in this chapter are a step forward.

Therefore, in the processes of determining causal factors of yield variation, prescribing small-scale differential treatments and the cost assessments of these actions, this form of correction will be crucial.

CHAPTER 6

CHAPTER 6

Crop-Yield Map Production

6.1 INTRODUCTION

The data gathered using a real-time crop yield monitor, and the possible sources of error have been examined in Chapter 4. Chapter 5 has explored a method for deconvoluting yield quantities and their spatial location along the header runs. This chapter shall concentrate on the process of spatial prediction required to produce estimates of yield values at points without an observation. Spatial prediction is required to regularise the spatial distribution of yield values within an area in order to produce an almost continuous surface for mapping.

Any form of spatial prediction is based on the premiss that observations made in close proximity to each other are more likely to be similar than observations separated by larger distances. This is the concept of spatial dependence which has been reviewed in Chapter 1. The process of spatial prediction requires that a model of the spatial variability (spatial dependence) in a data set be constructed or assumed so that estimates for the prediction points may be made on the basis of their location in space relative to actual observation points. It is the form of these models, and the assumptions underlying the choice of the same, which generally distinguish the major spatial prediction methods. Laslett et al., (1987) presented a straightforward taxonomy of spatial prediction methods using three categories namely, global or local, interpolating or non-interpolating, and smooth or non-smooth, predictors. Their categories will be outlined here.

Global methods use all the data in a data set to determine a model for spatial variation and then apply the one model to the prediction process at all unsampled points. They therefore use all the data for each prediction which may be computationally expensive for large data sets. Local predictors use only points 'neighbouring' the prediction point in the prediction operation. A singular form of variance model may be constructed for the entire data set and applied in each neighbourhood, or an individual model may be constructed, and used exclusively for, each neighbourhood. Local methods may therefore be the preferred option, especially on large data sets, and where a single model may be inappropriate.

Spatial prediction methods whose principle requires the prediction to exactly reproduce the data values at sites where data is available are said to act as interpolators. However, if measurement errors are known to be large, Laslett et al. (1987) suggest that this constraint may (or should) be relaxed a little. This principle may break down and not apply if there are replicate values which do not agree at a point so that only one value, such as the average, is honoured.

A smoother is a spatial predictor whose predicted surface and the first partial derivatives thereof are continuous. A non-smooth predictor is one for which the discontinuity of the predictor or its partial derivatives is readily detected by the eye, whereas discontinuity of second and higher derivatives is not usually detected. Despite these definitions, Laslett et al. (1987) indicate that the concept of smoothness of a spatial predictor is somewhat subjective.

Potentially a whole variety of prediction techniques may be used: inter alia, global means and medians; local moving means; inverse-square distance interpolation; Akima's interpolation (Akima, 1978); natural neighbour interpolation (Sibson, 1981); quadratic trend; Laplacian smoothing splines (Wahba & Wendelberger, 1980); and various forms of kriging (Goovaerts, 1997).

The prediction technique of choice for yield map production in Precision Agriculture will depend on the expected use of the map. However, real-time sensors that intensively sample variables such as crop yield produce large data sets containing a wealth of information on small-scale spatial variability. By definition, Precision Agricultural techniques should aim to preserve and utilise this detail.

Prediction Method		Characteristic	
Local moving means	global	non-interpolator	smoother
Inverse squared distance	global	interpolator	smoother
Local kriging (with global variogram)	local / global	non-interpolator	smoother
Local kriging (with local variogram)	local	non-interpolator	smoother

Table 6-1. Classification of prediction methods (after Laslett et al., 1987).

In this study, grain yield data from the 1996 sorghum crop is predicted onto a regular grid using the more commonly utilised prediction methods of: local moving mean, local inverse distance, and local kriging with a global semivariogram. These will be contrasted with a new technique employing local kriging with a local variogram (Haas, 1990a). Classification of these four methods according Laslett et al. (1987) is shown in Table 6-1. The results and implications of using each method in crop yield map construction will be presented and discussed.

6.2 MATERIALS & METHODS

A local neighbourhood is defined here as the observations within a 20m radius of each prediction point ($d_i \leq 20$). 20 m has been chosen based on the convolution results of Chapter 5, the spatial dependence range estimates from preliminary data analysis and the desire to include a minimum of 100 observations for spatial modelling. All the methods provide estimates using a local prediction procedure.

6.2.1 Prediction Methods

Prediction methods operate on the basis that the yield value $Y(x_0)$ at any unsampled location x_0, (where x denotes a two co-ordinate location descriptor) can be estimated using the values $Y(x_i)$ from the sampled locations x_i, where i = 1,2,3.......n, using the generalised function

$$Y(x_0) = f[w_1, w_2, ...w_n, Y(x_1), Y(x_2), ...Y(x_n)] \tag{6-1}$$

where:

w_i = the weight assigned to yield value $Y(x_i)$ at point x_i

All the prediction techniques to be applied in this study are linear predictors and use Equation 6-1 such that

$$Y(x_0) = \sum_{i=1}^{n} w_i Y(x_i) \tag{6-2}$$

The various prediction techniques do differ in the methods used to calculate the weights. These differences arise from contrasting agronomic assumptions regarding the spatial interdependence of yield estimates and to some extent the degree of certainty placed in the observed data. To ensure that the predictions are unbiased, the weights for each estimate must fulfil the condition of Equation 6-3.

$$\sum_{i=1}^{n} w_i = 1 \tag{6-3}$$

Local Moving Mean

The weights for the local moving mean prediction are determined for each prediction point using Equation 6-4.

$$w_i \quad = \quad 1/n \qquad \text{for } d_i \leq 20 \text{ m} \tag{6-4}$$

where:

d_i = Linear distance of observation $Y(x_{i'})$ from the prediction location x_0

Here the weight is obviously uniform for all observations, which assumes all observations within the neighbourhood have equal relevance to the yield at the prediction location. The spatial dependence is only a function of distance in so far as 'd' restricts the radius of the observation neighbourhood.

Inverse Distance

The inverse distance weights are determined for each prediction point by Equation 6-5.

$$w \quad = \quad \frac{1/d_i^p}{\sum_{i=1}^{n} 1/d_i^p} \qquad \text{for } d_i \leq 20 \text{ m} \tag{6-5}$$

where:

d_i = Linear distance of observation $Y(x_{i'})$ from the prediction location x_0
p = integer power parameter

Here the weights are calculated on the assumption that yield observations are correlated in space according to a universal function based separation distance between observations. No account is taken of the true spatial variance structure of the data set. Commonly $p = 2$ is employed and the procedure is termed 'inverse distance squared'

Local Kriging with a Global Semivariogram

The kriging process, developed by Krige (1951) and further extended and applied by Matheron (1963) and Journel & Huijbregts (1978), relies on the semivariogram model (discussed in Chapter1) to provide a function describing the spatial variance structure of the data set. While the semivariogram model is also a function of separation distance, unlike Equation 6-5, the model is conditioned on the actual spatial dependence observed in a data set. In this method a semivariogram model is fitted to the full data set, providing a single model (global semivariogram) for the spatial variance structure in the field. Weights are then obtained for the neighbourhood observations surrounding each prediction point through the kriging process which solves the equation series 6-6.

$$\begin{bmatrix} w_1 \\ \dots \\ w_i \\ \dots \\ w_n \\ \psi \end{bmatrix} = \begin{bmatrix} 0 & \dots & \gamma(x_1,x_i) & \dots & \gamma(x_1,x_n) & 1 \\ \dots & \dots & \dots & \dots & \dots & \dots \\ \gamma(x_i,x_1) & \dots & 0 & \dots & \gamma(x_i,x_n) & 1 \\ \dots & \dots & \dots & \dots & \dots & \dots \\ \gamma(x_n,x_1) & \dots & \gamma(x_n,x_i) & \dots & 0 & 1 \\ 1 & \dots & 1 & \dots & 1 & 0 \end{bmatrix}^{-1} \times \begin{bmatrix} \gamma(x_1,x_0) \\ \dots \\ \gamma(x_i,x_0) \\ \dots \\ \gamma(x_n,x_0) \\ 1 \end{bmatrix} \quad \text{for } d_i \leq 20 \text{ m} \qquad (6\text{-}6)$$

where:

ψ	=	Lagrange multiplier
$\gamma()$	=	semivariogram model for the function $Y(x)$

The equations are solved using the Lagrange multiplier in an optimisation method that ensures the prediction is unbiased and minimises the prediction variance (Olea, 1991). The prediction or kriging variance ($\sigma^2(x_0)$) is given by Equation 6-7.

$$\sigma^2(x_0) = \psi + \sum_{i=1}^{n} w_i \gamma(x_i, x_0) \qquad (6\text{-}7)$$

The standard error of the prediction is the square root of the variance.

Local Kriging with a Local Semivariogram

Unlike the global semivariogram method, this technique models a semivariogram for the data in each 'neighbourhood' around the prediction point. This provides a local model (local variogram) for the spatial variance structure that is intrinsic to the data that will be used in each prediction (Haas, 1990a). The variograms are individually applied using the kriging process within each neighbourhood. The weights are obtained as shown in Equation 6-6. The provision of a measure of prediction variance in both these kriging procedures is unique amongst the methods that will be examined.

All these methods will be compared quantitatively for the deviation of the prediction surface distribution statistics from those of the input data. Direct comparison between prediction values and observations not included in the prediction procedures is impossible because the observation pattern and density supplied by the yield monitoring system means that sampling point and prediction grid node alignment can not be controlled. Further qualitative analysis will be undertaken.

An area of 25 ha will be first examined using a prediction grid of 3.5m. A more detailed portrayal of the different surfaces produced by these techniques will then be made on a 6 ha portion of the larger area using a 2m prediction grid.

6.3 RESULTS & DISCUSSION

6.3.1 25 Hectare Region

The header runs and local neighbourhood are shown in Figure 6-1. In general, the neighbourhood will encompass between 5 and 7 header runs, its definition being conditioned on the inclusion of ≥100 observation points to ensure reasonably robust estimation (Webster and Oliver, 1992).

The total area comprises 5 contour bays, the dividing contour banks can be distinguished by tracing the header runs between the contour markers. An oversown roadway can also be traced running parallel with the first bank for most of its length. Crop yield data from the yield sensor, expressed as a continuous surface using a 5 m neighbourhood moving mean, can be seen in the eastern half of Figure B -16 (Appendix B). Table 6-2 records the distributions of the data produced by the prediction methods and Figures 6-2 and 6-3 map the spatial distribution of the predictions.

With less observations than the original field data, all the prediction techniques underestimate the data mean and standard deviation. The local moving mean best estimates the data mean while the local kriging with a local semivariogram most successfully maintains the variability in the data.

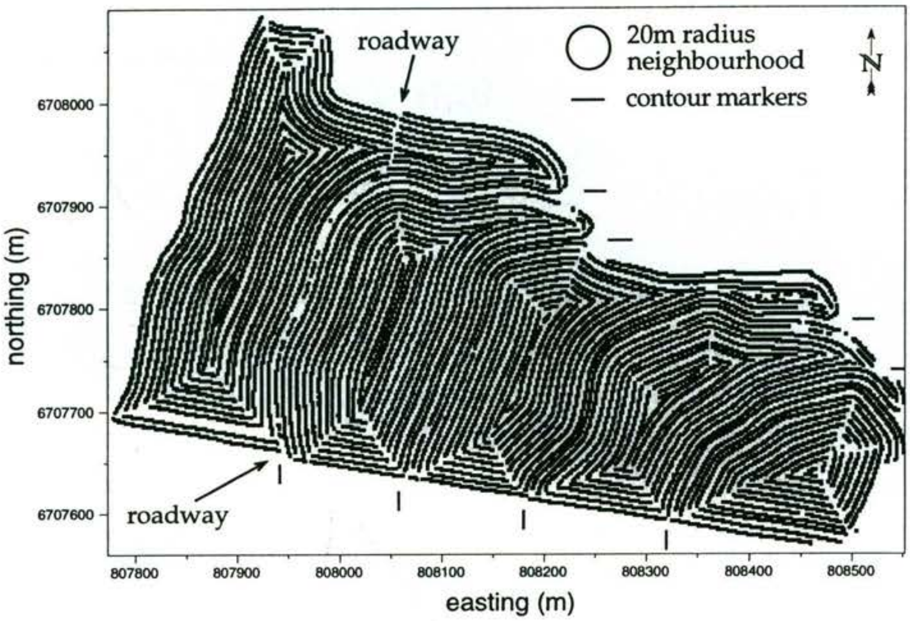


Figure 6-1. Site layout and header runs for 25 ha site.

Prediction Method	n	Min. (t/ha)	Max (t/ha)	Mean (t/ha)	Std Dev. (t/ha)	C.V. (%)
Original data	31813	2.70	9.50	6.82	1.14	16.7
Local moving mean	19252	3.69	8.53	6.75	0.82	12.1
Inverse distance squared	19252	3.42	8.62	6.72	0.94	14.0
Local kriging w/ global variogram	19252	3.17	8.71	6.70	1.03	15.4
Local kriging w/ local variogram	19252	2.90	8.70	6.69	1.05	15.7

Table 6-2. Descriptive statistics for the prediction surfaces generated by the various methods.

Local Moving Mean

Figure 6-2a maps the yield surface produced using the 20 m radius moving mean. This map shows only the gross features of the yield variability and generally fails to distinguish the influence of the contour banks. The mean value for the field is significantly different from the mean of the original data ($p = 0.001$).

Inverse Distance Squared

Figure 6-2b maps the yield surface produced using the inverse distance squared procedure. Far more detail is now evident as the distance model for spatial variance produces less smoothing. The effects of the contour banks and the roadway on yield can just be discerned but the prediction surface appears 'spotted' with very localised sharp changes in yield. The mean value for the field is significantly different from the mean of the original data ($p = 0.001$) and significantly different from the local moving mean ($p = 0.01$).

Local Kriging with a Global Semivariogram

Figure 6-3a maps the yield surface produced using the local kriging with a global semivariogram procedure. Far less smoothing is evident around the northern boundary of the field where the extent of yields below 4 t/ha has become more obvious. The roadway and contour banks are well defined and while some spottiness remains, it is less localised and more coherent. The mean value for the field is significantly different from the mean of the original data ($p = 0.001$) and significantly different from the local moving mean ($p = 0.01$). It is not significantly different from the mean of the inverse distance squared prediction surface.

Local Kriging with a Local Semivariogram

Figure 6-3b maps the yield surface produced using the local kriging with a local semivariogram procedure. The degree of smoothing imparted by the procedure is similar to that observed in Figure 6-3a, but a further reduction in the sharp localised changes within defined yield classes is obvious. The mean value for the field is significantly different from the mean of the original data and the local moving mean map ($p = 0.001$). It is significantly different from the mean of the inverse distance squared prediction surface ($p=0.1$), but not significantly different to the mean of the global semivariogram prediction surface.

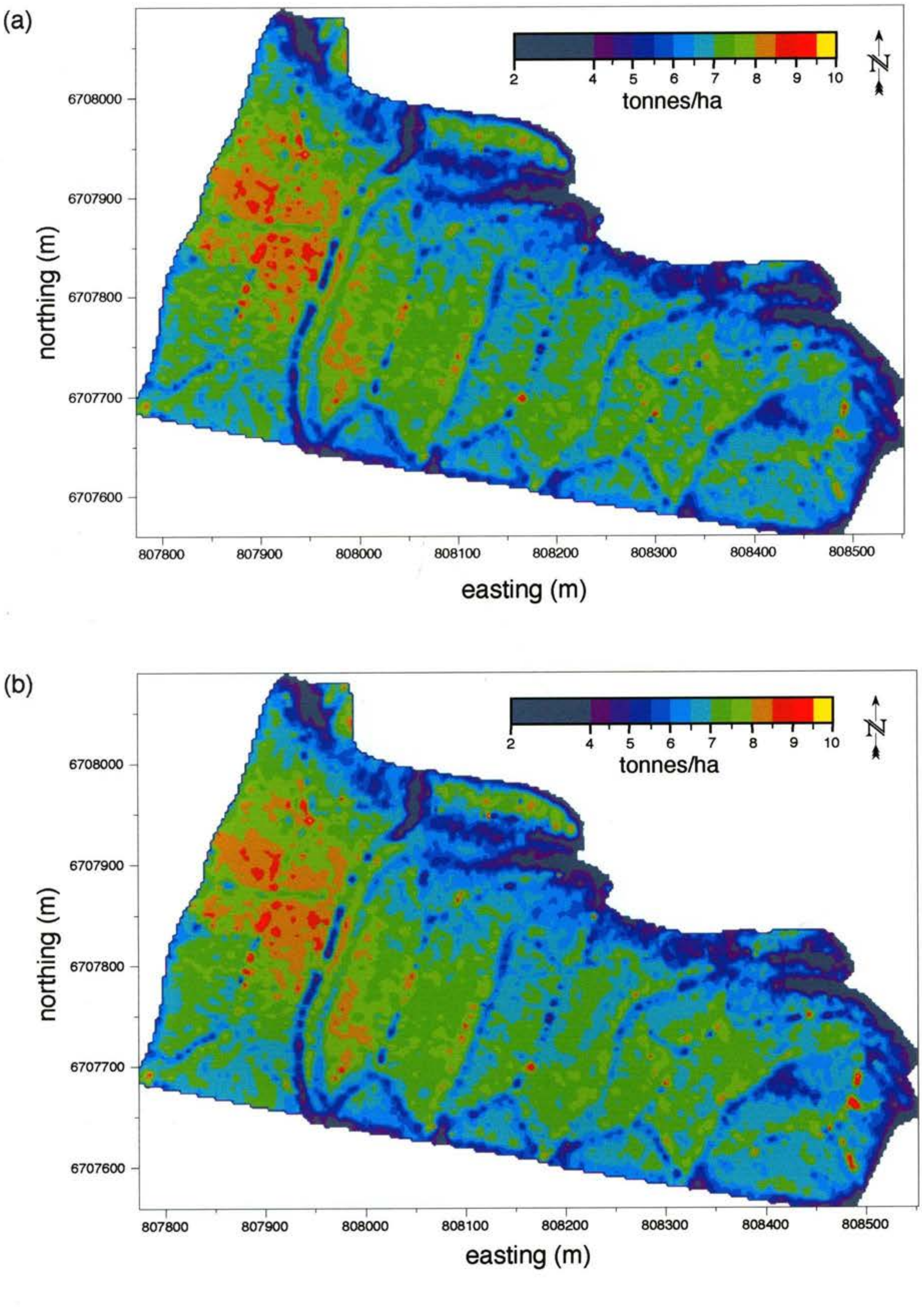


Figure 6-2. Crop yield maps for a 25ha region of the Creek field produced by different prediction methods - (a) local moving mean (b) inverse distance squared.

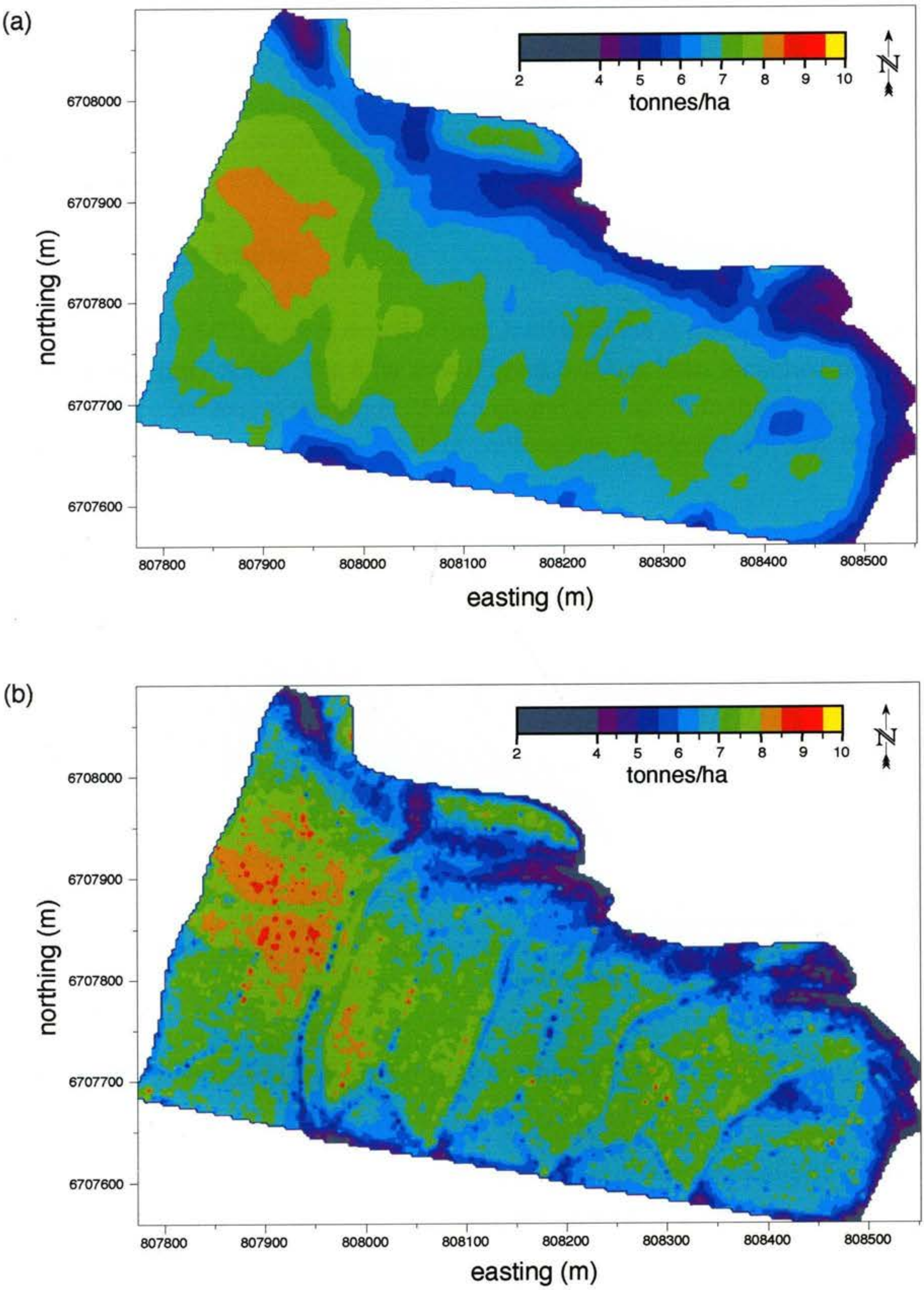


Figure 6-3. Crop yield maps for a 25ha region of the Creek field produced by different prediction methods - (a) local kriging with a global semivariogram (b) local kriging with a local semivariogram.

While Figures 6-2 to 6-3 provide an important overview of the differing effects of these prediction techniques, it would appear from Table 6-1 that the three more complex methods offer a similar impact on the frequency distribution of the original data. The crucial aspect, with respect to the construction of realistic crop yield maps, is the accurate spatial representation of the data.

6.3.2 6 Hectare Region

In Figures 6-4 to 6-7 a more instructive examination of the application of these techniques is made at a finer scale. The 6 ha area (Figure 6-4) has been sectioned from along the central horizontal axis of the larger 25 ha area and extends from the western boundary of that field to the eastern edge of the third contour bay. Table 6-3 displays the descriptive statistics for the prediction surfaces at this scale.

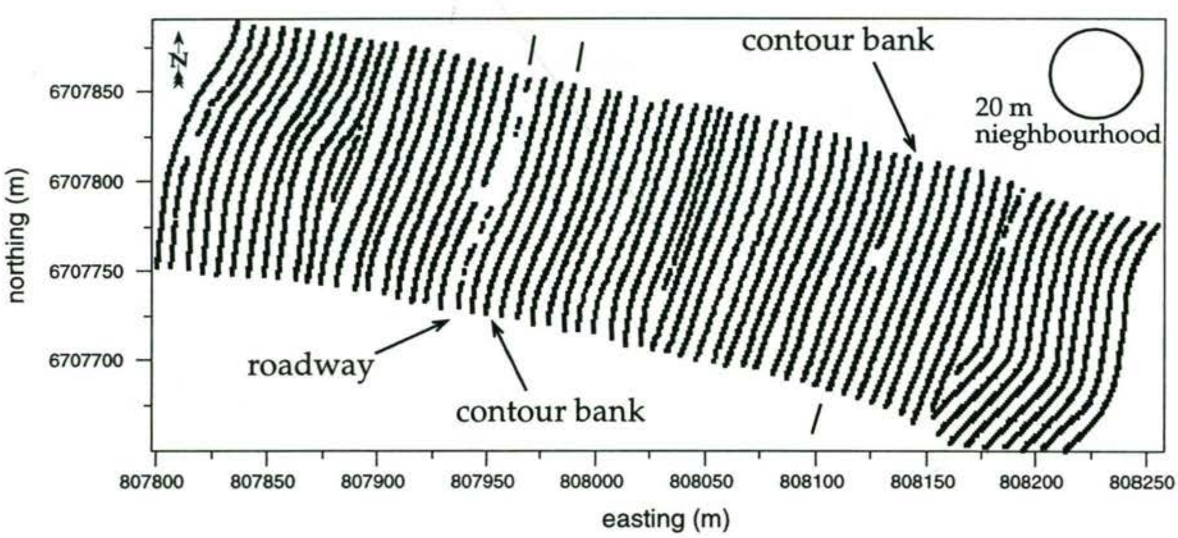


Figure 6-4. Site layout and header runs for the 6 ha site.

With more observations than the original data at this prediction scale, all the techniques provide a closer estimate of the data mean even though the three more complex procedures continue to produce a significant difference ($p = 0.01$). There is no significant difference between the means of these three techniques. The improvement in overall mean estimation has been accomplished by a reduction in the representation of the data variability in all the prediction surfaces. This is not as evident at the coarser grid scale and is probably a function of a smaller prediction grid to neighbourhood ratio.

Prediction Method	n	Min. (t/ha)	Max (t/ha)	Mean (t/ha)	Std Dev. (t/ha)	C.V. (%)
Original data	8504	3.07	9.95	7.41	0.85	11.5
Local moving mean	16815	6.30	8.50	7.40	0.41	5.5
Inverse distance squared	16815	4.14	9.64	7.39	0.54	7.3
Local kriging w/ global variogram	16815	4.06	9.34	7.38	0.56	7.6
Local kriging w/ local variogram	16815	3.68	9.50	7.38	0.58	7.9

Table 6-3. Descriptive statistics for the prediction surfaces generated by the various methods over the 6 ha site.

Local Moving Mean

Figure 6-5a highlights the compaction of the data distribution induced by the local moving mean technique. The yield covers a range of 2.5 tonnes and the presence of only one contour bank is evident in the map.

Inverse Distance Squared

In Figure 6-5b the inverse distance squared prediction method shows an increased range in the yield represented, and an increase in very localised sharp changes in yield evident as discrete spotting. The severity and linear alignment of these 'spots' suggests that they may be an artifact of the prediction process.

Local Kriging with a Global Semivariogram

Figure 6-5c, the local kriging prediction surface using a global semivariogram model, also displays the phenomenon described above (albeit slightly less pronounced) but with a decrease in overall smoothing as evidenced by the clearer depiction of the road and contour banks. Both this method and the inverse distance squared method use a single model for the spatial variation in the field.

Local Kriging with a Local Semivariogram

Incorporating a local semivariogram assessment into the local kriging process as in Figure 6-6a dramatically reduces both the number and linearity of the sharp circular changes in

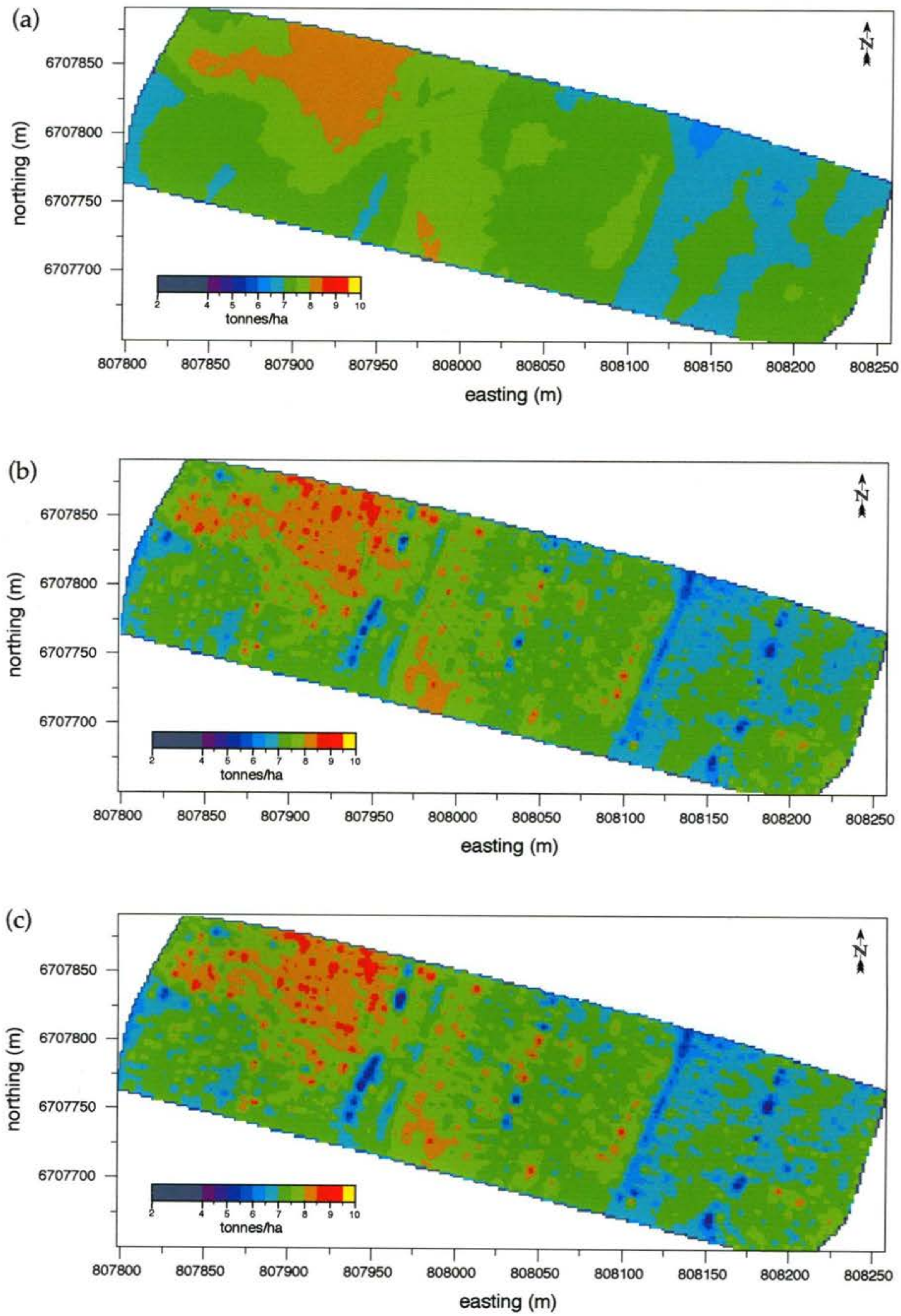
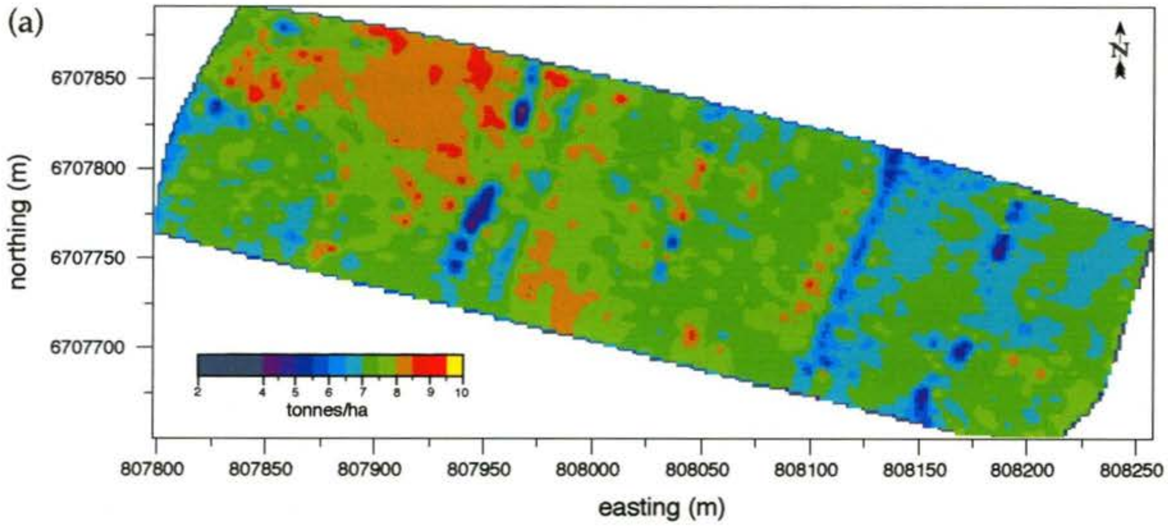
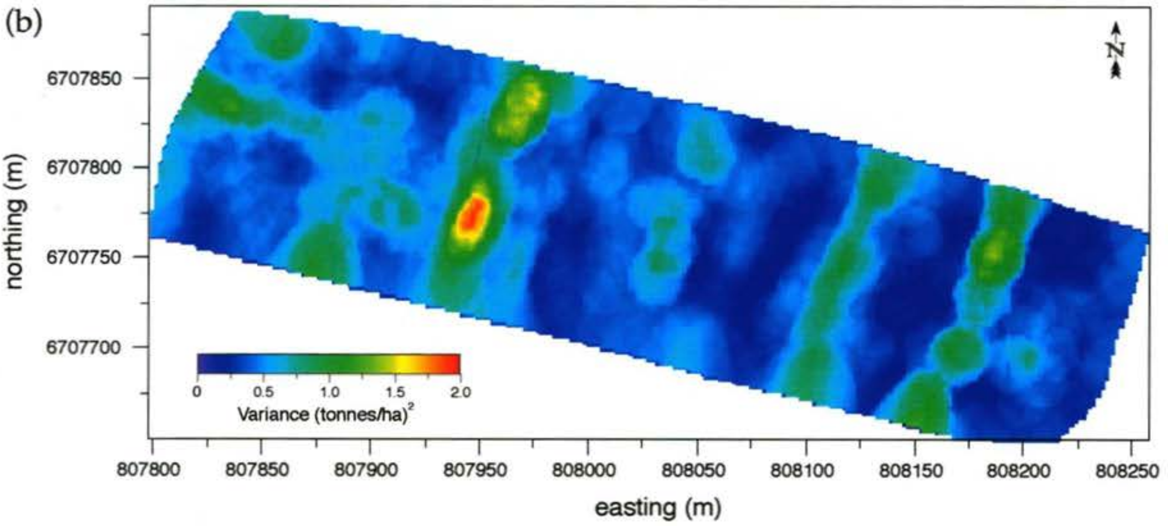


Figure 6-5. **Crop yield maps for a 6ha region of the Creek field produced by different prediction methods - (a) local moving mean (b) inverse distance squared (c) local kriging with a global semivariogram.**





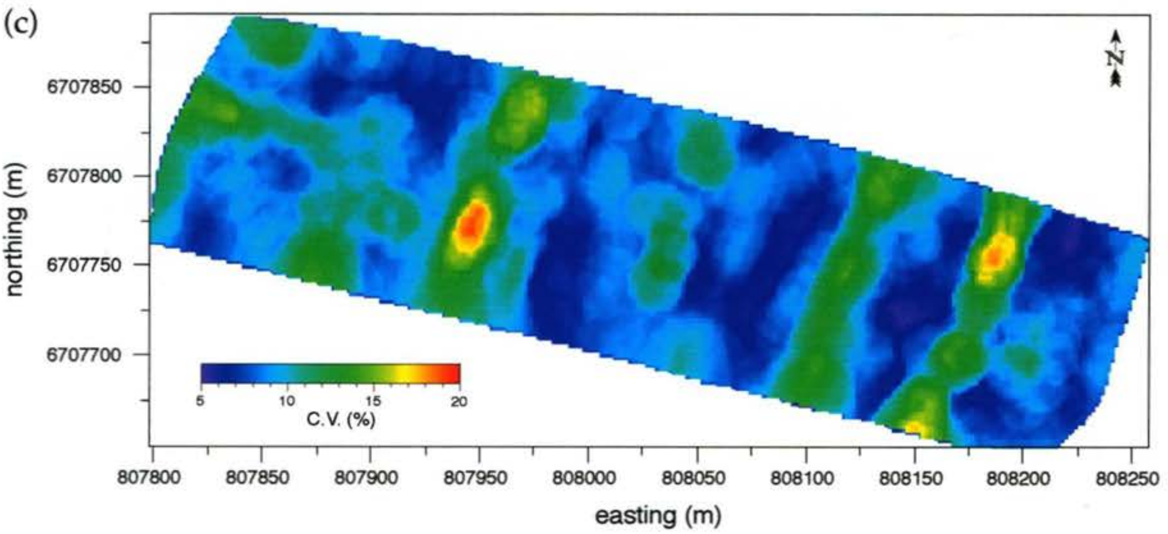


Figure 6-6. Maps for a 6ha region of the Creek field (a) prediction by local kriging with a local semivariogram (b) yield variance as estimated by the kriging variance (c) co-efficient of variation (CV).

yield values. This suggests that the spotting may be attributed to areas in the field where the spatial variability differs markedly from that described by the single inverse distance square or global semivariogram models. It would appear that in both the 25 ha and 6 ha areas these models are introducing an unrealistically high spatial variance structure to many areas in the field.

This hypothesis may be examined using the individual semivariograms determined for each neighbourhood in the local kriging with a local variogram procedure. The kriging method, as previously discussed, produces a prediction error that may be used to construct confidence intervals for each prediction. The individual semivariogram models may also be used to estimate the variance for an area around each prediction point, up to a radius of the maximum lag used in the semivariogram model.

This is unique among the prediction methods used here and allows the spatial variability of the neighbourhood yield variance to be mapped (Figure 6-6b). This map confirms that a single model for the spatial structure of the yield variance would be nonrepresentative of the data set. Converting the variance data to a coefficient of variation (Figure 6-6c) produces a map that may be used to examine the preceding yield prediction maps more directly. Areas in Figure 6-6c with a low C.V. infer that the coinciding areas on the yield maps should display a smooth yield classification, depicted as solid areas of colour without abrupt short distance 'spotting'. Both Figure 6-5b and 6-5c fail to acknowledge this spatial pattern in variance in all but the larger regions of high %C.V.

To further highlight the variation in spatial structure across the field, the distribution moments for the locally fitted exponential semivariogram model parameters are recorded in Table 6-4 and displayed as histograms in Figure 6-7. The distributions suggest that the application of a global semivariogram may be discarding information on the changing magnitude of yield variability within the field. In Figure 6-8a, a number of the local variograms representative of the suite of 16,815 is shown in comparison with the global (average) semivariogram model. These models have been calculated for the various points shown in Figure 6-8b. Here, the evidence is more easily understood. The semivariograms show that the sill value (C0 + C : equivalent to 0.95 the yield variance) may change substantially throughout the field.

The spatial distributions of these semivariogram parameters are displayed in Figure 6-9a to 6-9c. Interestingly, these maps show that the 'a" parameter of the exponential semivariogram models has little influence on the spatial structure of yield variance throughout the field (Figure 6-9a). Variation in the nugget parameter 'C0' begins to exert an influence (Figure 6-9b), but it is the 'C' parameter (the difference between the

Parameter	Min	Max	Median	Mean	Std Dev.
Exponential Variogram					
C0 (γ(h))	0	0.8	0.18	0.19	0.11
C (γ(h))	0	3.0	0.26	0.37	0.32
a' (m) *	3.3	41.4	5.86	5.79	1.34
Prediction					
Std Error (t/ha)	0.12	1.22	0.57	0.59	0.13
95% Confid. Interval (t/ha)	0.2	2.4	1.12	1.16	0.25

* a' = 1/3 apparent range (a)

Table 6-4. Descriptive statistics for the local semivariogram parameters, prediction error and confidence intervals.

semivariance observed at the lag 'a'' and 'C0') which demonstrates the greatest impact on the spatial structure of yield variance in the field.

The spatial distribution of the 95% confidence interval has not been mapped as the individual maps in their entirety are an impossible depiction of reality. The total yield expressed in each map would not match the quantity known to be harvested from the field. The limits are important however, as they summarise the error inherent in the point predictions, seen here to vary from ± 0.2 t/ha to ± 2.4 t/ha within the field. Again, the wide range in the standard error confirms the significant local variation in the spatial variance structure.

All these results can be compared with the parameters of the global semivariogram fitted to the same maximum lag for the whole field. An exponential semivariogram model provided the best fit with: C0 = 0.1, C = 0.45, a' = 2.7. The 0.55 sill value (C0 + C), which approximates the maximum modelled variance in data sets of this size, is equal to the mean value for the suite of local models (0.56). Such a result is to be expected and ensures the mean variance within each prediction surface are equated. The 'a'' parameter however is significantly smaller in the global model than the local mean value (5.79). In the kriging process this would cause close observations to be weighted much higher than if a the mean local model was used. Therefore the contribution of observations further than the

(a) (b) (c) (d)

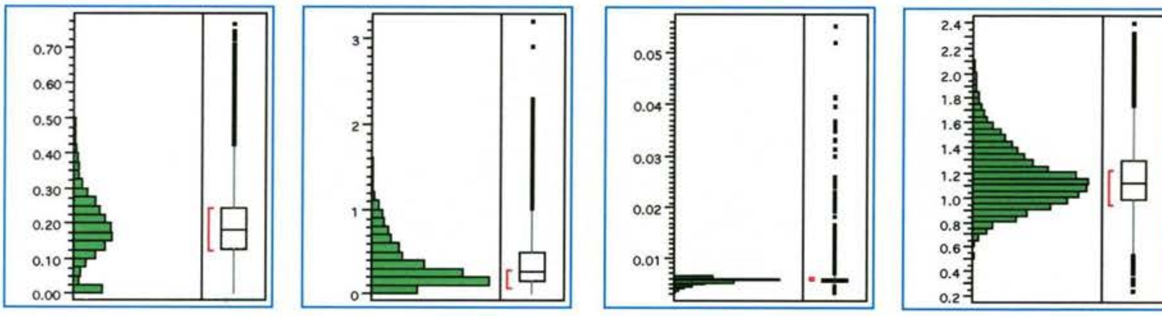
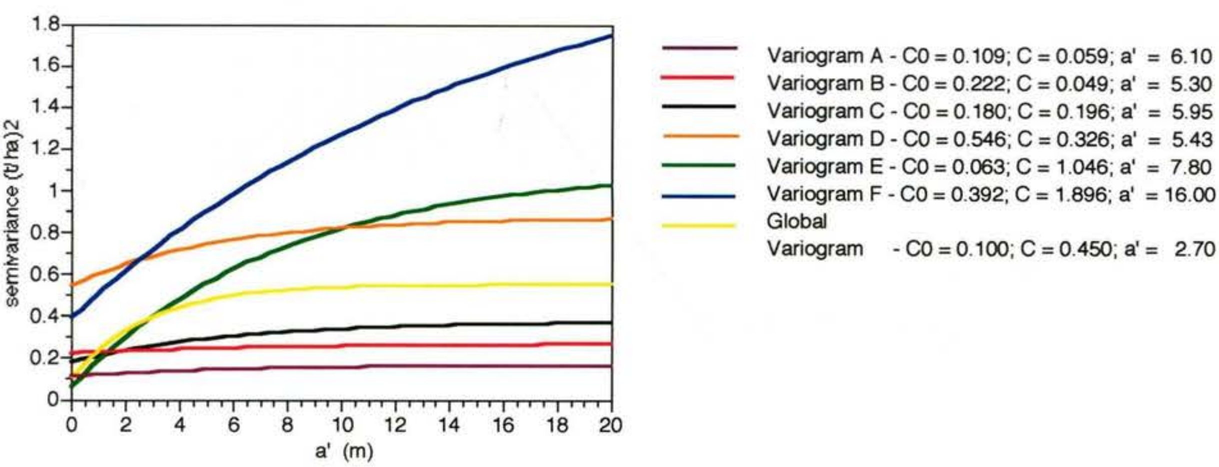


Figure 6-7. Distribution histograms of the model parameters for the suite of local semivariograms - (a) C0 (b) C (c) a' (d) confidence interval.

(a)



(b)

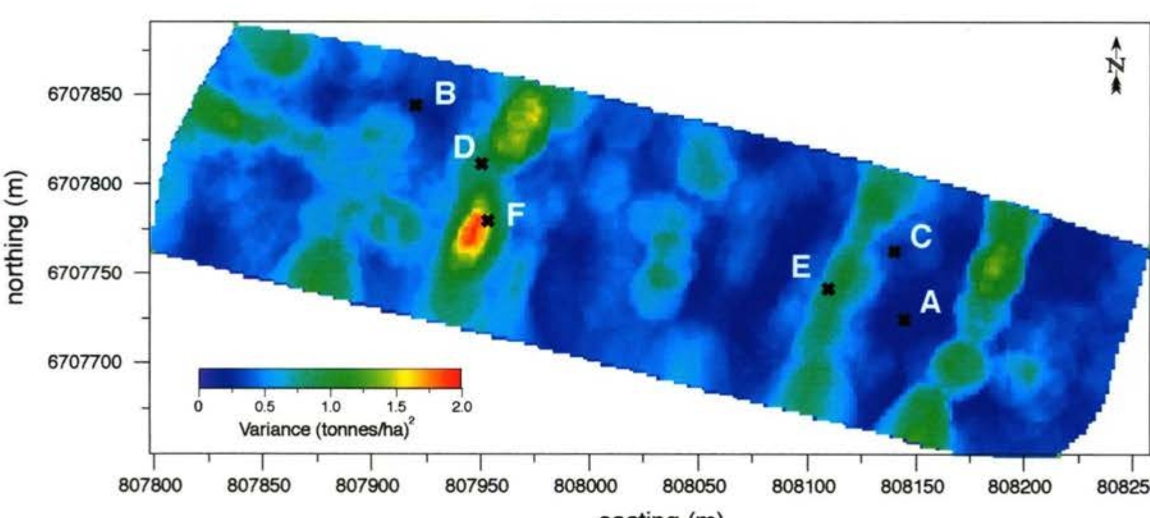


Figure 6-8. (a) Examples of semivariogram models from the suite of local variograms (A to F) as compared with the global semivariogram model (G). (b) Spatial location of the variograms within the yield variance map.

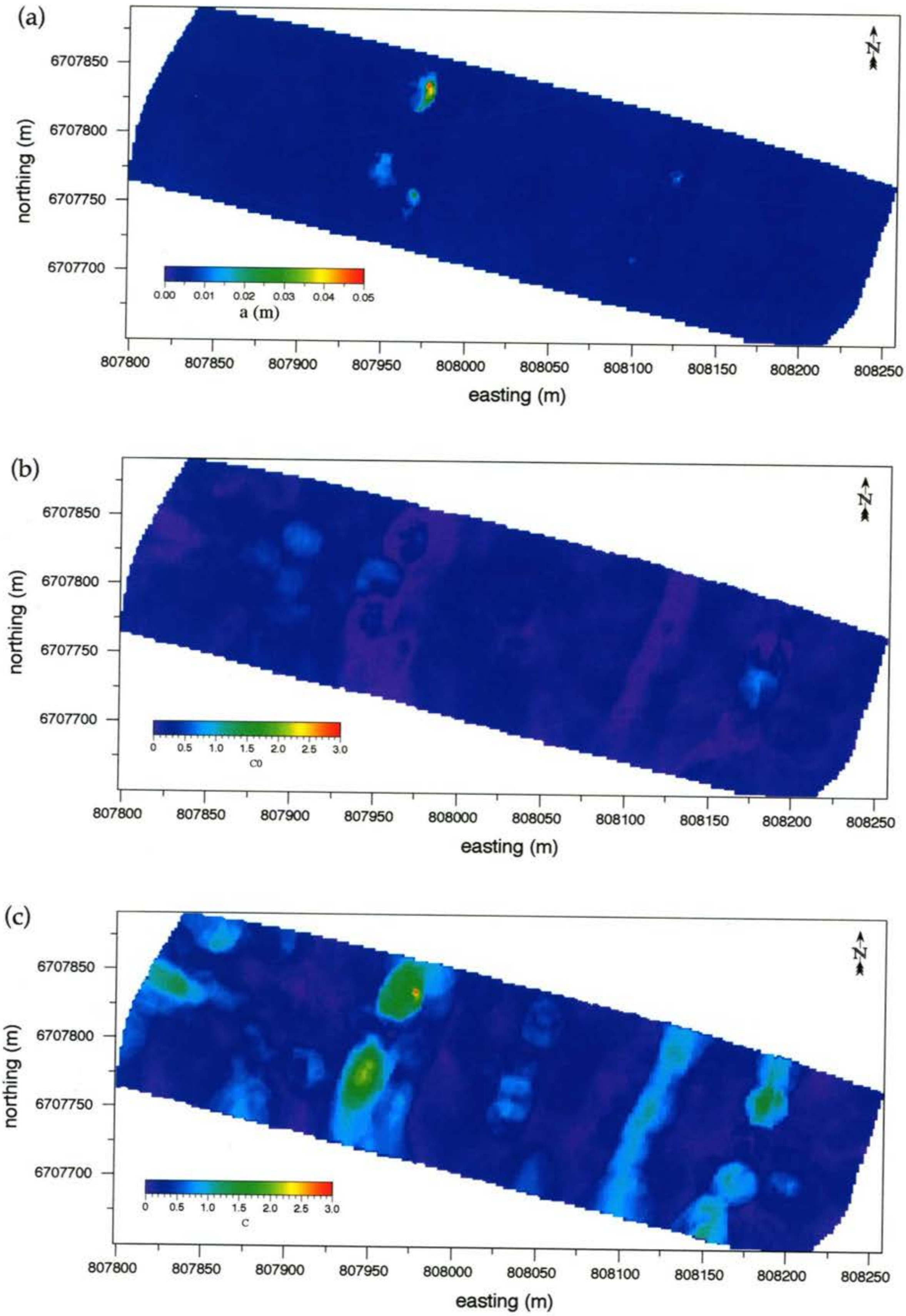


Figure 6-9. Variogram parameter maps for a 6ha region of the Creek field - (a) range value - *a′* (b) nugget value - *C0* (c) sill minus nugget value - *C*.

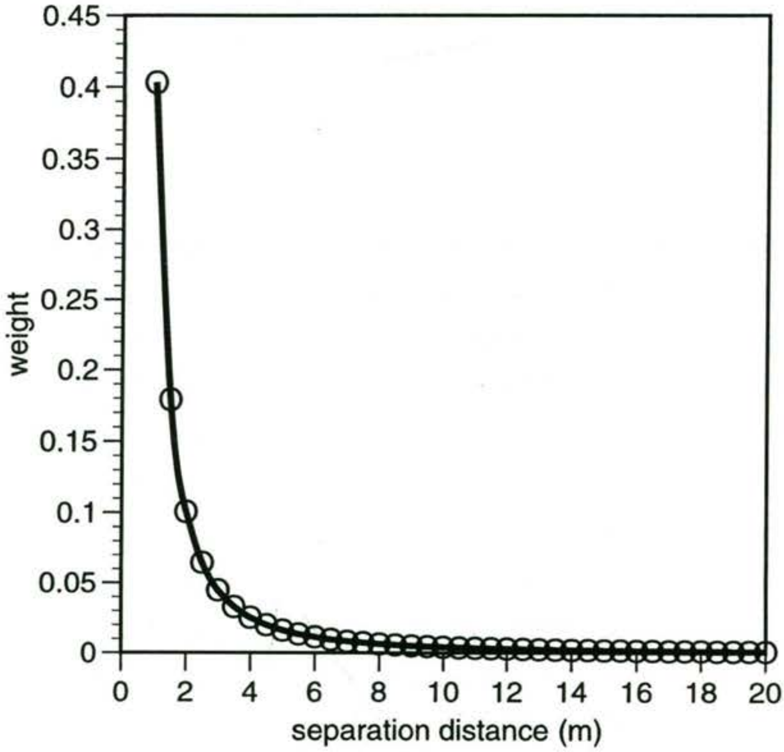


Figure 6-10. Inverse distance squared weight model for a maximum separation distance of 20m in 40 lags.

value of 'a", considered influential in the local models, would be effectively disregarded in the application of the global model. Greater short-range variation would be expected as a result.

In Figure 6-10, an inverse squared distance model for the 20m neighbourhood shows that the weights effectively reach zero at approximately 8 m. This is a similar distance to the apparent range of the global semivariogram model ($2.7 \times 3 = 8.1$) and offers an explanation to the similarity between Figures 6-5b and 6-5c.

6.4 GENERAL DISCUSSION

That the form of spatial prediction chosen for map construction may be significantly influential on the final prediction surface is not a new concept. Laslett et al. (1987) examined soil pH data (0-10 cm layer) sampled on a 10m grid within a 1 ha field in Samford, Queensland, Australia to test and compare spatial prediction techniques. The performance of global means and medians; moving averages; inverse square distance interpolation; Akima's interpolation; natural neighbour interpolation; quadratic trend; Laplacian smoothing splines; and ordinary kriging was tested. Comparisons were made by assessing the predictions against 64 observations made within the grid and withheld from model construction.

The authors concluded that all the methods showed some deficiencies in spatial prediction. Interpolation methods were generally very poor predictors, while of the non-interpolating methods, Laplacian smoothing splines and kriging performed best. Whelan et al. (1996) constructed isarithms of soil pH from the results of Laslett et al. (1987), which were contoured to compare the spatial prediction of inverse-square distance interpolation and ordinary global kriging. Global kriging produced a much smoother surface but an examination of the two methods' predictions at assessment points along a transect showed that neither method appeared to predict the pH of the field very well in this case. Laslett & McBratney (1990) compared interpolators, Laplacian smoothing splines, intrinsic random functions, and universal kriging fitted by restricted maximum likelihood (REML). The kriging technique fitted with the REML consistently proved to be the best method.

Wollenhaupt et al. (1994) also compared the accuracy of a number of prediction techniques in a soil phosphorus and potassium mapping study. At a grid spacing of 32m, the authors concluded that inverse-distance squared produced more accurate results than those obtained using the kriging procedure. At greater sample grid spacings, the techniques provided similar accuracy. These accuracy results are based on comparison with a data set constructed using Delaunay triangulation, and not on validation with independent observations. As such, the legitimacy of the conclusions rest on the accuracy of the triangulation estimates and the comparative results can only be regarded as offering accuracy relative to the triangulation method.

In a more comprehensive study, Weber & Englund (1994) evaluated the accuracy of inverse distance and ordinary kriging prediction techniques using elevation and elevation variance data sets to simulate data with a relatively unskewed, continuous surface (e.g. geological surfaces, soil OM) and those with highly skewed noisy surfaces (e.g. soil nutrients) respectively. They compared predictions based on data subsets of increasing sample size with observations from larger original data sets.

The results suggest that inverse distance techniques are sensitive to the type of data set, the neighbourhood population used in each prediction and the power of distance (p; refer Equation 6-5) used in the weighting. The accuracy of the prediction (assessed by mean square error) for the more smoothly variable elevation data increased as the neighbourhood population decreased and the power of distance increased. For the more variable data sets, the opposite was true. Alternatively, ordinary kriging displayed little sensitivity to the variability in the data sets and the accuracy of the estimates continually improved with increasing neighbourhood populations.

In a similar prediction-validation study Gotway et al. (1996b) compared inverse distance methods with point kriging using various sampling densities. The attributes of interest were soil OM (low variance) and $N0_3^-$ (high variance). The results also showed that the accuracy of inverse distance methods generally improved with an increase in the power parameter (*p* value - refer Equation 6-5) if the variability in the data set was low. The $N0_3^-$ data sets displayed greater variability and analysis using higher power parameters proved less accurate than using a value of $p = 1$. The authors concluded that there was no single value for the power parameter that could be considered optimal in all cases. On the other hand, the kriging procedure using a global semivariogram based on the prediction data sets was generally unaffected by the variability within data sets and indeed the accuracy remained relatively high for each sampling configuration.

The observed inefficiencies of the inverse distance squared prediction technique can be attributed to two main problems. Firstly, the prediction does not take into account the relative distances among observation points in the model of spatial variability, so the observation weighting is singularly based on an arbitrary function of distance to the prediction grid node. Secondly, the method is an exact interpolator that passes through the data points, this may not be sensible if there is uncertainty in the observations. Such uncertainty may arise in either the value of the observed attribute or its spatial location. Kriging only operates as an interpolator in the nugget value (C0) is zero. With any positive C0 value, close range uncertainty in the observations will be reflected in the kriged surface which will be discontinuous at the observation sites.

This point is often overlooked in assessing the suitability of prediction techniques but should be a given a high priority in SSCM owing to the potential errors associated with proposed observation techniques. Obviously real-time sampling and position recording using GPS receivers will increase the individual observation error.

A further advantage in the use of kriging techniques over inverse distance methods lies in the provision of a prediction error estimate (Laslett et al., 1987; Weisz et al., 1995b; Brus et al., 1996; Gotway et al., 1996a). Especially in SSCM, the production and reporting of the kriging standard error for a prediction should be essential. The error value provides an estimate of uncertainty that will have important ramifications in the extrapolation of management information (i.e. differential fertiliser application maps) from predicted soil attribute and crop yield maps.

On the other hand, criticisms have been generally levelled at the kriging techniques' complexity and related computational expense (e.g. Murphy et al., 1995). Astoundingly, this one line of criticism has apparently overridden all the advantages discussed above, and led to the general acceptance of the inverse distance method as the prediction method of choice in the emerging mapping packages for Precision Agriculture. While there may be some instances where a prediction map is required quickly (e.g. soil attribute maps for interpolation to fertiliser application maps), at present the author believes this is not a rational reason for discarding the advantages incumbent with kriging techniques. Certainly for crop yield maps, the computational time would be far outweighed by the single fact that the map represents a great deal of time, effort and expense taken to grow a crop. Ultimately, it is the integration of an entire seasons crop growth information.

Where the computational expense may become important (and indeed the choice of prediction technique possibly unimportant) is when the observation sampling scheme is inadequate in terms of sample size, sample strategy, or both. Sample size is probably considered the most crucial parameter (Englund et al. 1992) with an increasing number of observations generally offering greater prediction accuracy. Numerous studies on the effect of sample strategy for regionalised variables have been reported since the early theoretical work of McBratney et al. (1981). The general axiom to emerge is that sampling schemes which fail to produce a sample set representative of the actual spatial variability in the attribute of interest will hinder accurate prediction by any method.

The impact of sampling scheme inadequacies is more than likely behind the reported results of several authors (including Laslett et al., 1987; Weisz et al., 1995b; Brus et al., 1996; Gotway et al., 1996a) who have found inverse distance squared interpolation to perform reasonably when compared with kriging for modest sample sizes (100 or less). A low sample size or poorly structured design may severely effect the accuracy of semivariogram estimation and often introduces unrealistically high nugget effects.

For SSCM it is therefore possible to argue that the optimal spatial predictor will depend on both the sample size and the sampling intensity (sampling design in relation to a minimum area of interest - MAI). The MAI is limited by the smallest differentially manageable land unit (usually governed by implement width and operational dynamics) and the field boundary.

First let us consider categorising sample size. Sample sizes of less than 10 will not allow any kind of localised spatial prediction and estimates of the mean for the field will be rather poor. In the commercial realm of soil attribute analysis, the sampling size usually ranges between 10 to 100 observations which should probably be considered inadequate for formal spatial statistical techniques (kriging and Laplacian splines) and may explain why methods such as inverse distance squared are often used. As seen from the earlier discussion, the quality of the estimation must be questioned. With more than 100 observations, the more sophisticated techniques such as kriging and Laplacian smoothing splines should work well.

For between 100 and 500 observations, kriging with a local neighbourhood of points and a global variogram is often employed. At this sample size the assumption of a global variogram is born of necessity but once sample sizes get above 500 it seems wasteful to assume a single variogram within the field and local variograms can be easily estimated for moving neighbourhoods (Haas, 1990b).

The second consideration is the sampling intensity. A way of representing the sampling intensity is via the number of observations per MAI. Sparse, moderate and intense categories will be defined here as 0.0001–0.01, 0.01–1 and > 1 observations per MAI, respectively. Given these definitions, the purpose of spatial prediction is to convert x observations per MAI to a least 1 prediction per MAI. For sparse sampling intensities this represents a 100 to 10 000 fold increase from the number of observations to the number of predicted data points which would seem to stretch belief in the validity of the predictions. Here the prediction task seems too large and spatial prediction is probably inappropriate.

For moderate sampling intensities up to a 100-fold increase from the number of observations to the number of predicted data points is required which appears reasonable for valid prediction. In fact, at the most intense end of this range, and for intense sampling, one might ask why prediction is required. However, in many circumstances it may be useful to have more than one prediction per MAI but more importantly it may be necessary to move the location of predictions. This is particularly the case for crop yield maps where the observation intensity may be 10 per MAI but these observations are linearly clustered within the area and it would be beneficial to obtain an even intensity of observations.

In this instance, kriging using a global variogram may prove too restrictive in its representation of local spatial correlation whereas local variogram estimation and kriging offers the ability to preserve the true local spatial variability in the predictions as shown by the yield mapping results presented in this Chapter. If the chosen area of influence is reasonably small, the use of local semivariograms may also negate the possible requirement for trend analysis and removal prior to variogram estimation and kriging. It must be remembered that the area of influence chosen for semivariogram modelling may effect the resulting model, however the density of data supplied by real-time crop yield monitoring and the objective to accurately define management areas, should make the use of local semivariogram models appealing .

These recommendations are summarised in Table 6-5.

	Sampling Intensity (No. per minimum area of interest)		
	Sparse	Moderate	Intense
Sample size	0.0001-0.01	0.01–1	>1
<10	NA	NA	NA
10–100	NA	?IS	?IS/NR
101-500	NA	GK	GK/NR
>501	NA/GK	LKS	LKS/NR

NA : not applicable - don't do it.
?IS : inverse square or some informal prediction method but there may be problems with the accuracy of the estimates.
GK : a geostatistical method such as ordinary kriging or universal kriging with a global variogram or Laplacian smoothing splines
LKS: a local neighbourhood kriging method or Laplacian smoothing splines
NR: spatial prediction will only be necessary if the sampling strategy is poor ly aligned.

Table 6-5. Generalised recommendations for the use of spatial prediction methods in relation to sample size and intensity for Precision Agriculture.

Spatial prediction onto a regular grid is not the only method of constructing a yield map. Another technique, proffered in the early stages of yield sensor development, is cell-based mapping. A cell size is chosen and superimposed over the sampling scheme. The mean value of all observations falling within a cell boundary is then allocated as the yield value for the cell.

Schueller & Bae (1987) used a 10m square cell chosen apparently arbitrarily, but with a subjective influence based on the perceived variability and the desired accuracy of the mean estimate. Searcy et al. (1989) mapped using a 6m square cell size determined by the cutting width of the combine harvester. Missotten et al. (1996) employed a 20m cell size which was based on the experimental sampling design. This method, unlike the moving average process defined in Equation 6-4, requires that yield observations be used for a single cell average only. The yield from adjacent cells is considered uncorrelated, even if an observation is located close to a boundary. The underlying model of the spatial structure in yield variability appears arbitrarily rigid and a biologically unrealistic representation.

Another method, suggested by Blackmore & Marshall (1996), involves map construction by summing the total mass of grain sensed within a designated cell boundary and then calculating the yield per unit area based on the area of the cell. The authors named the process 'Potential Mapping' and justify the procedure on the basis that cutting width error is removed. This error is significant (as discussed in section 4.4) and its possible removal adds merit to the proposal. On the other hand, the cell size remains an arbitrary rigid boundary with the associated non-biological assumptions, a large field-edge effect is produced unless the cell size is extremely small, and this method fails where data points are missing or removed by expert filtering. The procedure also offers no statistical estimate of error.

Murphy et al. (1995) have proposed recording the grain yield by distance rather than the standard time basis. The distance would be chosen to match the combine harvester cutting width and so provide data on a regularised grid. Prediction methods may then be unnecessary, however the potential minimum resolution of the subsequent map will fall. Murphy et al. (1995) also suggest combining prediction methods within a local neighbourhood. Within an inner radius, the observations are averaged and combined with inverse distance weighting for observations extending out to a maximum radius. Again, this method appears highly subjective in terms of neighbourhood maximum and partial radius determination.

While these methods show limitations, in the future it may be advantageous for cell or 'block' estimates to be determined so that yield values for MAI's or management units can be represented. The alternative methods outlined above are not the only options available. Spatial prediction need not be at points as has been the focus of this Chapter, but prediction can be made onto 'blocks' which represent these management areas, e.g., 20×20 metres. In the process of block kriging these blocks can overlap unlike the more rigid operations described above. For example, a map on a 1 metre raster can then represent the average of a relevant quantity over the 20×20 metre block centred on the prediction point (Burgess and Webster 1980). Geostatistical methods appear the most advanced for such predictions, particularly for SSCM where an estimate of prediction accuracy is required.

In any form of cell-based estimation or block prediction method, the cell size and/or prediction block size will effect the smoothness of any subsequent map. Bigger cells/ blocks leading to smoother maps. This also holds true for the neighbourhood size chosen in the point prediction methods described earlier. Smoothness can also be effected by the spatial dependence models underlying the prediction methods. These models obviously control the weight attributed to observations. Only in the kriging procedures is the model (semivariogram) conditioned on the actual observation data set and not an arbitrary function of distance. The range parameter of the semivariogram (which estimates the distance of spatial correlation between observations) is therefore a tool for determining sensible neighbourhood or cell/block sizes.

Intertwined with the dilemma of appropriate neighbourhood size is the resolution at which the yield maps should be presented. Resolution should probably be governed by ensuring that the raster size is of a dimension that maintains a management determined uncertainty level within the map. Uncertainty in the individual yield estimates reported in this thesis is probably dominated by the harvester mechanical dynamics. The results presented in Chapter 5 suggest that a resolution below 20m along the harvester path would not satisfy this criterion. Lark et al. (1997) provide an estimate of 15m to 20m for the same characteristic. It would appear that 20m $\times$ combine harvester cutting width could be a base raster size with which to begin standardising mapping resolution.

Finally, the most suitable mapping class size (e.g. 0.5, 1.0, 2.0 t/ha demarkations) remains unstandardised and basically unknown. This attribute also effects the degree of spatial variability presented in a map which will in turn influence the observers perception as well as management decisions based on the classified yield variability. Searcy et al. (1989) classified crop yield based on percentiles using +/- set percentages of the mean yield as the categories. Such an idea is quite plausible as the basis for standardisation because it would fix the maximum number of classes that can be displayed in yield maps. The determination of the most suitable percentile bands remains a project for research.

As an alternative, a useful approach would be to ensure that the uncertainty in crop yield data influenced the classification decision. For example, if the 95% confidence interval in crop yield estimates is +/- 1.0 t/ha, classifying a field using classes less than 1.0 t/ha may be misleading. A classification system based on the uncertainty in the yield data may prove useful in the future.

6.5 CONCLUDING REMARKS

Spatial prediction methods should be employed in Precision Agriculture to accurately represent the spatial variability of moderate to intensely sampled field attributes and maintain the principle of minimum information loss. To this end, the sampling intensity should guide the prediction method utilised. However, data used in any spatial prediction procedure should be of known precision and that precision can then be built into the spatial predictor. Because of imprecision in crop yield measurement and within-field location, interpolators (exact spatial predictors) are generally not optimal.

The results presented show that the form of spatial prediction chosen for yield map construction has a significant influence on the final prediction surface. Local kriging using a local variogram appears well suited for use as a spatial prediction method for real-time sensed crop yield data. Mapping attribute values using this procedure and depicting the changing variability within a whole field should be of benefit in the process of determining whether a field warrants differential treatment and to what degree. However, there remains a considerable amount of preprocessing and deconvolution required to obtain yields of known accuracy from real-time sensed crop yield data so that prediction neighbourhood size and map resolution can be confidently and above all, usefully determined

Ultimately, the software devised for spatial prediction in Precision Agricultural applications should include options that will optimally support the management decisions that will be formulated upon the prediction results.

SECTION IV

THE POTENTIAL FOR ECONOMIC AND ENVIRONMENTAL BENEFITS FROM PRECISION AGRICULTURE

CHAPTER 7

CHAPTER 7

Modelling the Economic and Environmental Impact of Site-Specific Fertiliser Treatment

7.1 INTRODUCTION

Site–specific management appears a logical approach to utilising valuable resources in an often fragile cropping environment. The question of its acceptance will depend on the benefits displayed, and initially the economic benefit will be valued more highly in any on–farm decision. The economic benefits to be gained from the inclusion of information on spatial variation are also more easily substantiated than the environmental or social gains (Wollenhaupt & Buchholz 1993). This arises because these latter gains include broad societal improvements such as reduced contamination of the landscape and foodstuffs, along with a potential for improved sustainability through increased recognition of natural and anthropogenic diversity.

Any analysis of the economic benefits will ideally require some knowledge of the nature and degree of soil variation exhibited at a site as this will influence the form of differential treatment undertaken. For the example of differential fertiliser treatment, a site may possess (or be believed to possess) a uniform yield potential but irregular initial soil concentrations of the nutrient in question. The differential application of fertiliser to bring the whole site concentration to a single, required baseline level may be a sufficient treatment (areas already above this baseline would be untreated). Should the yield potential at a site, as well as the initial soil nutrient concentrations, be deemed to fluctuate over the field, a range of baseline levels would need to be calculated to co-ordinate the optimum fertiliser application regime.

The possibility of financial benefits from these two different approaches will be examined separately. Firstly, the uniform case for phosphorus (P) under sorghum and NO_3^--N under cotton. Secondly, the more complex scenario of variable yield potential for NO_3^--N under cotton will be explored for 2 consecutive growing seasons. Environmental implications will be drawn in all cases.

7.2 UNIFORM YIELD POTENTIAL ACROSS A SITE

Uniform yield potential within a field may arise from the actual or perceived homogeneity of critical soil attributes governing crop yield. Such homogeneity is assumed in the majority of management systems where soil sample test results are averaged to provide a single estimate of the whole field status. Uniform yield may also be a goal of production.

7.2.1 Site Sown to Sorghum

Materials & Methods

A one dimensional simulation model is developed based on phosphorus (P) application to broadacre sorghum grown on lateritic red–brown earth (rhodic palexeralf). The model employs a fertiliser response function to quantify the expected grain yield obtained from fertilisation treatments on a theoretical 1000 ha site. Differences in financial return are compared for fertiliser application based on differential or 'mean-of field' treatments.

Six log–normally distributed populations of 1000 initial soil P levels were generated, giving six site descriptions. Three sites were produced with the same mean P level but with increasing degrees of P variance and three sites were constructed with increasing mean P but identical P variance. The P distributions were generated using a first-order autoregressive function (Box & Jenkins, 1970) (Equation 7-1).

$$Ps_i = \beta\, 10^{\,s_i} \tag{7-1}$$

where:

Ps_i = soil phosphate level (kg ha^{-1})

β = median regulating coefficient

s_i = $\alpha\, s_{i-1} + k\,\mathrm{h}$

α = autoregressive parameter

k = 'noise' coefficient

η = random sample from a normal distribution (N(0,1))

For each of the six sites, three levels of knowledge of the spatial variability in initial soil P content across the site are used to determine the quantity of fertiliser to apply in each of the 1000 zones. The three data knowledge scenarios were:

(i) exact information at each point - which describes the ultimate goal of site-specific soil management;

(ii) an inexact model of information at each point - derived from fitting a smoothing spline (De Boor, 1978) to the P distribution data, it is taken to represent the general level of information available when only minimal spatial soil sampling is undertaken or inadequate data is used in soil fertility models.

(iii) the mean value of the site - the traditional method of formulating fertiliser application regimes. An example of the information levels for one initial soil P distribution is presented as Figure 7-1.

The fertiliser response curve employed in the model (Equation 7-2) is a modified form of that reported in Helyar & Godden (1977) and is based on Australian experiments.

$$y^R = 2500\,[1 - e^{-0.04\,(f + 8.8)}] \qquad (7\text{-}2)$$

where:

y^R = yield (kg ha^{-1})

f = available P (kg available P ha^{-1})

Applying marginal analysis (Dillon, 1968) to equation 7-2, the Maximum Economic Yield (MEY) and the optimum soil P level (OSP) may be determined for the field. This is the point on a response curve where the financial return for applying 1 unit of input (P fertiliser in this case) equals the unit cost of the input. It is calculated by equating marginal revenue (MR) with marginal cost (MC). The economic parameters used in the analysis were: sorghum grain @ $150.00 /tonne[1] ; Single super phosphate (8.6% available phosphorous (P)) @ $247.00 / tonne = $2.87 / (kg available P); maximum grain yield @ 2.5 tonne /ha. An OSP of 32.7 kg available P/ ha was obtained corresponding to an MEY of 2.025 tonnes/ha.

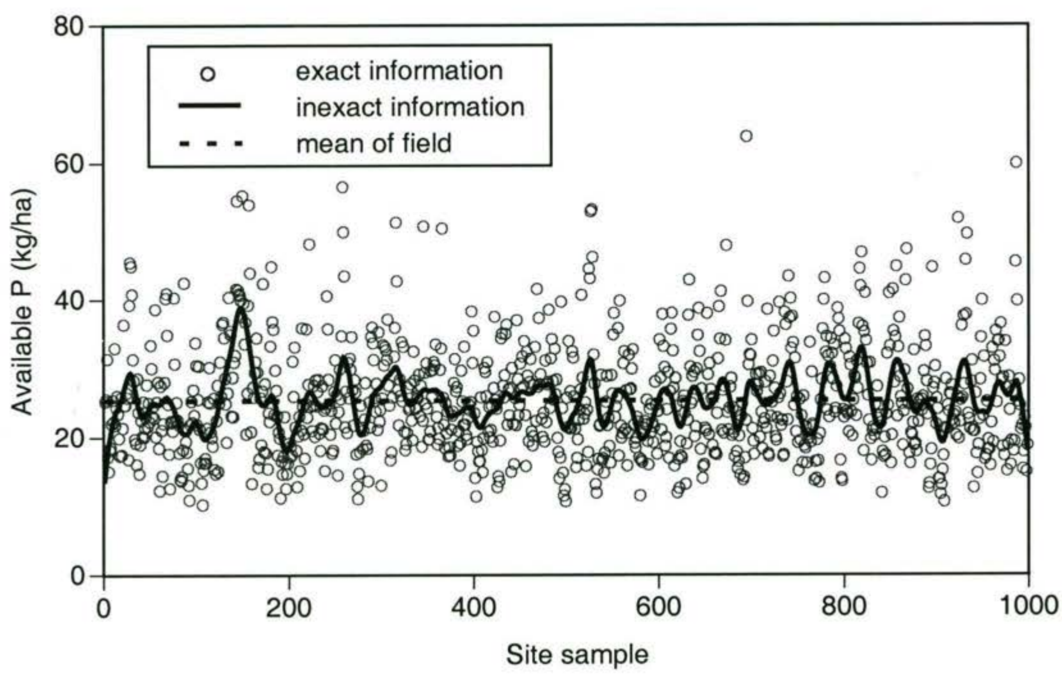


Figure 7-1. Simulated P distribution and associated data knowledge levels.

1 "The Land", February 10, 1994. Rural Press, Richmond, Australia.

The quantity of available P required to be applied to each zone on a site was calculated for each treatment by differencing the known soil P level (KSP) from the OSP. In calculating the returns for each site, exact information on the initial P fertility (RSP) provided the simplest scenario as each point in the field was correctly fertilised to the optimum (except where the zone was initially above the optimum and no fertiliser was applied). When other than exact initial P fertility information was used, a residual P level for each zone on the site was calculated by differencing the exact levels (RSP) with the known levels (KSP). These residuals were used to determine zones of under or over fertilisation within a site. Under-fertilised sites received a yield penalty in the model and over–fertilised sites had excess fertiliser (APW) costs charged. However, this was tempered by any increase in yield achieved from the higher fertility. The model can be expressed mathematically as Equation 7-3.

$$
\begin{aligned}
\text{Returns (\$/ha)} = {} & \text{MEY (kg/ha)} \times \text{unit crop value (\$/kg)} \\
& - \text{total applied P (kg)} \times \text{unit P value (\$/kg)} \\
& - \text{total applied P wastage (kg)} \times \text{unit P value (\$/kg)} \\
& - \text{total yield wastage (kg/ha)} \times \text{unit crop value (\$/kg)} \\
& + \text{total yield gain (kg/ha)} \times \text{unit crop value (\$/kg)}
\end{aligned}
\tag{7-3}
$$

where:

MEY	=	2025 kg/ha
unit crop value	=	\$0.15 /kg
unit P value	=	\$2.8721/kg

$$\text{total applied P} = \sum_{i=1}^{1000} \begin{cases} OSP_i - KSP_i & \text{if } OSP_i > KSP_i, \\ 0 & \text{otherwise.} \end{cases}$$

$$\text{total applied P wastage} = \sum_{i=1}^{1000} \begin{cases} \left.\begin{matrix} OSP_i - KSP_i & \text{if } RSP_i > OSP_i, \\ RSP_i - KSP_i & \text{otherwise.} \end{matrix}\right\} & \text{if } KSP_i < RSP_i, \\ 0 & \text{otherwise.} \end{cases}$$

total yield wastage =

$$\sum_{i=1}^{1000} \begin{cases} \left.\begin{matrix} (\text{MEY}-(\text{MEY}_i \times [1 - e^{-0.04\,(((OSP_i - KSP_i) - |RSP_i - KSP_i|) + 8.8)}])) & \text{if } RSP_i < OSP_i, \\ 0 & \text{otherwise.} \end{matrix}\right\} & \text{if } KSP_i > RSP_i, \\ 0 & \text{otherwise.} \end{cases}$$

total yield gain =

$$\sum_{i=1}^{1000} \begin{cases} ((\mathrm{MEY}_i \times [1 - e^{-0.04\,(((OSP_i - KSP_i) + APW_i) + 8.8)}]) - \mathrm{MEY}) & \text{if } KSP_i < RSP_i, \\ 0 & \text{otherwise.} \end{cases}$$

The model, as applied, implicitly assumes that the levels of soil P are uniformly available and that the crop response to soil P is uniform across the 1000 ha site. The cost of fertiliser spreading has not been included, as this simulation is aimed at providing a valuation of increased returns to site-specific agronomy that may be available for allocation to site-specific operations.

Results & Discussion

Table 7-1 displays the results of applying the knowledge model to 3 simulated fields with similar variance in the initial soil P distributions but with differing mean values. This simply examines the effect of between-field variability by testing the hypothesis that differential P treatment would be suitable across a range of field mean soil P levels. Exact information produced an increase in returns over the less detailed information ranging from \$3.37/ha to \$8.12/ha. Importantly, the gain in returns for more precise information appears to increase and subsequently decrease as the mean of the soil P distribution falls from that of the desired fertiliser level.

Fields with very high inherent P fertility will show the least response to exact information, and this simulation suggests that returns are actually decreased by inexact information (as compared with the mean treatment) due to greater misplacement of fertiliser. Dropping the mean to a moderate fertility level of 25.4 kg P/ha provides the largest increase in returns to both levels of information. A further reduction in mean initial soil P fertility to a relatively low 11.04 kg/ha, results in a decrease in the response to both exact and inexact information, although not to the extent evident in the high fertility scenario. This suggests the presence of a mean P fertility window that is best suited to differential fertiliser application in sorghum under these conditions.

By maintaining a constant mean initial P level and modifying the variance, the influence of within-site variability on differential fertilisation programs can be examined. Table 7-2 shows the results for 3 fields each with a mean of 25.40 kgP/ha but with increasingly larger variance. The returns to exact information over mean application increase exponentially from \$4.83/ha to \$9.74/ha as the variance is increased. The use of inexact data however, increases returns over mean application as the variance increases to a moderate range then decreases as the variance is widened. This suggests that the more

	Available P distribution (kg/ha) min. = 4.45; med. = 10.52; mean = 11.04; max = 27.73			Available P distribution (kg/ha) min. = 10.24; med. = 24.21; mean = 25.40; max = 63.78			Available P distribution (kg/ha) min. = 12.90; med. = 30.52; mean = 32.03; max = 80.40		
	Exact information	Inexact information	Mean application	Exact information	Inexact information	Mean application	Exact information	Inexact information	Mean application
Total available P required (kg/ha)	21.63	21.63	21.63	8.38	7.40	7.30	4.34	1.96	0.67
% site fertilized	100	100	100	82.6	97.8	100	60.6	58.9	100
Available P wastage (kg/ha)	—	1.16	1.36	—	1.66	2.05	—	0.53	0.29
Yield wastage (kg/ha)	—	23.6	27.7	—	58.95	69.97	—	75.56	92.34
Yield gain (kg/ha)	—	20.16	23.13	—	28.25	34.48	—	9.36	5.34
Return ($/ha)	241.63	237.78	237.04	279.69	273.20	271.57	291.28	286.66	287.91
Difference from mean appl. ($/ha)	4.59	0.74	—	8.12	1.63	—	3.37	−1.25	—

Table 7-1. An economic analysis of information-based fertiliser programs. Autoregressive initial P distributions with a range of mean values.

	Available P distribution (kg/ha) min. = 16; med. = 25.11; mean = 25.40; max = 40			Available P distribution (kg/ha) min. = 10.24; med. = 24.21; mean = 25.40; max = 63.78			Available P distribution (kg/ha) min. = 3.45; med. = 21.91; mean = 25.40; max = 119.5		
	Exact information	Inexact information	Mean application	Exact information	Inexact information	Mean application	Exact information	Inexact information	Mean application
Total available P required (kg/ha)	7.39	7.30	7.30	8.40	7.40	7.30	10.80	7.84	7.30
% site fertilized	96.1	100	100	82.6	97.8	100	76.5	89.0	100.0
Available P wastage (kg/ha)	—	1.21	1.42	—	1.66	2.05	—	1.75	2.21
Yield wastage (kg/ha)	—	26.53	31.22	—	58.95	69.97	—	118.06	125.63
Yield gain (kg/ha)	—	21.27	24.64	—	28.25	34.48	—	28.94	36.88
Return ($/ha)	282.54	278.52	277.71	279.69	273.20	271.57	272.86	262.83	263.12
Difference from mean appl. ($/ha)	4.83	0.81	—	8.12	1.63	—	9.74	−0.29	—

Table 7-2. **An economic analysis of information-based fertiliser programs. Autoregressive initial P distributions with a range of variance values.**

variable a field, under these conditions, the greater the return for detailed information but that an optimum for inexact information is reached in the moderately variable range.

These simulations suggest that in fields with highly variable or moderate mean P fertility the returns to site-specific management will be maximised. However, as the site mean approaches the desired fertility level the mean P may be an economical estimate for constructing P fertiliser programs. In all instances it would appear that the use of inexact information offers little improvement to the mean application.

7.2.2 Site Sown to Cotton

Materials & Methods

A similar one-dimensional model has been employed to examine the effect of site-specific management of N in cotton fields with uniform yield potential. In this example, the difference in financial return obtainable when comparing fertiliser programs based on differential versus mean-of-field treatment is examined under scenarios with two mean initial soil nitrate (NO_3^-) contents and three NO_3^- variances. This design tests the interaction between mean NO_3^- levels and the variance and the influence of within-site variability on the fertiliser application program. Separate fertiliser response curves are employed for the respective means and the process of calculating the required fertiliser application has been refined to include local industry recommendations.

A theoretical 1000 ha site is again examined using the same data knowledge levels employed in the previous example, namely exact, inexact and mean. The initial NO_3^- distributions were also generated using a first-order autoregressive function of the form:

$$Ns_i = \beta\, 10^{\,s_i} \qquad (7\text{-}4)$$

where:

Ns_i	=	soil NO_3^- level (kg ha^{-1})
β	=	median regulating coefficient
s_i	=	$\alpha\, s_{i-1} + k\,\eta$
α	=	autoregressive parameter
k	=	coefficient
η	=	random sample from a normal distribution (N(0,1))

Six log–normally distributed populations comprising 1000 initial soil NO_3^- values were constructed, three based on each of two mean initial soil NO_3^- levels (16.7 & 45.3 kg/ha). These values were chosen from the minimum tillage treatments of an N fertiliser management study by Constable *et al.* (1992).

Two yield response functions based on Equation 7–5 were utilised. This is a rearrangement of a function from the minimum tillage treatments reported in Constable *et al.* (1992). The co-efficients used to discriminate the function for the two soil NO_3^- means are shown in Table 7-3.

$$y = e^{-(-a - bN + cN^2)} \qquad (7\text{-}5)$$

where:

y = yield cotton lint (kg ha^{-1})

N = N application rate (kg available N ha^{-1})

Mean soil NO3- (kg/ha)	Co-efficient *a*	Co-efficient *b*	Co-efficient *c*
16.77	6.7714035	0.0055853	0.00001367
45.24	7.53871	0.004117	–0.000011

Table 7-3. Response function co-efficients for the two mean initial soil NO_3^- levels.

Marginal analysis using the functions derived from Equation 7-5 produced optimum N applications (ONA) for maximising financial return of 190 kg N/ha for a mean site NO_3^- level of 16.77 kg/ha and 177 kg N/ha for a mean site NO_3^- level of 45.24 kg/ha. The maximum economic yield (MEY) was calculated as 1.54 t lint/ha and 2.76 t lint/ha respectively. The simulations are based on minimum tillage management of cotton grown on a Grey Cracking Clay (Vertisol) and the following economic parameters : N fertiliser @ $1.07 per kg of applied N (supplied pre-sowing as anhydrous ammonia and including associated increases in the cost of irrigation, insecticide and defoliant); cotton lint @ $1.80/kg.

In the Australian cotton industry, nitrogen application to fields with soil test NO_3^- levels below 25 mg/kg (97.5 kg/ha : 0-30cm depth ; r = 1.3) is recommended. The application rate increases at 1.845 kg N/ha for every 1 kg unit decrease in soil NO_3^-/ha levels (Daniells & Larsen 1991). Differencing the known soil NO_3^- level (KSN) at each point in a simulation from the mean soil NO_3^- level (MSN) produced a residual soil NO_3^- level. The required N application for each zone on a site simulation was then calculated using this residual and the scale suggested by Daniells & Larsen (1991) to augment the OSA level. Again, it is implicitly assumed in this experiment that the levels of soil N are uniformly available across the sites.

When other than exact initial N fertility information was used, a residual N level for each zone on the site was calculated by differencing the exact levels (RSN) with the known levels (KSN). These residuals were used to determine zones of under or over fertilisation within a site. Under-fertilised sites received a yield penalty based on the relevant response curve, and over–fertilised sites incurred excess fertiliser (ANW) costs and a yield adjustment based on the effect of increased fertility on the relevant response curve. The model can be expressed mathematically as Equation 7-6.

$$\begin{aligned}\text{Returns (\$/ha)} = {} & \text{MEY(kg/ha)} \times \text{unit crop value (\$/kg)} \\ & - \text{total applied N (kg)} \times \text{unit N value (\$/kg)} \\ & - \text{total applied N wastage (kg)} \times \text{unit N value (\$/kg)} \\ & - \text{total yield wastage (kg/ha)} \times \text{unit crop value (\$/kg)} \\ & + \text{total yield gain (kg/ha)} \times \text{unit crop value (\$/kg)}\end{aligned} \tag{7-6}$$

where:

MEY	=	variable with mean
unit crop value	=	\$1.80 /kg
unit N value	=	\$1.07/kg
total applied N	=	NAR_i

NAR_i =
(nitrogen appl. rate)

$$\sum_{i=1}^{1000} \left\{ \begin{array}{ll} \left. \begin{array}{ll} OSA_i + (\,|KSN_i - MSN_i| \times 1.845) & \text{if } KSN_i - MSN_i \leq 0, \\ OSA_i - (\,|KSN_i - MSN_i| \times 1.845) & \text{otherwise} \end{array} \right\} & \text{if } KSN_i < 97.5, \\ 0 & \text{otherwise} \end{array} \right.$$

total N wastage =

$$\sum_{i=1}^{1000} \begin{cases} \begin{cases} \begin{cases} ((RSN_i - KSN_i) \times 1.845) & \text{if } RSN_i < 97.5 \\ ((\mid KSN_i - MSN_i \mid) \times 1.845) & \text{otherwise} \end{cases} & \text{if } RSN_i > KSN_i \\ 0 & \text{otherwise} \end{cases} & \text{if } KSN_i < 97.5 \\ 0 & \text{otherwise} \end{cases}$$

total yield wastage =

$$\sum_{i=1}^{1000} \begin{cases} \begin{cases} \begin{cases} MEY - (e^{-(-a - b \times Naug1_i + c \times (Naug1_i)^2}) & \text{if } RSN_i < 97.5 \\ MEY - (e^{-(-a - b \times Naug2_i + c \times (Naug2_i)^2}) & \text{otherwise} \end{cases} & \text{if } RSN_i < KSN_i \\ 0 & \text{otherwise} \end{cases} & \text{if } KSN_i < 97.5 \\ 0 & \text{otherwise} \end{cases}$$

$$Naug1 = (OSA_i - ((KSN_i - RSN_i) \times 1.845))$$

$$Naug2 = (OSA_i - ((KSN_i - MSN_i) \times 1.845))$$

total yield gain =

$$\sum_{i=1}^{1000} \begin{cases} \begin{cases} \begin{cases} MEY - (e^{-(-a - b \times Naug3_i + c \times (Naug3_i)^2}) & \text{if } RSN_i < 97.5 \\ MEY - (e^{-(-a - b \times Naug2_i + c \times (Naug2_i)^2}) & \text{otherwise} \end{cases} & \text{if } RSN_i > KSN_i \\ 0 & \text{otherwise} \end{cases} & \text{if } KSN_i < 97.5 \\ 0 & \text{otherwise} \end{cases}$$

$$Naug3 = (OSA_i - ((RSN_i - KSN_i) \times 1.845))$$

Results & Discussion

Table 7-4 displays the results of applying the model to 3 'fields' with mean initial soil NO_3^- levels of 16.77 kg/ha but dissimilar soil NO_3^- distributions. The maximum increase in returns arose from the comparison of fertiliser application based on exact information with that using the 'mean-of-field' value, and ranged from \$3/ha for the narrower NO_3^- distribution to \$18/ha for the wider NO_3^- distribution. Fertilising using exact information produced an increase in returns over inexact information that ranged from \$2 to \$14/ha.

	Available NO_3^- distribution (kg/ha) min. = 10.78; med. = 16.56; mean = 16.77; max = 26.91			Available NO_3^- distribution (kg/ha) min. = 6.77; med. = 15.96; mean = 16.77; max = 42.14			Available NO_3^- distribution (kg/ha) min. = 3.5; med. = 14.6; mean = 16.77; max = 73.8		
	Exact information	Inexact information	Mean application	Exact information	Inexact information	Mean application	Exact information	Inexact information	Mean application
Total available NO_3^- required (kg/ha)	190	190	190	190	190	190	190	190	190
% site fertilized	100	100	100	100	100	100	100	100	100
Applied N wastage (kg/ha)	—	1.64	1.91	—	3.26	3.82	—	5.41	6.35
Yield wastage (kg/ha)	—	1.15	1.36	—	2.56	3.06	—	4.75	5.66
Yield gain (kg/ha)	—	+0.78	+0.87	—	+1.04	+1.01	—	+0.15	-0.52
Return ($/ha)	2567.55	2565.15	2564.61	2567.55	2561.34	2559.77	2567.55	2553.48	2549.65
Difference from mean appl. ($/ha)	2.94	0.54	—	7.78	1.57	—	17.90	3.83	—

Table 7-4. An economic analysis of information-based fertiliser programs. 16.77 kg/ha mean initial NO_3^- distribution with three different variances.

	Available NO_3^- distribution (kg/ha) min. = 29.09; med. = 44.70; mean = 45.24; max = 72.60			Available NO_3^- distribution (kg/ha) min. = 18.25; med. = 43.10; mean = 45.24; max = 113.70			Available NO_3^- distribution (kg/ha) min. = 9.44; med. = 39.54; mean = 45.24; max = 199.11		
	Exact information	Inexact information	Mean application	Exact information	Inexact information	Mean application	Exact information	Inexact information	Mean application
Total available NO_3^- required (kg/ha)	177	177	177	176.7	177	177	175.7	177	177
% site fertilized	100	100	100	99.6	100	100	96.0	100	100
Applied N wastage (kg/ha)	—	4.42	5.15	—	9.04	10.56	—	15.90	18.42
Yield wastage (kg/ha)	—	4.42	5.41	—	11.61	14.29	—	24.53	29.62
Yield gain (kg/ha)	—	+0.60	+0.23	—	-5.60	-8.79	—	-28.94	-40.01
Return ($/ha)	4777.67	4766.07	4762.83	4777.96	4737.32	4725.11	4779.07	4665.81	4634.03
Difference from mean appl. ($/ha)	14.84	3.24	—	52.85	12.21	—	145.04	31.78	—

Table 7-5. **An economic analysis of information-based fertiliser programs.**
45.24 kg/ha mean initial NO_3^- distribution with three different variances.

The savings afforded by employing inexact information compared to the 'mean-of-field' value ranged from \$0.5/ha to \$4/ha.

Table 7-5 displays the results of applying the model to 3 'fields' with equal mean initial soil NO_3^- levels of 45.24 kg/ha but, as above, differing variances producing dissimilar soil NO3- distributions. The maximum benefit, obtained from the comparison of fertiliser application based on exact information with that using the 'mean-of-field' value, ranged from \$15/ha to \$145/ha. A fertiliser program using exact information produced an increase in returns over the use of inexact information that ranged from \$12/ha for the narrower NO_3^- distribution to \$113/ha for the wider NO_3^- distribution. The financial benefit of including inexact information compared to the 'mean-of-field' value ranged from \$3ha to \$32/ha.

The results suggest that in a field with very low initial NO_3^- fertility or a small initial NO_3^- variance, the site mean may remain a reasonably economical estimate for constructing N fertiliser programs when compared with inexact models of the site NO_3^- levels. As the initial NO_3^- fertility, or the inherent NO_3^- variability increases, the improvement in returns offered by such inexact models in a N fertiliser application regime become more significant. With the exception of sites with very low, evenly distributed initial NO_3^- levels, the benefits of accurately determining the small scale spatial variation in initial NO_3^- levels proved quite substantial.

These simple economic models provide a basic insight into the economic effects of a site-specific management program in a field where the yield potential is perceived to be uniform. The validity of such an assumption is debatable, however it is continually accepted in constructing traditional fertiliser application programs. The inclusion of a more complex, and arguably more realistic scenario is warranted in an effort to more thoroughly examine the consequences of site-specific management.

7.3 DIVERSE YIELD POTENTIAL ACROSS A SITE

Usually, the inherent diversity in soil will extend beyond the initial levels of soil nutrients and in many instances spatial variation in the soil may arise from substantial compositional changes that affect the total yield potential of the soil regardless of management intervention. Such soil variability underlies the natural variation in vegetative growth and yield observed in most native ecosystems. Incorporating this natural variation in a crop management scheme would require a knowledge of the variation in yield response across a site.

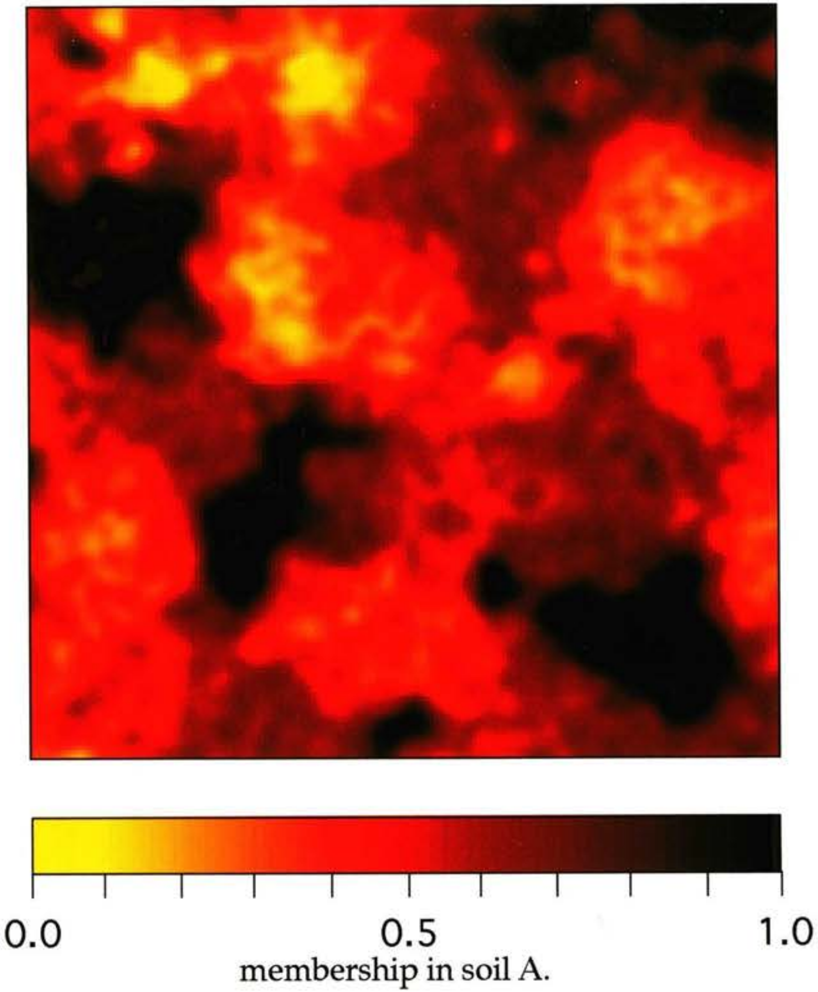


Figure 7-2. Site map of membership in soil A.

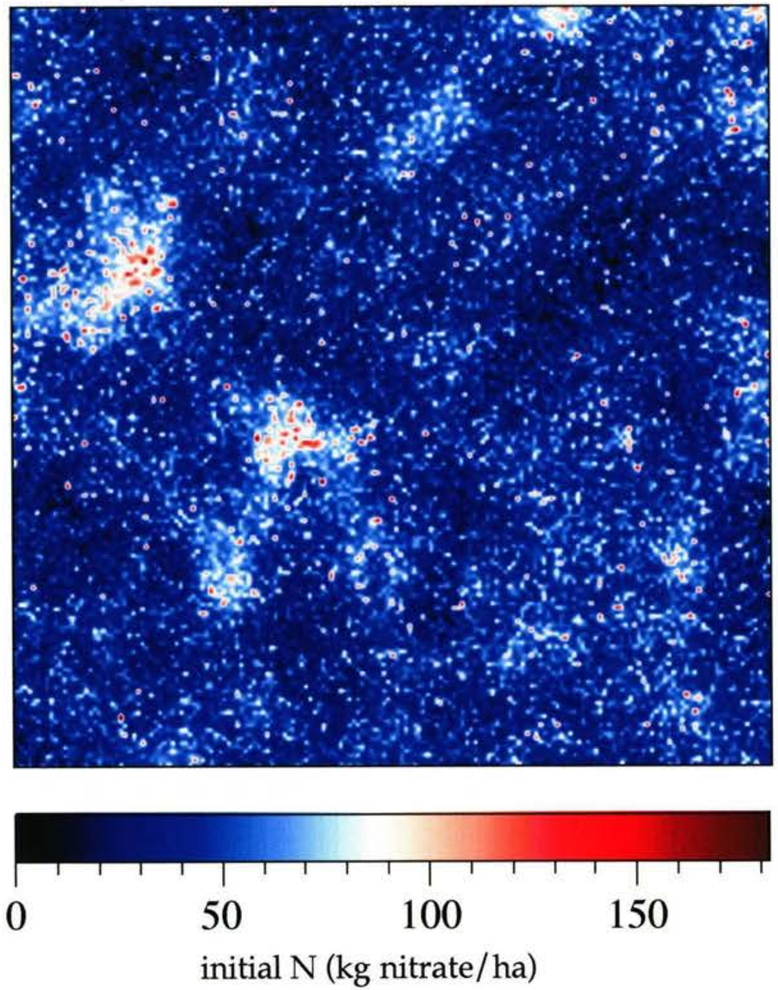


Figure 7-3. Site map of initial soil nitrate.

Here, the economic and environmental implications of varying yield potential on a nitrogenous fertiliser regime is examined. Comparisons are made for two consecutive seasons on simulated cotton fields that display spatial variability in initial soil NO_3^- concentrations. The fields are also characterised by continuous spatial variation in soil type, which forms the basis for calculating the spatial variation in yield response.

7.3.1 Cotton - Season 1

Materials & Methods

For this more complex management scheme, the yield potential at 30625 individual points across the fields were manipulated by assuming each point to be a mix of two soil types (designated A & B) that possess differing yield response functions. A random field describing the degree of membership in soil A at each point was generated (Figure 7-2). Membership at each point in soil B is the complement of the membership at each point in soil A i.e., the membership in A and B at each point must sum to 1.

Initial NO_3^- levels at each point were obtained from a log-normal distribution with a mean of 45.24 kg/ha (based on a mean field level reported by Constable *et al.* 1992) and a standard deviation of 23 kg/ha. The assumption that this standard deviation represents the variation in a 'real' field is supported by co-efficient of variation (CV) figures obtained from field sampling by the authors (CV = 50%) and data reported by Rochester *et al.* (1991) (CV range of 14% to 98%).

A map of the initial NO_3^- levels is shown as Figure 7-3. A correlation of 0.3 between initial NO_3^- and membership in soil A is included on the assumption that soil with greater yield potential would posses more organic matter and therefore retain higher reserves of mineralisable N and thus NO_3^-.

Yield response functions for Soil A (Figure 7-4) and B (Figure 7-5) were generated using quadratic approximations of those available in Constable *et al.* (1992). The form of the yield response function is dependent on the initial soil NO_3^- concentration up to an initial concentration of 97.5 kg/ha, the limit where N fertiliser application is assumed to be non-beneficial to cotton production (Daniells & Larsen 1991).

Combining the functions for a particular soil produces a two-dimensional yield response surface function that encompasses the range of initial NO_3^- and applied N parameters that were used in its construction i.e. initial NO_3^- : 0 to 97.5 kg/ha ; applied N : 0 to 300 kg/ha. These are shown for soil A as Figure 7-6 and soil B as Figure 7-7.

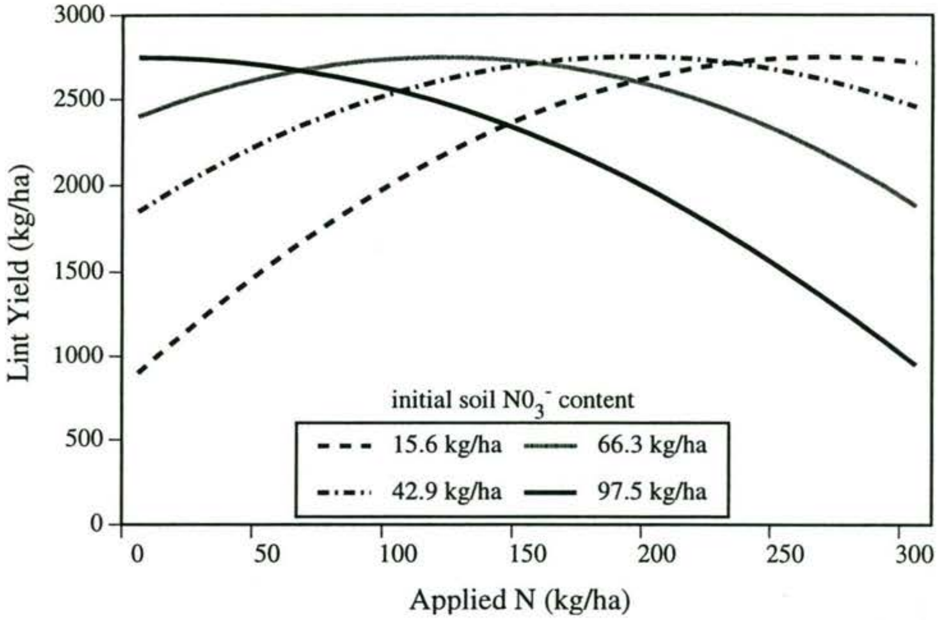


Figure 7-4. Soil A yield response functions

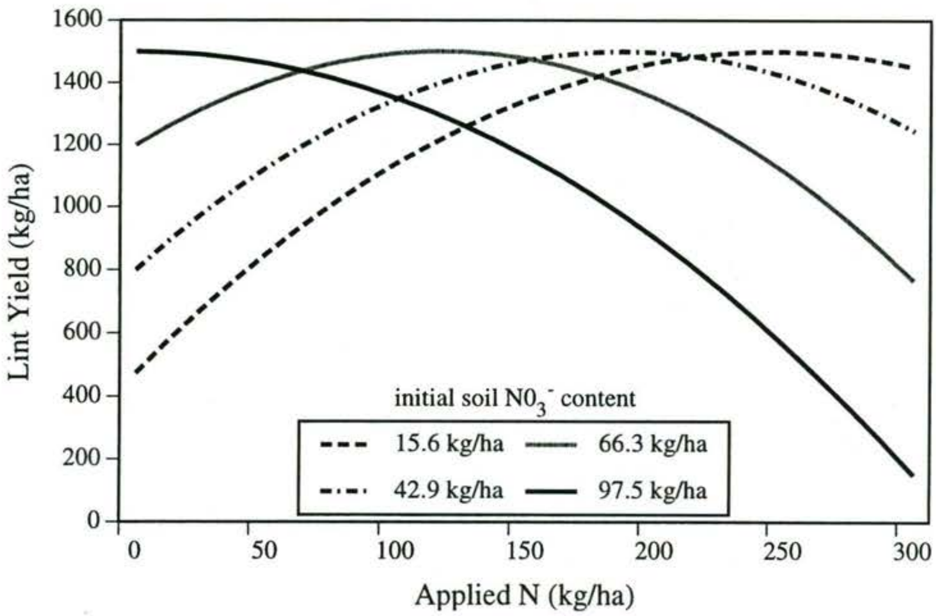


Figure 7-5. Soil B yield response functions

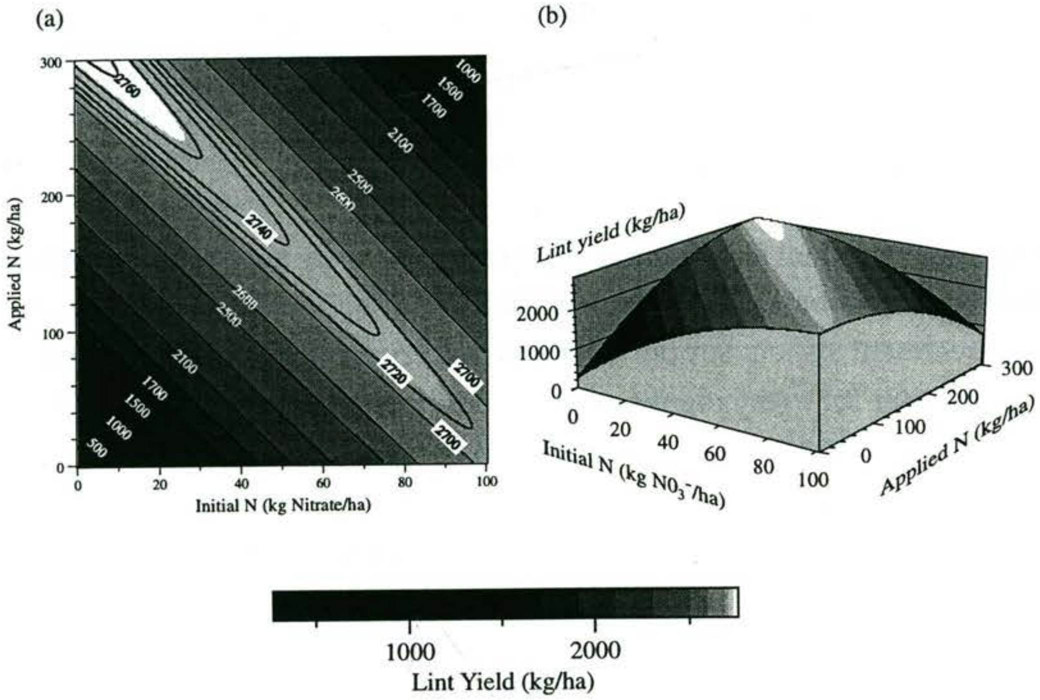


Figure 7-6. Soil A: yield response surface as a function of initial N and applied N. Shown in contour plan (a) and perspective (b)

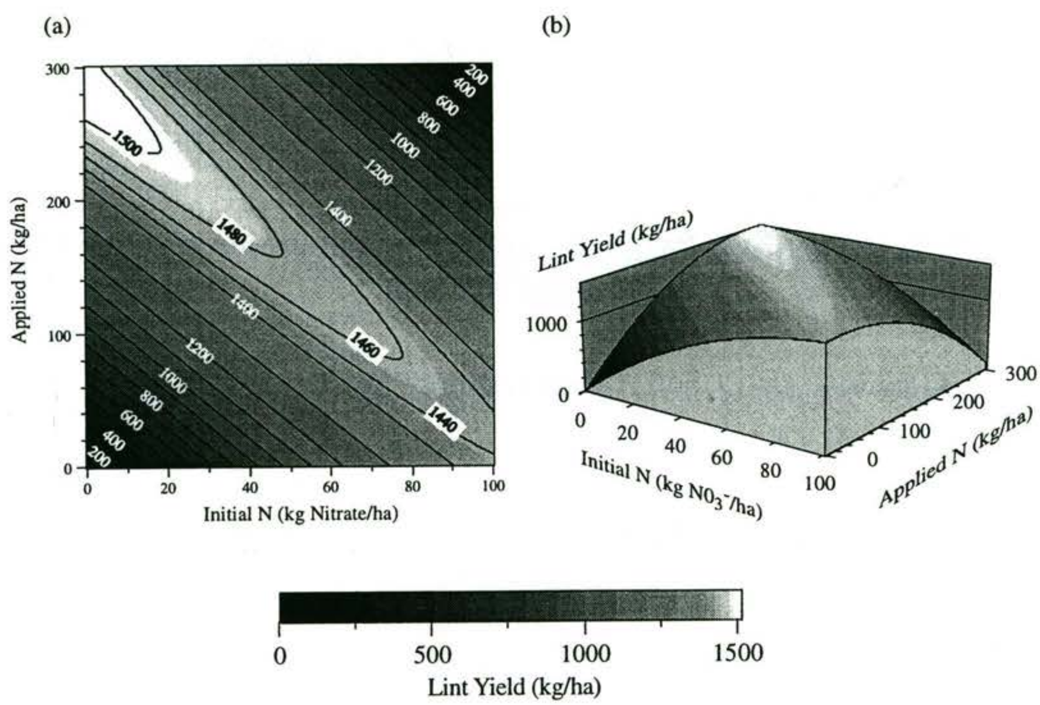


Figure 7-7. Soil B: yield response surface as a function of initial N and applied N. Shown in contour plan (a) and perspective (b).

Using this information, an individual yield response function for applied N can be constructed for each point on the site. This function can be used to determine the yield at each point for a given amount of applied N or, conversely, determine the amount of applied N required to achieve a yield goal. Here, the yield goal is again defined by the economic optimum point on each respective yield response function.

In this study, conventional fertiliser management (where the adoption of a fixed quantity application regime is based on mean-of-field initial NO_3^- levels) is compared with a differential treatment system supported by the determination of the economic optimum quantity of fertiliser for every identified point on the site. For the mean-of field case, the mean initial NO_3^- level of 45.3 kg/ha is assumed to represent the value at each point, and each point is characterised as having a membership of 1 to the soil A class. This results in a single yield response curve and the calculation of a single fertiliser application level for the entire site.

In the differential treatment scenario, individual initial NO_3^- levels are known for each point and each point is characterised by its membership to both soil A and B. Equations 7-7 and 7-8 show the generalised functions describing yield response to initial NO_3^- and applied N for soil A and soil B respectively.

$$Y_A(N_i, N_{app}) = c_A + d_A.N_i + e_A.N_{app} + f_A.N_i^2 + g_A.N_{app}^2 + h_A.N_i.N_{app} \tag{7-7}$$

where:

$Y_A(N_i, N_{app})$ = Soil A yield response as a function of Initial NO_3^- (*Ni*) and Applied N (*Napp*)

$c_A, d_A, e_A, f_A, g_A, h_A$ = Soil A yield response function co-efficients

$$Y_B(N_i, N_{app}) = c_B + d_B.N_i + e_B.N_{app} + f_B.N_i^2 + g_B.N_{app}^2 + h_B.N_i.N_{app} \tag{7-8}$$

where:

$Y_B(N_i, N_{app})$ = Soil B yield response as a function of Initial NO_3^- (*Ni*) and Applied N (*Napp*)

$c_B, d_B, e_B, f_B, g_B, h_B$ = Soil B yield response function co-efficients

Values for the co-efficients as used in this study are given in Table 7-6.

Co-efficient	c_A	d_A	e_A	f_A	g_A	h_A
Value	261.62	47.04	15.59	-0.225	-0.024	-0.148
Co-efficient	c_B	d_B	e_B	f_B	g_B	h_B
Value	16.10	26.71	10.44	-0.125	-0.018	-0.096

Table 7-6. Co-efficient values for soil yield response functions.

The yield response function applicable to each point is then constructed using a linear mixing procedure. Equation 7-9 is the generalised form of this function, where the membership values weight the response function co-efficients for soil A and B.

$$\begin{aligned} Y(N_i, N_{app}, m_A) &\\ = (c_B + (c_A - c_B).m_A) + (d_B + (d_A - d_B).m_A).N_i &\\ + (e_B + (e_A - e_B).m_A).N_{app} + (f_B + (f_A - f_B).m_A).N_i^2 &\\ + (g_B + (g_A - g_B).m_A).N_{app}^2 + (h_B + (h_A - h_B).m_A).N_i.N_{app} & \end{aligned} \tag{7-9}$$

where:

$Y(N_i, N_{app}, m_A)$ = Soil yield response as a function of Initial NO_3^- (Ni), Applied N ($Napp$) and Membership in soil A (m_A)

From this model the economic optimum N application can be calculated for each individual point. For example, a point in the study site with an initial NO_3^- level of 39.53 kg/ha and a membership in Soil A of 0.593, has a yield response function that falls between the functions characterising the yield response for soil at this initial NO_3^- level and with full membership of 1 in soil A or B (refer Figure 7-8).

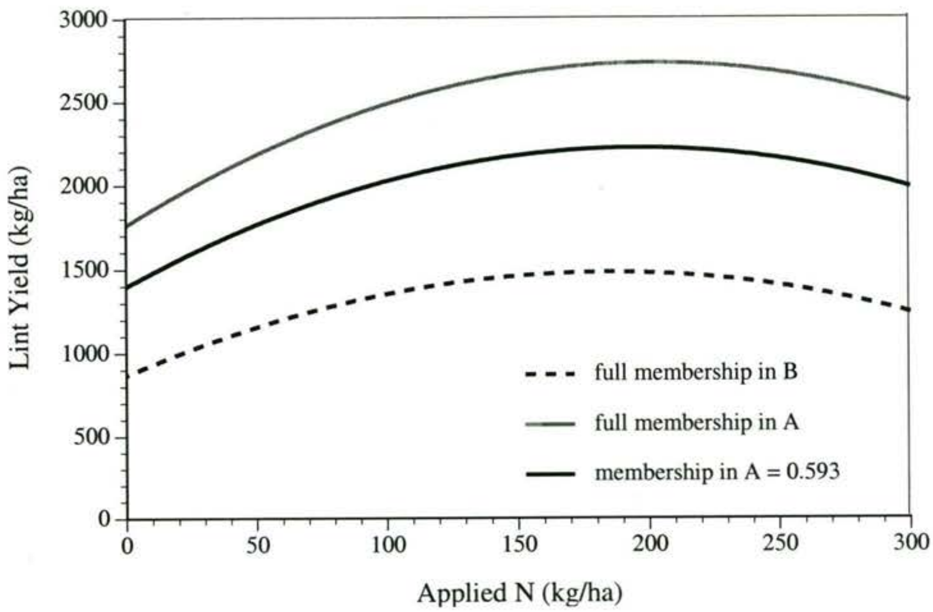


Figure 7-8. Yield response functions for a point with an initial NO_3^- level of 39.53 kg/ha and soil memberships of 0.593 and 1 in soil A; 1 in soil B.

Results & Discussion

The final yield achieved in both these scenarios is calculated from the yield response functions determined using the actual membership in both soil A and B at each point. This mimics the effect of natural soil variation encountered even if a mean initial soil NO_3^- test as been used to determine a uniform N fertiliser application. Table 7-7 details the production differences in running the two management systems on this simulated site.

	N Applied (uniform)	N Applied (differential)	Yield (uniform)	Yield (differential)
Mean (kg/ha)	171	165.0	2114.1	2202.3
Standard Deviation		60.1	321.8	266.4
CV (%)		36.4	15.2	12.1

Table 7-7. Mean N application and lint yield for uniform and differential fertiliser management.

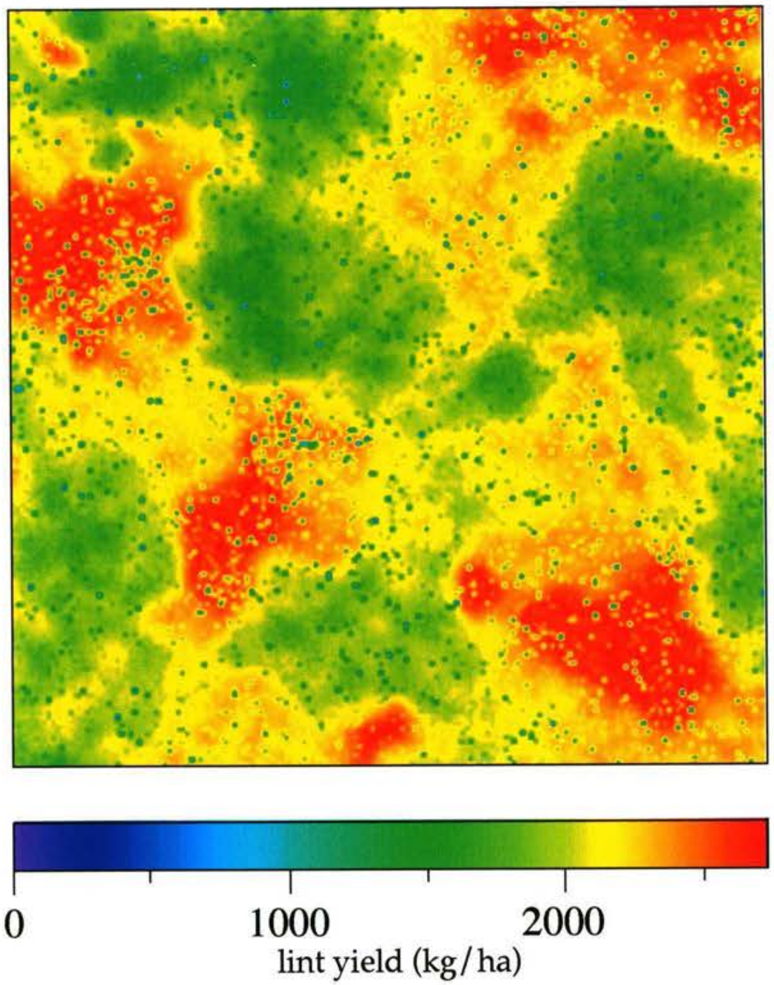


Figure 7-9. Site map of lint yield following uniform fertiliser management.

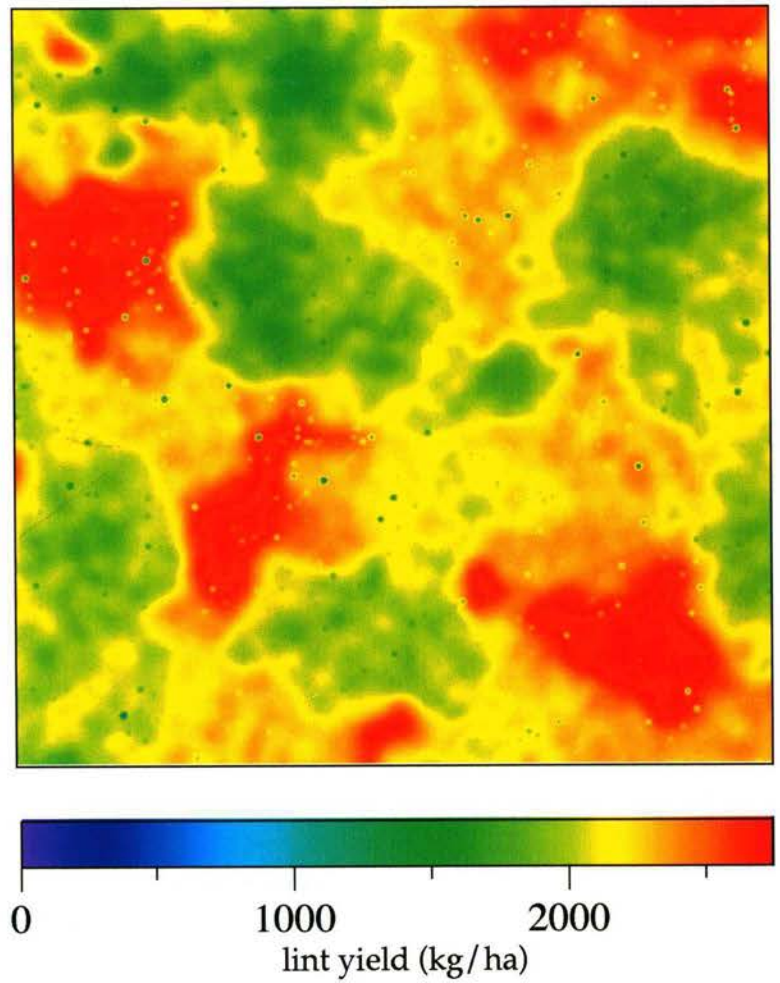


Figure 7-10. Site map of lint yield following differential fertiliser management.

Differential management has utilised a 6 kg/ha lower mean N application to attain an 88 kg/ha increase in lint yield. The lower variation in lint yield from differential treatment compared with uniform treatment can be easily seen in the respective yield maps displayed in Figures 7-9 and 7-10. In Figure 7-9, the discrete dark spots, indicating lower yield, are more numerous and indicate that many zones of over- or under-fertilisation are occurring following uniform treatment. Following differential treatment (Figure 7-10), considerably less 'noise' is evident in the yield pattern and the small number of discrete dark spots are the result of areas where the initial NO_3^- level was above the 97.5 kg/ha mark assumed to be limiting.

Table 7-8 details the financial differences that may be extrapolated from operating the two management systems on this simulated site. The higher mean yield and lower mean N application associated with the differential management has resulted in a positive gross profit differential of A$165/ha. This figure does not account for the increased costs of implementing a differential management system, however equally, the environmental benefits and risk reductions remain unaccounted. An insight into the impact of such a management system on environmental risk reduction can be gleaned from Table 7-9. It documents that 44% of the points on the site have been over-fertilised by the uniform treatment when compared with the optimum determined using differential treatment.

Type of Application	Uniform	Differential
Yield (kg/ha)	2114	2202
N Application (kg/ha)	171	165
Gross Profit ($A/ha)	3622	3787
Difference ($A/ha)		+ 165

Table 7-8. Financial comparison between differential and uniform N application.

	Number	% of Total Sites	% of Total Applied N	Mean (kg/ha)	Standard Deviation
Overfertilised sites	13,458	44	16	59.8	50.1

Table 7-9. Over-fertilisation following uniform treatment.

This information is most easily displayed as a site map (Figure 7-11). The map reveals many instances where between 50 kg/ha and 171 kg/ha of unnecessary N fertiliser has been applied. These indicate areas of potentially excessive denitrification emissions, nitrate leaching and general resource waste. In the future, it is likely that such environmental effects will be penalised financially.

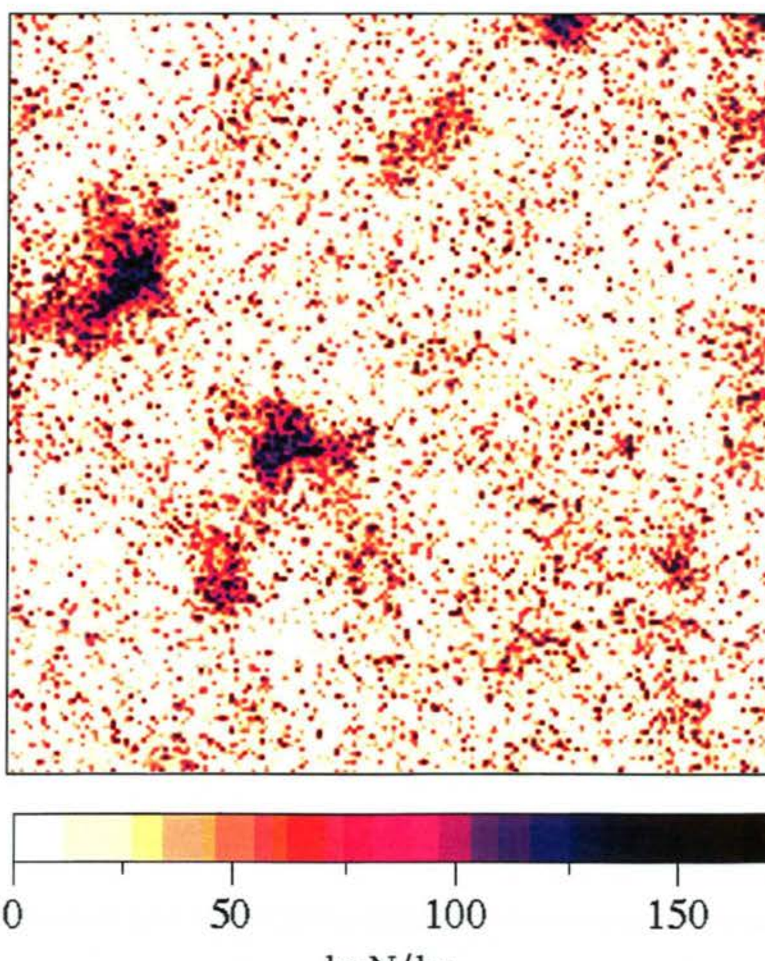


Figure 7-11. Zones of over-fertilisation at the simulated site

7.3.2 Cotton - Season 2

Materials & Methods

Appraising the impact of fertiliser management for the next season requires that an N nutrient budget be estimated for the previous season and the intervening fallow to establish the initial concentration and spatial distribution of N for season 2.

Separate N budgets were calculated at each point for the 'uniform' and 'differential' treatments in season 1 to facilitate monitoring the different treatments through season 2. These budgets were constructed using a modified balance sheet approach (Neeteson, 1990) by estimating the N uptake as a function of lint yield and partitioning this total into contributions from applied fertiliser, indigenous soil N and N mineralised over the growing season as per Equation 7-10.

$$N_{UP} = N_{FERT} + N_{SOIL} + N_{MIN} \tag{7-10}$$

where:

N_{UP} = Total N uptake by crop (at each point)
N_{FERT} = N contribution from applied fertiliser
N_{SOIL} = N contribution from initial soil N
N_{MIN} = N mineralisation during the growing season

The N uptake at each point was determined using functions from Constable *et al.* (1992) which pertain to the trial data used in year 1. Separate functions are shown for soil A (Equation 7-11) and B (Equation 7-12). The uptake at each point being calculated as a composite of these functions weighted by the relevant soil membership value.

$$N_{UP} = 90.8 + 0.8855.N_{app} - 0.002574.N_{app}^2 \tag{7-11}$$

$$N_{UP} = 51.7 + 0.8148.N_{app} - 0.00219.N_{app}^2 \tag{7-12}$$

where:

$Napp$ = Total N fertiliser applied

Of this total N uptake, the N actually supplied from fertiliser (N_{FERT}) is assumed to be 50% of the amount applied at each point. This figure is based on a mean recovery of 52% from pre-sowing, hill applied anhydrous ammonia (Constable et al., 1992). The contributions to the total N uptake originating from the initial soil N concentration (N_{SOIL}) and mineralisation (N_{MIN}) during the growing season constitute the balance and are calculated as follows:

$$N_{SOIL} = (N_{UP} - N_{FERT}) \times 0.5 \tag{7-13}$$

$$N_{MIN} = (N_{UP} - N_{FERT}) \times 0.5 \tag{7-14}$$

The site maps of soil NO_3^- for season 2 can then be constructed as a summation of unused soil N from season 1 ($N_{SOIL\ RESID}$), a residual fertiliser factor based on the quantity applied in season 1 ($N_{FERT\ RESID}$), and a quantity of mineralised N achieved over the 6 month fallow ($N_{POST\ MIN}$).

$$N_{INIT\ 2} = N_{SOIL\ RESID} + N_{FERT\ RESID} + N_{POST\ MIN} \tag{7-15}$$

where:

$$N_{SOIL\ RESID} = N_{INIT\ 1} - N_{SOIL}$$

$$N_{FERT\ RESID} = (0.12875 - 0.0002708 \times Napp) \times Napp$$

$$N_{POST\ MIN} = N_{SOIL} \times 0.5$$

The function that estimates $N_{FERT\ RESID}$ was constructed from data on the N contribution from rotational cropping to cotton production and soil nitrate on a Vertisol (Standley et al., 1988). It provides for a maximum 12.8% residual, decreasing as the quantity of fertiliser applied increases.

The budget model produced an increase in mean soil NO_3^- concentrations for both treatments (Table 7-10), however as expected, the 'uniform' treatment in Season 1 has contributed a larger residual to Season 2. Table 7-10 also shows a reduction in soil NO_3^- distribution variance that is more pronounced by the accurate targeting of fertiliser to N requirements from the 'differential' treatment in Season 1.

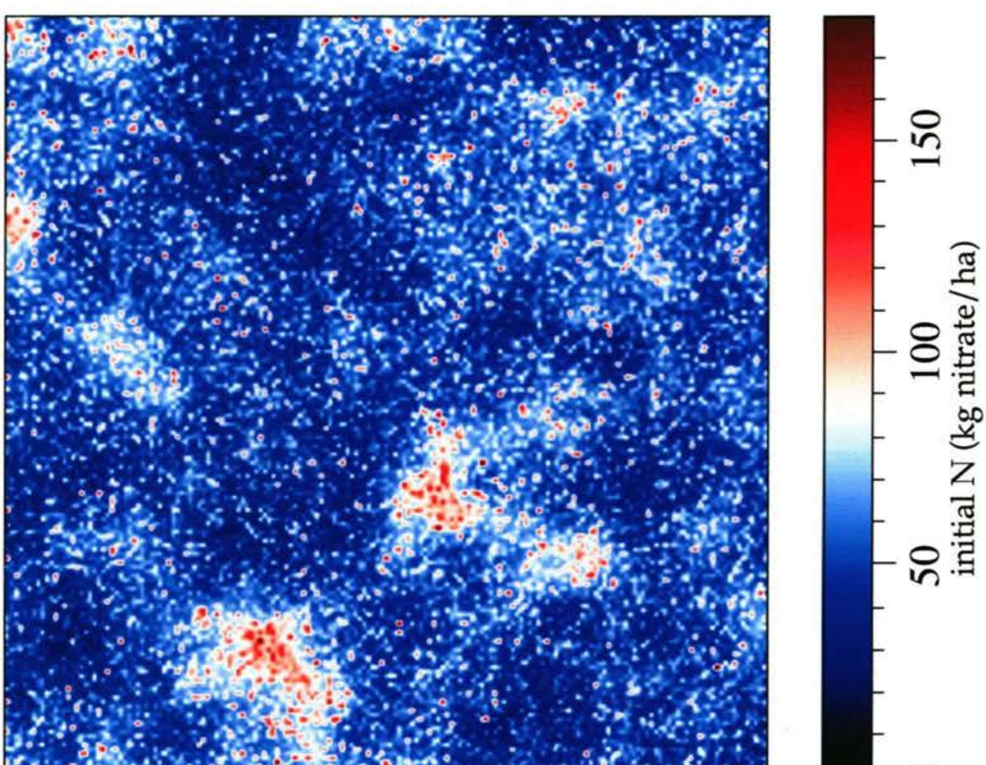


Figure 7-12. Season 2 site map of initial soil nitrate following uniform fertiliser application in Season 1.

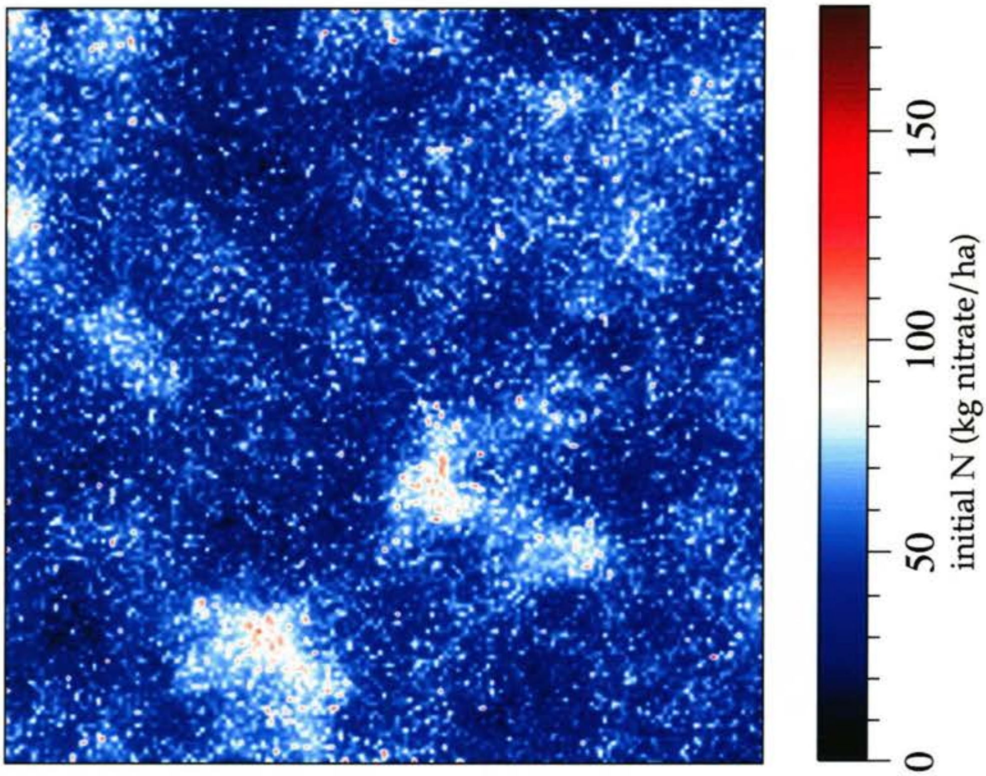


Figure 7-13. Season 2 site map of initial soil nitrate following differential fertiliser application in Season 1.

NO_3^- Distribution	Season 1	Season 2 (post uniform)	Season 2 (post differential)
Mean (kg/ha)	45.2	56.9	50.8
Standard Deviation	23.1	23.3	19.6
CV (%)	51.0	40.9	38.6

Table 7-10. Soil nitrate concentrations prior to Season 1 and prior to Season 2.

The spatial distribution of initial NO_3^- levels for the two scenarios leading into Season 2 are shown in Figure 7-12 and Figure 7-13. Soil-type membership and yield response curves from Season 1 are maintained at each point in Season 2, while the changes to initial NO_3^- concentrations for the two treatments require the calculation of new N application rates to achieve the economic optimum yield. Lint yield obtained by the application of each treatment in Season 2 is determined using the procedures previously outlined.

Results & Discussion

Table 7-11 documents the calculated mean N application rates and yield for the two treatments. The lint yield under uniform management of fertiliser application continues to be lower than the economic optimum yield. The differences in yield obtained over each field are displayed in Figures 7-14 and 7-15. Uniform treatment in Season 2 (Figure 7-14) continues to produce zones of miscalculated fertiliser application that appear as 'noise' in the yield map. In Figure 7-15, the discrete dark spots, indicating lower than optimum yield (points where the initial NO_3^- concentration was above the 97.5 kg/ha cutoff assumed to be limiting to growth) have been reduced from the amount in Season 1 by continued differential treatment.

Table 7-12 presents the financial statistics for the two management systems on the respective sites. Mean yield has increased marginally (0.2kg/ha) for the differential treatment in Season 2 as a result of differential treatment in Season 1 reducing the number of sites with initially excessive NO_3^- levels. A comparative gross profit of $162/ha is predicted for continuing the differential treatment into Season 2 as compared with on-going treatment based on the field mean.

	N Applied (uniform)	N Applied (differential)	Yield (uniform)	Yield (differential)
Mean (kg/ha)	135.5	147.6	2105.3	2202.5
Standard Deviation		53.7	321.3	263.2
CV (%)		36.4	15.3	12.0

Table 7-11. Mean N application and lint yield for uniform and differential fertiliser management (season 2).

Type of Application	Uniform	Differential
Yield (kg/ha)	2105	2203
N Application (kg/ha)	135	148
Gross Profit ($A/ha)	3645	3807
Difference ($A/ha)		+ 162

Table 7-12. Financial comparison between differential and uniform N application (season 2).

Mean yield for the uniform treatment has been reduced by 9kg/ha from that achieved in Season 1 as a result of greater misallocation of the total fertiliser applied. Table 7-13 compares the fertiliser applied to the field under uniform management in Season 2 with the fertiliser that would have been applied if that field had been treated differentially in Season 2. A comparison of this sort between the two fields in Season 2 would be misleading because their initial conditions vary at the beginning of Season 2. By contrasting Table 7-13 with Table 7-8 the total number of sites fertilised has slightly decreased from Season 1, however the percentage of total fertiliser over-applied has risen from 16% to 18%. The amount under-applied also increases proportionally. Figure 7-16 graphically represents zones of the field that have received more fertiliser than required for the economic optimum yield on the uniform site in Season 2.

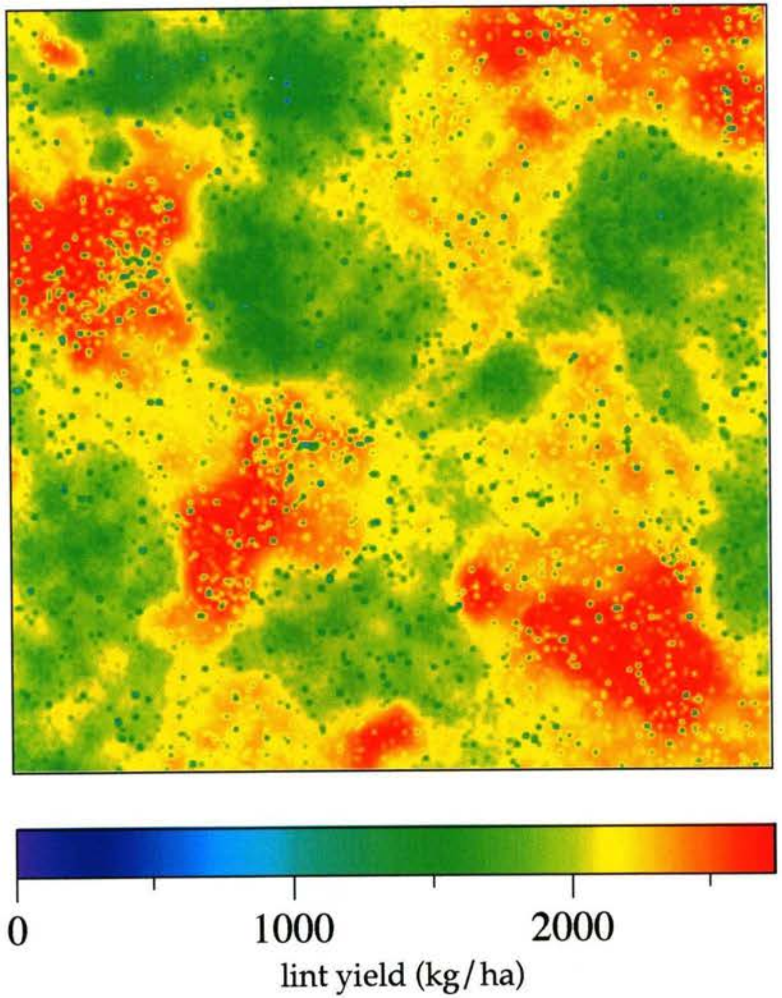


Figure 7-14. Season 2 site map of lint yield following uniform fertiliser application in Season 1.

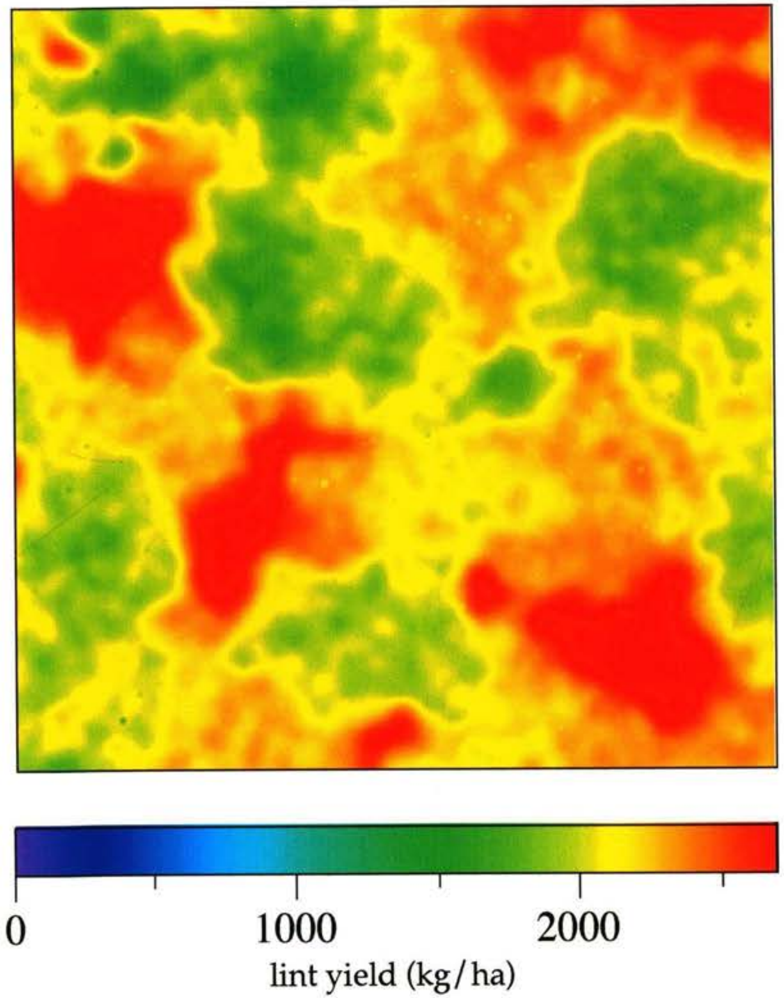


Figure 7-15. Season 2 site map of lint yield following differential fertiliser application in Season 1.

	Number	% of Total Sites	% of Total Applied N	Mean (kg/ha)	Standard Deviation
Overfertilised sites	13,308	43	18	56.9	50.1

Table 7-13. Over-fertilisation following uniform treatment in season 2. (A comparison with optimal application rates calculated for the same site in season 2).

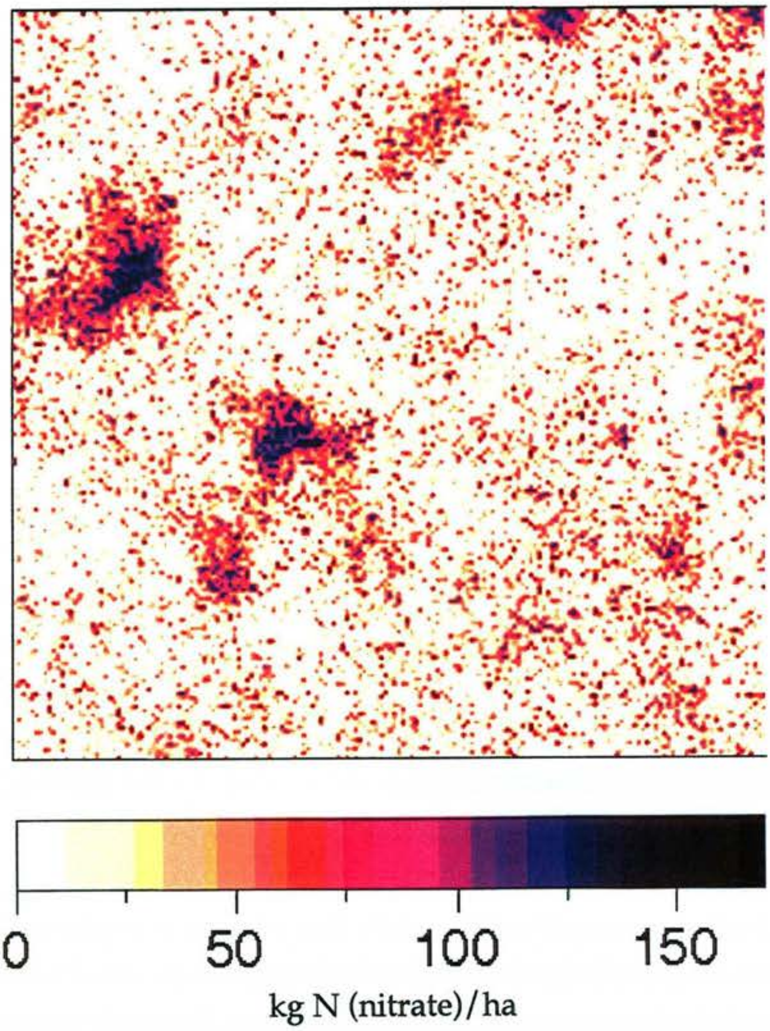


Figure 7-16. Zones of over-fertilisation at the uniform treatment site in season 2.

7.4 GENERAL DISCUSSION

The benefits of differentially treating variability in field attributes that may be considered influential to crop growth will obviously depend on the degree of variability exhibited over the area of interest. It could further be hypothesised that the divergence of the field mean of an attribute from the desired field level of that attribute may also play a role in quantifying the benefits. These simulations have provided some insight into such questions.

From the uniform yield potential examples it is possible to generalise that as the variance within an area increases, the percentage of input wastage and the adverse yield impact from under-application of the input both rise. These negative production indicators also increase as the field mean of an attribute approaches the desired field level. The actual percentage increases will be specific to the simulation conditions as will the financial returns attributed to each scenario. This is the nature of site-specific management. Nevertheless, it would appear that the returns will also follow this upward trend until a point where the field mean is very close to the desired level and then the field mean is probably a reasonable estimate on which to base a fertiliser program (refer Table 7-1).

Assuming a uniform yield potential at almost any spatial scale accommodates a broad, simplistic analysis of the trend effects of attribute variance and mean on differential treatment. The more realistic scenario of diverse yield potential, while requiring greater complexity in the model, should provide sound estimates of financial differences between the treatments. Differential treatment of N fertiliser application to cotton, under the conditions simulated here, offers an increase in returns over uniform fertiliser management of approximately $160/ha for two successive years. This figure is higher than the $145/ ha calculated for a similar field restrained to uniform yield potential (refer Table 7-5). The difference arising from the correct accounting for diversity in yield potential even when a uniform application is made. These estimates do not include the increased cost of operating a differential system which will be discussed later.

The discussion of either simulation procedure has also not considered that the traditional approach to estimating the field mean of an attribute is to use a very small number of samples. These simulations compare differential treatment with an estimate of the mean based on all the samples in each site. The disparities in financial returns would be far greater if a random sample of 50 points was used to estimate the mean. These simulations are however not attempting to calculate maximum benefit but aimed at providing conservative financial estimates for use in the process of determining the viability of site-specific management.

A framework for such a financial evaluation procedure has been described by Lowenberg-DeBoer & Swinton (1995). They outline a stepwise process of (i) partial budget analysis; (ii) inclusion of annualised capital costs; (iii) inclusion of net revenue risk assessment; (iv) inclusion of finance and management skill costs. After both steps (i) and (ii), if the returns outweigh the costs, an environmental benefit estimate may be included.

Determining the true cost of a differential treatment regime will therefore be complex and partially subjective. While the costs of sampling, analysis and chemical application may be identified, the costs allocated to gaining the required understanding of concepts and equipment is less tangible. Furthermore, the information compiled for a differential treatment regime will be more than likely applicable to decision making processes in future years, so the yearly costs may be reduced through annualisation.

Financial returns information provided by the simulations presented here would represent the major portion of a partial budget analysis. The only additional variable cost that must be included is the additional cost associated with sampling and application for differential treatment. The financial literature published on this subject to date has been based on the US environment and agricultural markets. Overall, the cost of performing differential treatment has apparently declined slightly over the past 3 years.

Originally the costs were typified by the report of Wollenhaupt & Buchholz (1993) where a conventional treatment cost of $A 10.75/ha was compared with a differential application cost that varied between $A 24/ha to $A 33/ha, showing a difference of between $A 13/ha and $A 23/ha. In a later study, Lowenberg-De Boer & Swinton (1995) calculate the annualised cost (over 4 years) of differential application at $A 23.50/ha which, when using the same conventional application costs results in a conservative difference estimate of $A13/ha which is in the lower range of that quoted by Wollenhaupt & Buchholz (1993). Initially, the cost in Australia is likely to be higher due to greater soil analysis charges and technology costs. The figures outlined above may be used as a rough forecast for future contract application, but with a conservative tripling of the cost the partial budget would appear strongly positive for cotton in these simulations.

Annualised capital costs will be dependent on the technology utilised, farm size and the period of effective utilisation of the capital. Commercial information available in 1997 places the costs of yield monitoring and mapping equipment and software in Australia between $A 9,000 and $A 20,000 depending on product choice. Variable-rate application equipment is more difficult to cost at present, Lowenberg-De Boer & Swinton (1995) suggest the use of a 3-year capital obsolescence strategy, which would give the maximum annualised cost for the monitoring and mapping at $A 7,000. This cost would need to be apportioned on a per hectare basis to all farm operations that utilise the equipment or information gathered.

Lowenberg-De Boer & Swinton (1995) also suggest there is no indication that site-specific management will increase the variability in net returns to production leaving premature obsolescence as the major risk to investment. This factor can only be included as a subjective assessment. The cost of commercial finance can be simply factored using interest rate calculations as can any extra labour costs deemed necessary to oversee and operate the system. Both these costs will be farm dependent.

Environmental impact may be divided into human health or ecotoxic effects (Gustafson, 1993). However, in either case, the quantification of environmental benefits derived from site-specific management does not easily fit the standard accounting paradigm. The allocation of monetary value to environmental gains is a fledgling science. Straightforward instances where payments may be made for positive actions or fines imposed for negative actions can be dealt with traditional accounting. At present Australia has no such remunerative or punitive legislation in place although Europe (Blackmore et al., 1995) and the United States of America (Castelnuovo, 1995) are moving in this direction.

More difficult to assess are the societal or non-monetary gains such as overall environmental welfare, production sustainability and non-contamination of foodstuffs that are gaining importance in the community. A number of studies have examined the willingness of agricultural producers to include a personal cost to reduce these risks (Higley & Wintersteen, 1992; Beach & Carlson, 1993) and customers to bear a premium adjustment to retail costs (van Ravenswaay, 1995) but there has only been conjecture that site-specific management will provide such benefits.

However, the simulations based on diverse yield potential undertaken here dramatically highlight the wastage that may be associated with uniform management (Figures 7-11 & 7-16). The extrapolation from this misplacement of N to some environmental impact through denitrification, leaching or future uptake is not difficult to make. An economic adjustment based on product premiums or elimination of environmental management charges may be reasonably included in the future.

Given such complexity in the cost/analysis process, the studies of profitability based on production physicalities have been few and as yet incomprehensive. Wollenhaupt & Buchholz (1993) examined results from four states in the USA where the differential treatment of fields were based on soil unit yield potential or whole field grid sample analysis. These fields were sown to wheat, barley or corn and showed no major reduction in yield or profits when compared to uniform treatment but only a small number displayed significant improvements under differential nutrient management. The main contributors to these ambivalent results were an inability to accurately delineate soil unit boundaries and a difficulty in calculating the appropriate yield goals for soil units or whole fields for the upcoming growing season.

DeBoer & Swinton (1995) summarise the profitability results from 11 variable rate fertiliser trials (N and/or P and/or K) and reported that five studies displayed non-profitability, four produced an inconclusive evaluation and two suggested potential profitability. The authors conclude that the treatment of sampling and application costs, along with the degree of yield gain attainable, governs the financial outcome of all the trials reviewed.

The salient points from these studies are that fertiliser response varies within a field (possibly at a soil unit scale), that accurately calculating yield goals will ultimately depend on environmental prediction for the growing season and the amortisation of costs will be important in determining the profitability or otherwise of site-specific management.

7.5 CONCLUDING REMARKS

It is important to acknowledge that the results presented here are the culmination of field simulations. They are only a guide to the degree of financial benefit, in terms of increased yield and targeted fertiliser use, that may be obtained from differential fertiliser treatment. The cost of additional equipment and operating expenses has not been taken into account, however, neither have the environmental benefits and risk reductions.

Intuitively, as the financial difference increases between the unit cost of a field operation (e.g. fertiliser application) and the unit value of a commodity, the per-unit savings afforded by differential treatment will decrease. It is, however, difficult to conceive a situation where accurate knowledge of the variability in an influential soil attribute would not produce some degree of financial and environmental benefits under differential management.

More importantly, the value of these simulations can be found not so much in the output values but the processes that are used to achieve the estimates. Decision support systems will require models to substantiate the actions that variability in soil condition will demand. The uniform yield potential simulations show that such an assumption will be unworkable in most cropping situations. The ideal of promoting a uniform yield across a field is therefore also shown to be unworkable. The simulations based on diverse yield potential have shown, as a mimic of a more realistic natural system, that the potential for site-specific management may be enormous and its impact will increase in crops of higher inputs and greater market value.

Future decision support systems must acknowledge that fields generally comprise a diverse range of yield potentials and the success of a site-specific soil management program will depend on the accuracy with which the variation in significant soil parameters are monitored and treated to suit this diversity of potentials. The processes developed in the diverse yield potential simulation offer an improvement to the detail available for fertiliser application decisions and may increase the probability and profitability of more site-specific management programs.

SECTION V

GENERAL DISCUSSION, CONCLUSIONS AND FUTURE WORK

CHAPTER 8

CHAPTER 8

General Discussion, Conclusions & Future Work

While comprehensive discussion has been provided within the relevant chapters of this thesis, some points are worth briefly revisiting as an overview of the thesis work and its implications for Precision Agriculture.

8.1 GENERAL DISCUSSION

One cornerstone in our understanding of the existence and development of natural populations is the variability evident within them. To this end, the magnitude of variation within populations of attributes that influence agricultural systems has been noted at a variety of observation scales. Chapter 1 has endeavoured to review the current knowledge on the variation to be found in a number of the more important soil and crop parameters and Table 1-14 summarises the median variation (expressed as CV %) that may be expected across a range of observation scales.

The recorded magnitude of variation is greater in the physical and chemical components that form the soil than in soil attributes that may be considered as functional derivatives. Variation in crop yield also appears to be smaller than that observed in the fundamental soil attributes, however this may be due to the traditionally larger geometric support for crop yield samples. As the sample size, or representative area increases, so more total variation is partitioned within each sample and less between sample variability is evident.

Information discovered on the heterogeneous nature of agricultural system components has previously only been incorporated into management decisions at the coarser scales of regions, farms or in latter years, individual fields. This may be a symptom of the general inability to separate the magnitude of variation from its spatial structure until relatively recently. Fairfield Smith, in his prescient Australian work of 1938 assessed this dilemma and noted that:

"So far as present evidence goes total variability and the manner in which varying fertilities are distributed appear to be two distinct features which must be separately considered in any quantitative measure of soil heterogeneity."

Since then the theory of regionalised variables has been developed and employed in analysing the spatial component or structure in observed variation. The median spatial structure parameters presented in Table 1-15 summarise observations reported in the literature along with an assessment of the "strength" inherent in the spatial structure. It is the information on spatial structure provided by this analytical technique that offers an opportunity to reliably assess the manner in which variation changes within a crop field and ultimately improve the options for management of variation.

For the attributes considered in Chapter 1, spatial structure is evident up to a maximum separation distance of 180m. This distance is well within the normal dimensions of a broad-acre farm field and suggests that management of variation could be useful at the within-field scale. As reviewed in Chapter 2, the arrival of affordable and accurate GPS receivers that provide repeatable location determination, the embryonic development of numerous new, more efficient observation tools and methodologies (Tables 2-2 and 2-3), and the widespread availability of differential-rate controllers (Table 2-4), appears to signal that the time to put this information to use has arrived.

I think that this may be a presumptive assessment and one which has led to a number of failures in the early development of Precision Agriculture internationally. If Precision Agriculture is to be elevated beyond a collection of new technologies and be adopted as an holistic management system as described in Figure 3 then the agronomic rationale and scientific methodology for identifying areas for differential placement of ameliorants must be established. At present, the quality of the monitored and mapped data and the mechanisms for decision-making on the basis of the information remain unclear. The work presented in this thesis is an attempt to help clarify our understanding in these two areas.

With regard to the monitored data it is evident that soil attributes and grain yield can vary widely within an Australian field and that the spatial pattern of this variation may change over time. Chapter 4 confirms that real-time crop yield monitors can be considered quite accurate at measuring the bulk yield of an entire field but less is known about the accuracy of the monitoring systems at the 1m-2m level where individual yield measurements are matched with dGPS position. In Chapter 5 the integrity of the data at this scale has been examined and it would appear that substantial grain mixing during the harvesting and threshing process operates like a moving average filter on the sensed yield data. This data, in conjunction with information from less intensive studies (Lark et al., 1997) suggests that this averaging process has an effective range of approximately 20m. Point estimates of crop yield at the 1m-2m scale cannot therefore be considered as accurate representations of the true value.

This knowledge has important ramifications for the entire Precision Agriculture management system (Figure 3). Firstly, it implies the yield variability over short ranges is greater than that routinely displayed in crop yield maps. Figure 5-16 tends to confirm this, as the variability evident in hand sampled grain appears to be much greater than that expressed in the real-time yield monitor data. This may improve the perceived prospects for the differential treatment of causal factors of yield variation in some instances where variability was originally considered minor, and decrease the prospects in others where the random component becomes too high. At present though this really remains conjecture for while more monitoring must be undertaken to fully examine the range of yield variability within fields, agronomically critical levels for the magnitude and structure of the variation remain to be determined. Obviously these will be necessary for profitable and sustainable differential management.

Secondly, the impact on crop yield of any step-wise differential actions performed at resolutions less than 20m will not be easily detected in the monitored crop yield due to the operational resolution of the yield monitoring systems. This in turn has significant implications for the design and development of experiments aimed at establishing changes in treatment response within fields. The yield monitor resolution should also be considered when using yield maps to assess the financial benefits of differential actions .

This greater local variability also means that the uncertainty associated with yield estimates made through prediction techniques must also be considered as higher in reality than originally believed. In Table 6-4 the uncertainty in point estimates within the 6ha area of Creek field is recorded as ranging between 0.2 t/ha and 2.4 t/ha (mean 1.16 t/ha). With greater local variability, at some points in the field the yield estimate could actually be incorrect by more than ± 2.4 t/ha. Such uncertainty in the point predictions signals that further improvements in the methods for monitoring must be made if data at these scales is required.

If the 20m resolution is considered sufficient, then perhaps other methods of spatial prediction may prove useful. Crop yield mapping has brought the process of digital map construction into wider use. All digital maps are based on some form of map model (Figure 8-1) whereby values are represented as a set of blocks (B) the centres of which are located on a grid (G). According to Goodchild (1992) the blocks may have sides equal to the grid spacing (a raster model), the blocks may be points on a regular grid (a grid model) or they may be points and the grid irregular or infinitely fine with missing values or values equal to zero (a point model).

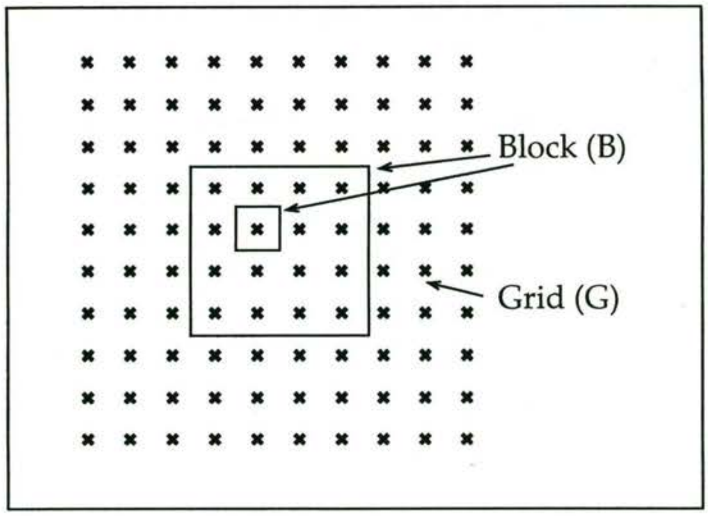


Figure 8-1. Generalised map model.

When Burgess & Webster (1980) first introduced geostatistical spatial prediction techniques into soil science, they discussed two techniques - point (or punctual) kriging and block kriging. Since then almost all of the attention has been placed on point kriging, i.e. to a method that interpolates at any given location a variable with a point support.

Block kriging has rarely been used and software for performing it is rather scarce. Block kriging attempts to predict the average of a variable over some block of length (*dx*) and width (*dy*) centred about some prediction point (*x0, y0*). It should be noted that the locations (*x0, y0* - the prediction grid or raster) can be closer together than the block length or width. This in fact gives an aesthetically pleasing smooth map. The major advantage of using block kriging is that the estimate of the block mean, not surprisingly, improves as the block dimensions increase.

Block kriging does require that the variable to be estimated is additive, which crop yield is clearly, as its total at many points divided by the area over which those are measured is the accepted measure of yield no matter how large the area. The same could not be said for soil pH or hydraulic conductivity which may not be additive. Figure 8-2 shows a comparison of uncertainty calculated for original yield sensor data and the deconvoluted equivalent. It shows that the uncertainty in yield predictions is in fact underestimated when data is not deconvoluted. It also shows that as prediction support increases from points to blocks the prediction uncertainty decreases with block size. The value at 20m being approximately 0.35 t/ha in this instance which is probably acceptable. There is no

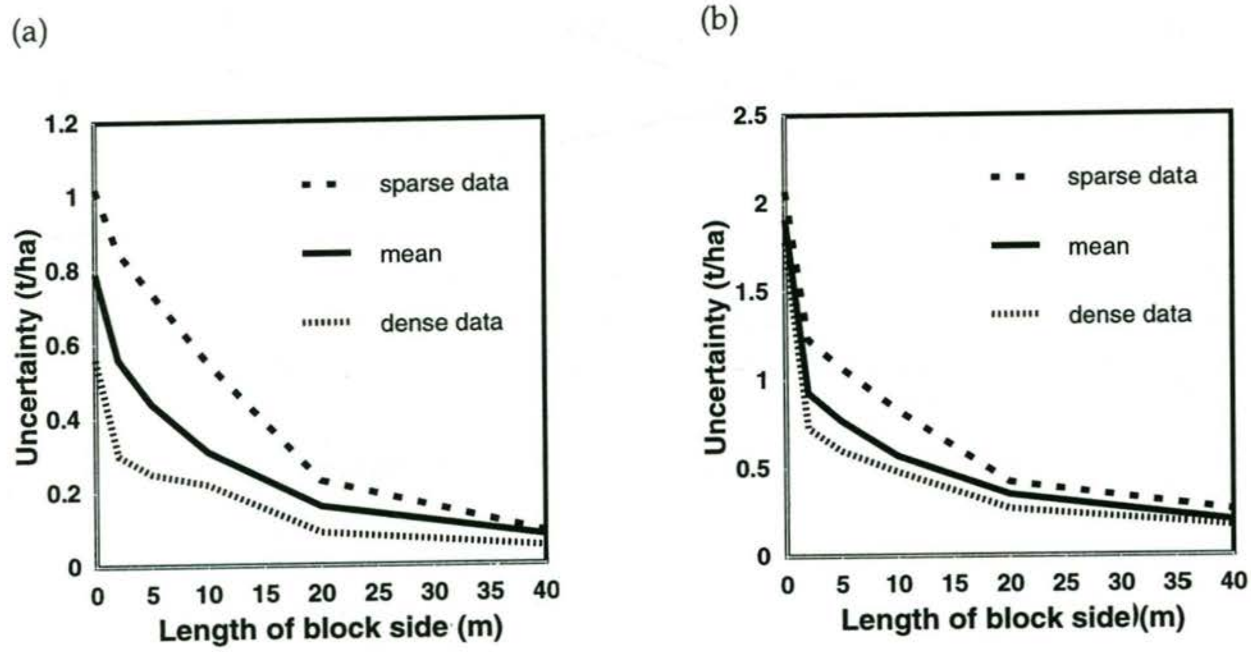


Figure 8-2. Uncertainty associated with increasing block size. (a) original sensor data. (b) deconvoluted equivalent data.

point in increasing the block size further as the uncertainty plateaus and further increases may lead to the loss of site-specific management opportunities provided by smaller blocks.

The effect of observation distribution on the resulting prediction uncertainty is also shown in Figure 8-2. Where there is less observation data within and area for use in prediction then there is greater uncertainty at all block sizes and vice versa. It appears then that the uncertainty may vary within a mapped area depending on the observation data and its density.

Block kriging can also employ local variogram models for neighbourhood kriging as with punctual kriging. Block kriging in this manner onto a fine raster of 2m to 5m using 20m × 20m blocks would provide a reduction in estimate uncertainty when compared with punctual kriging estimates and may be an optimal mapping technique. In the absence of block kriging software, PA practitioners may best be advised to produce maps using a 10m radius moving average rather than the support-limiting inverse square distance method presently popular. A simple estimate of the variance within those blocks would also be also useful in assessing the uncertainty.

Whether improvements are made in the sensors (or sensor location) or alternative prediction techniques are employed, the level of variation represented in a yield map must be seriously considered during its construction. Yield classes of 0.5 tonnes are meaningless if the uncertainty in the yield estimates is of a similar or greater order. Until a robust standard is achieved for yield prediction and the subsequent map presentation, the emerging Precision Agriculture industry will remain confused about the accuracy of yield maps and the detail they should, and do attempt to display. I believe it is important that the uncertainty incorporated in the individual yield estimates be known and minimised in the final map representation. Further it is desirable that the inherent uncertainty be quoted along with any digital map as a matter of best practice.

Answers are less abundant in the search for information on what may be causing the observed yield variation. Data is required on the same raster dimensions as yield data (i.e. every 2-5m). This will eventually require sensors that either externally scan or invasively measure soil attributes as they pass in the field. At present, the development of such tools remains distant and manual sampling must continue to be relied upon. New, more efficient sampling designs are required to maximise efficiency and variation identification. It is also possible that soil analytical techniques are overly precise for the sample they are usually required to analyse. A bulked composite sample, which in the end may provide a poor representation of a field, does not require precise analysis. More samples and swifter, less accurate analyses may provide more valuable information on within-field variability.

When considering variability in soil attributes that govern crop yield potential it is also worth noting that such variation may contribute to fluctuations in treatment response within a field. Variability observed in check plot yield across fertiliser response trials is simple but crucial evidence that the nutrient requirements or supply potential varies across fields. Vetsch et al. (1995) have suggested that observed variability in "N supply power" and variability in the response function slope ("fertiliser use efficiency") indicates that variable-rate N application should be beneficial. Chapter 7 has proposed a method for combing knowledge of variability in soil type, response functions and indigenous nutrient concentrations with economic information to determine variable-rate fertiliser application. Future decision support systems must acknowledge that fields generally comprise a diverse range of yield potentials and the success of a site-specific soil management program will depend on the accuracy with which the variation in significant soil parameters are monitored and treated to suit this diversity of potentials. The processes developed in the diverse yield potential simulation offer an improvement to the detail available for fertiliser application decisions and may increase the probability and profitability of more site-specific management programs.

In all, the variability observed in crop yield at the within-field scale reflects interactions between influential field attributes and also between these attributes and the environment. Given the substantial temporal variability that has been shown here to often dominate the spatial variation, the identification of a significantly yield limiting factor in one year may have limited bearing on the next growing season if its influence is considered singularly. Yield, soil, pest and environment variability data may need to be collected for a number of years (possibly up to 10 in highly variable environments) to adequately characterise and model this interaction. In this manner a map of yield potential for a field may be constructed and then used each year in conjunction with early season environmental indicators and crop response models to guide differential actions. Establishing a baseline understanding of the variability in yield potential within a field becomes essential if the most significant soil-based contributors to variability are shown to be difficult to manipulate. Soil factors such as clay content and organic matter levels are known to contribute to nutrient availability and moisture storage capacity of the soil. They are also extremely difficult or impractical to amend in the short-term.

Intuitively, factors contributing to variability in the soil moisture regime will be important in the majority of cereal growing regions in Australia. The more easily adjusted soil factors such as available nutrient levels and pH will also be important in many areas. However if the more rigid factors are going to limit yield then it would seem prudent to allow these to govern the application rates of any ameliorants in the field. The reader is referred back to Figure 2-5 for one example of the differential management decision process.

Precision Agriculture should not be about treating a field to produce a uniform yield unless the potential is uniform. Its potential will be only be realised by acknowledging diversity in yield potential and environmental conditions when formulating field management operations. By gathering and understanding the improved production information provided by Precision Agriculture techniques, management may also be provided with an ideal tool for risk assessment in potentially poor growing seasons. For example, well documented areas of low yield potential may be removed from production or have their inputs reduced to minimise potential financial losses. Such assessments would form part of the decision-support system, so that management actions may be used to disperse or lower production or capital risks across a whole farm.

Information such as that displayed in this thesis should eventually be considered as an economic necessity, as is production information in any industry. The technology is now becoming available to monitor agricultural input/output at an increasingly detailed level. At present, it is necessary to gather data on output to characterise the variability that may be expected over space and time. Understanding the causes will be more difficult at this scale and require committed research from the agricultural industry and improvements in soil sampling and analysis technology. Ultimately these will be available but the impact of Precision Agriculture in Australia will depend on ensuring only suitable techniques are adopted within a fertile research, educational and political framework.

8.2 CONCLUSIONS

Substantial spatial variation exists in soil and cropping system attributes at scales that suggest that management of the variability within fields may prove economically and environmentally advantageous. The components of the Precision Agriculture system are at different stages of development and implementation. It is true to say that the technology required to gather detailed data leads the agricultural science of deciphering and applying the information it contains.

With regard to the within-field variation in cropping system attributes in north-west NSW it is concluded:

- Spatial variability is such that manual sampling at a spacing less than 60m would be required to successfully characterise within-field variation in most attributes.
- Temporal variation is larger than the spatial variation in soil moisture content and crop yield
- The magnitude of within-field crop yield variation decreases with increasing mean yield.
- Sorghum (*Sorghum bicolor*) shows greater variability at the within-field scale than wheat (*Triticum aestivum*).
- Cluster analysis of crop yield and yield derivative maps provides a method for stratifying yield variability within fields.

With regard to the grain-flow dynamics within a conventional combine harvester:

- The threshing and delivery process provides significant mixing of grain harvested over a 20 metre interval.
- An Inverse Gaussian distribution function well describes the convolution transfer function.
- Present crop yield sensors are less accurate in estimating yield at the 1m-2m scale than larger scales.

With regard to spatial prediction techniques for crop yield mapping:

- The fluctuations in yield variability within fields, and the density of yield data supplied by real-time yield sensors is such that local models of variability are useful in spatial prediction.
- An estimate of the prediction uncertainty would be a valuable addition to crop yield maps.

With regard to the economic and environmental analysis of variability in simulated N response:

- Knowledge of response variability will need to be accurate to provide economic benefits to cropping systems using variable-rate treatments.
- Environmental costs of over fertilisation should be assessed and included in future analysis of differential treatment experiments.

8.3 FUTURE WORK

There is much exciting and challenging research ahead for scientists and engineers in the field of Precision Agriculture. The development of soil-sensing systems to replace the present requirement for manual sampling is high on the list. The design of new yield sensors that do not require contact with the grain flow and can be positioned closer to the harvester front will also provide much fuel for thought.

There are a number of areas that demand further investigation arising specifically from the work presented in this thesis. The cluster analysis of crop yield maps and there derivatives provided an apparently useful method for stratifying fields into management zones. It remains to be seen if these zones can be replicated when analysed for yield-determining factors. Strategic soil sampling within the identified zones should now be undertaken to establish whether there is justification for the differential treatment of one or more factors. This work would also be useful in the preliminary investigation of dominant yield determining factors for inclusion in Decision-Support Systems in Northern NSW.

While the current yield-sensing systems are in use, it would also be useful to investigate more rapid methods for determining the grain transfer function within harvesters. It is apparent that, while the form of the distribution function is likely to remain constant, the parameters may change for different harvesters and possibly different crops. Swifter methods for the determination of this function would also allow investigation into the question of parameter variation within fields. The most readily adaptable option would involve the use of wetted grain strips and observation using the grain-flow moisture sensor.

It is also apparent that the uncertainty inherent in the yield estimates resulting from prediction onto a regular grid is too large. The value of using local semivariogram models in the kriging process has been shown, but estimates for a block rather than a point now appears most desirable. Software for local block kriging should now be developed for use in yield mapping applications. This would then enable the presentation of uncertainty estimates in conjunction with a crop yield map which would further enhance the information available for management decisions. Ultimately, this is the reason for gathering production information in such detail and it is beholden to the agricultural scientific community to optimise the accuracy of this information.

Site-Specific Crop Management represents the desire (and ability) to identify and respond to large in-field variation in agricultural production processes in an optimal and timely manner. The ultimate objective should be the construction of a fully unified, real-time data acquisition–integration–decision process that, when appropriate, provides differential treatment to suit the variation in influential cropping system components. Economic optimisation of resource use and the minimisation of environmental impact is mandatory.

General work for the future design of such a system should give consideration to:

(1) *Data acquisition* – continue development, or adaptation, of continuous yield and soil monitoring devices. New methods for EM attenuation yield sensors could have a wide application in the industry. Nitrate, organic matter and soil strength sensors are under development. Ideally, work on such instruments, designed for local conditions, should be instigated in Australia, but co-operation with the prototype manufacturers abroad may hasten their adaptation to the Australian environment. In addition, a real-time soil moisture sensor needs to be developed to suit local soil conditions.

(2) *Data integration* – experimentation is required to ascertain the most suitable model for the efficient collation of variability data already available with that obtained from real-time sensors. An agronomic study to define the importance of yield response surfaces or whole crop growth models in estimating crop yield potential at a site also necessary.

(3) *Management options* – development or adaptation of machinery and controlling software for differential treatment is essential. Differential application of nutrient fertiliser and pesticides would appear to offer the greatest benefit to the industry in the future, given the probability of more restrictive environmental legislation. Engineering projects that consider the adaptation of tillage and seeding implements to respond to real-time commands would also seem prudent.

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"Siddhartha bent down, lifted a stone from the ground and held it in his hand. 'This' he said, handling it, 'is a stone, and within a certain length of time it will perhaps be soil and from the soil it will become plant, animal or man. I do not respect and love it because it was one thing and will become something else, but because it has already long been everything and always is everything' "

– Hermann Hesse (1954) *Siddhartha*

APPENDICES

APPENDIX A1

Yield Monitor Calibration Results

Run Number	Area (ha)	Estimated yield (t)	Actual yield (t)	Error (%).
1	2.56	8.06	7.92	1.76
2	3.41	9.16	9.26	-1.15
3	3.41	8.76	8.87	-1.26
4	2.52	7.35	7.34	0.08
5	2.80	7.37	7.54	-2.32
6	3.04	7.92	8.01	-1.12
7	2.78	7.03	7.04	-0.10
8	6.20	16.86	16.34	3.20
Mean		9.06	9.04	±1.37

Table A1-1. Calibration results for 1995 wheat - JD7720 Titan II.

Run Number	Area (ha)	Estimated yield (t)	Actual yield (t)	Error (%).
1	0.32	2.45	2.49	-1.65
2	0.32	2.41	2.40	0.40
3	0.32	2.43	2.41	1.05
4	0.32	2.41	2.40	0.40
5	0.32	2.51	2.50	0.33
6	0.13	1.03	1.03	-0.09
7	0.42	3.33	3.36	-0.91
8	0.31	2.35	2.36	-0.27
Mean		2.37	2.37	±0.64

Table A1-2. Calibration results for 1996 sorghum - JD7720 Titan II.

Run Number	Area (ha)	Estimated yield (t)	Actual yield (t)	Error (%).
1	0.18	0.88	0.88	-0.41
2	0.19	0.95	0.93	1.21
3	0.58	2.92	2.87	1.58
4	0.57	2.87	2.81	2.08
5	0.22	1.02	1.03	-0.09
6	0.21	1.00	1.03	-2.51
7	0.23	1.03	1.02	1.02
Mean		1.53	1.51	±1.27

Table A1-3. Calibration results for 1996 wheat - JD7720 Titan I.

Run Number	Area (ha)	Estimated yield (t)	Actual yield (t)	Error (%).
1	0.19	0.72	0.74	-2.70
2	0.20	0.81	0.80	1.48
3	0.20	0.79	0.80	-0.80
4	0.20	0.79	0.80	-0.63
5	0.20	0.76	0.77	-0.65
6	0.20	0.73	0.73	0.12
7	1.38	4.93	4.92	0.28
Mean		0.90	0.89	±0.95

Table A1-4. Calibration results for 1996 wheat - JD7720 Titan II.

Run Number	Area (ha)	Estimated yield (t)	Actual yield (t)	Error (%).
1	0.18	0.83	0.83	-0.11
2	0.17	0.96	0.96	-0.09
3	0.17	0.93	0.92	0.94
4	0.17	0.93	0.92	1.28
5	0.18	0.89	0.89	0.20
6	0.17	0.86	0.86	-0.11
Mean		1.36	1.36	±0.45

Table A1-5. Calibration results for 1997 sorghum - JD7720 Titan II.

APPENDIX A2

Real-Time Monitored Crop Yield Statistics by Field, Season and Farm

Field Name	Area (ha)	Yield (tonnes)	Yield (t/ha)	Mosture (%v/v)
B1	3.53	7.69	2.18	9.9
B2	12.52	13.03	1.04	8.7
Horse	10.43	27.60	2.64	9.9
B4	7.91	14.62	1.85	12.6
N3	14.61	32.07	2.20	9.7
Season Summary	49.00	95.00	1.98	10.2

Table A2-1. Monitored yield statistics - 1995 wheat season.

Field Name	Area (ha)	Yield (tonnes)	Yield (t/ha)	Mosture (%v/v)
N2	12.25	84.68	6.91	12.7
N6	14.64	104.21	7.12	12.8
N10	15.24	103.79	6.81	12.6
S2	11.60	74.76	6.45	13.2
S6	11.23	72.57	6.46	12.9
S10	11.39	73.07	6.42	12.5
Creek	71.25	521.65	7.32	13.2
Pine	66.84	369.87	5.53	13.1
CWest	44.20	255.87	5.79	12.1
CEast	46.72	313.50	6.71	13.2
Season Summary	305.36	1973.98	6.55	12.8

Table A2-2. Monitored yield statistics - 1996 sorghum season.

Field Name	Area (ha)	Yield (tonnes)	Yield (t/ha)	Mosture (%v/v)
B1	3.36	11.04	3.28	10.8
B2	12.78	43.01	3.37	9.5
Horse	10.51	48.73	4.64	10.9
B4	8.12	32.03	3.95	11.8
B5	14.05	52.87	3.76	10.5
80	25.80	112.95	4.38	13.1
N1	10.79	49.39	4.58	10.7
N4	15.97	62.10	3.89	9.3
N5	17.47	64.77	3.71	8.9
N8	12.68	51.46	4.06	10.7
N9	16.62	69.27	4.17	12.0
S1	11.70	41.57	3.55	8.1
S4	14.88	49.02	3.29	10.0
S5	9.74	33.09	3.40	9.4
S8	8.25	32.01	3.88	9.4
S9	16.67	57.18	3.43	9.5
S12	12.15	35.59	2.93	10.8
Maidens	77.29	341.36	4.42	10.9
Bommera	26.78	65.84	2.46	10.6
Bull	7.36	35.10	4.77	9.7
SDam	16.11	88.69	5.51	11.7
Skurr	5.84	29.86	5.11	12.8
Creek	83.66	444.36	5.31	11.5
Lease	89.14	495.40	5.56	10.9
CabroW	142.40	527.71	3.71	9.5
CabroE	62.74	243.31	3.88	11.4
KWeeN	114.78	470.54	4.10	11.7
KWeeS	62.39	264.33	4.24	11.2
Season Summary	910.00	3852.58	4.05	10.6

Table A2-3. Monitored yield statistics - 1996 wheat season.

Field Name	Area (ha)	Yield (tonnes)	Yield (t/ha)	Mosture (%v/v)
S2	11.55	32.18	2.79	11.4
N Silo	6.61	5.86	0.89	13.8
S Silo	10.52	19.74	1.88	12.5
W80	41.17	183.14	4.45	8.7
Well	33.01	98.58	2.99	18.9
Pine	65.95	177.78	2.70	12.8
Season Summary	168.81	517.27	2.61	13.0

Table A2-4. Monitored yield statistics - 1997 sorghum season.

Year & Crop	Field Name	Area (ha)	Yield (tonnes)	Yield (t/ha)	Mosture (%v/v)
1995 Wheat	Marinya Summary	49.00	95.00	1.98	10.2
1996 Sorghum	Marinya Summary	76.35	513.09	6.69	12.77
	Romaka Summary	138.09	891.51	6.43	13.14
	Cabro Summary	90.92	569.37	6.25	12.64
1996 Wheat	Marinya Summary	221.53	846.08	3.78	10.30
	Romaka Summary	202.10	1093.42	3.78	11.32
	Maidens	77.29	341.36	4.42	10.9
	Bommera	26.78	65.84	2.46	10.6
	Cabro Summary	205.14	771.02	3.79	10.43
	KWee Summary	177.17	734.87	4.17	11.43
1997 Sorghum	Marinya Summary	102.86	339.49	2.60	13.06
	Romaka Summary	65.95	177.78	2.70	12.8

Table A2-5. Monitored yield statistics - total by farm and season.

APPENDIX B

Real-Time Crop Yield Data

Data for the 1995/6 and 1996/7 harvest of sorghum and wheat on 6 properties in northern NSW. Maps present the yield data as 5m radius moving average calculated on a 3m grid and linearly interpolated onto a 1m grid.

Properties are located in the Moree Shire near Biniguy and all lie within an area of approximately 40sq km south of the township of Biniguy. The properties referred to are: "Marinya", "Romaka", "Cabro", "Maidens", "Keelawee", and "Bomera".

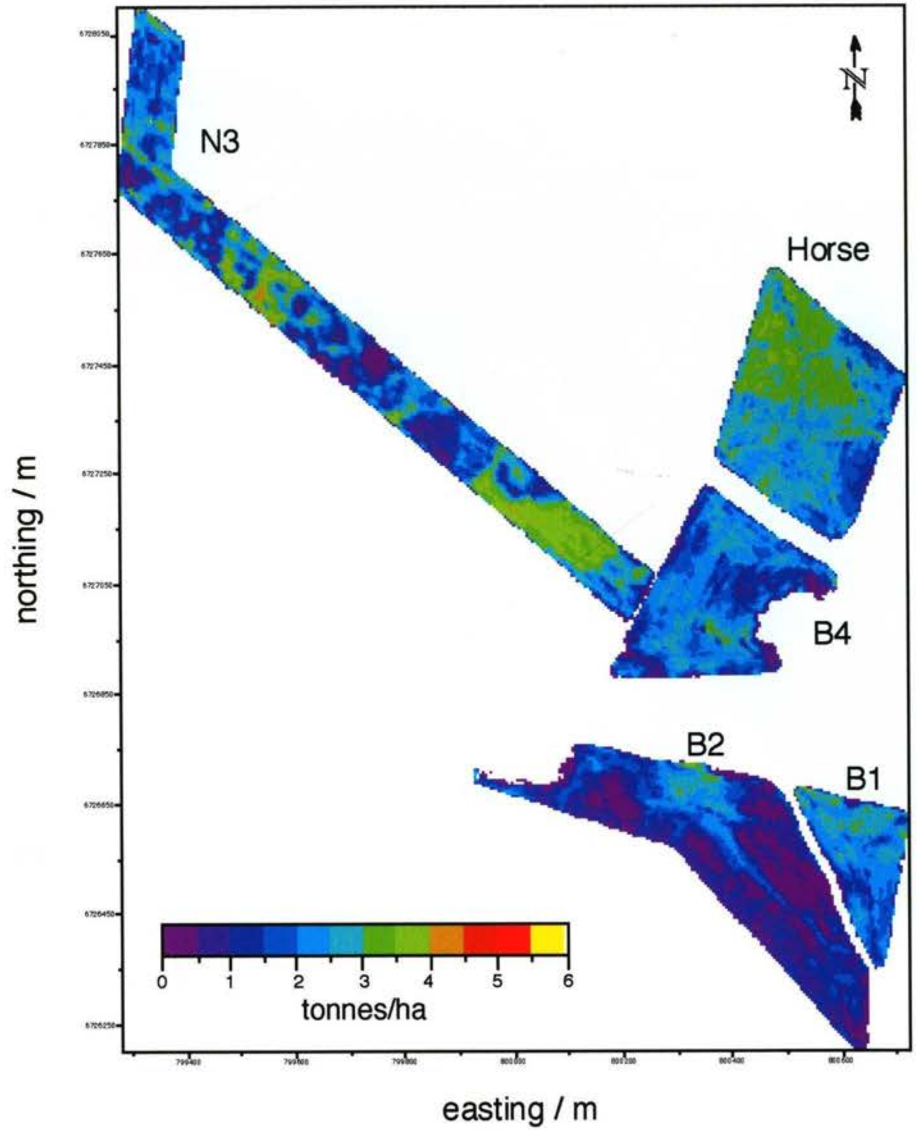

Figure B-2. Marinya 1995 wheat yield overview.

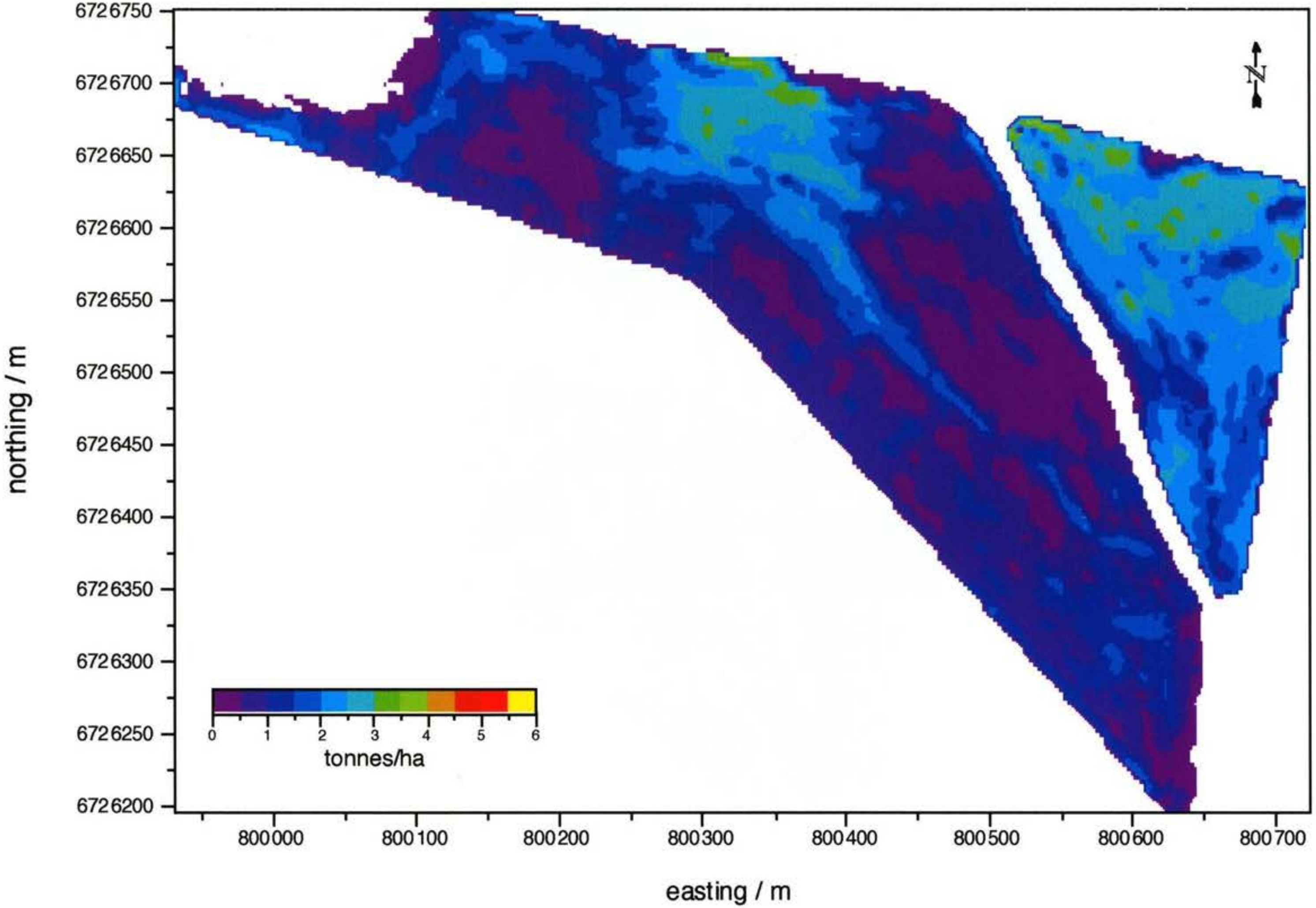

Figure B-3. Field B1 & B2 - Marinya 1995 wheat.

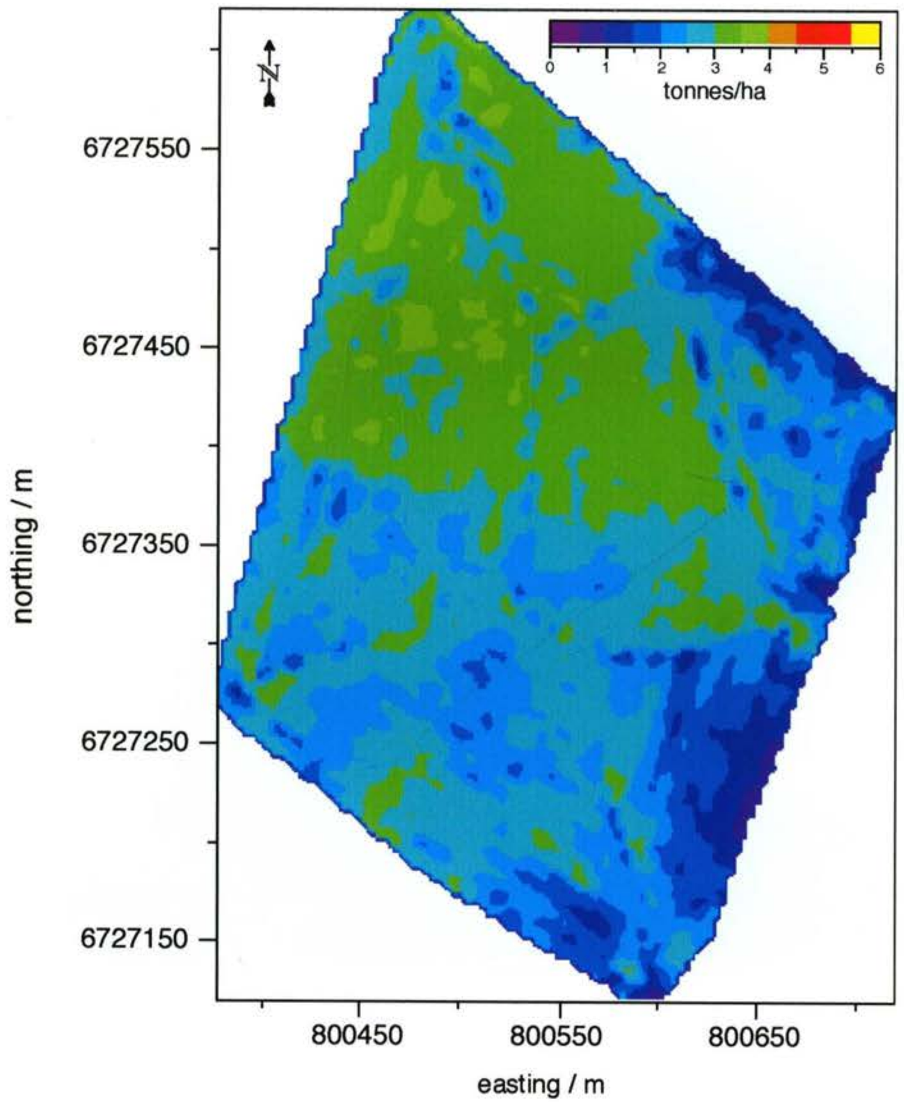

Figure B-4. Field Horse - Marinya 1995 wheat

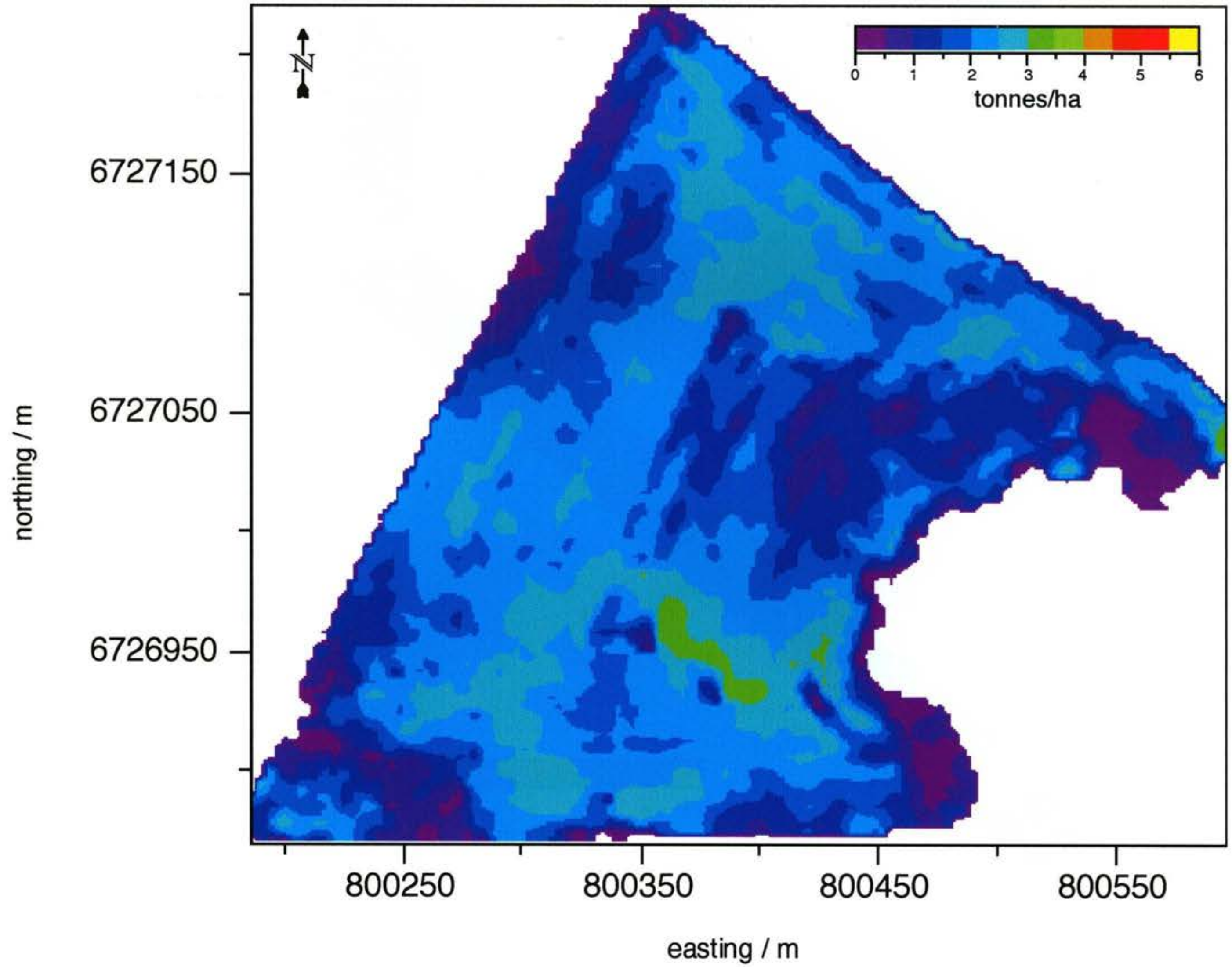

Figure B-5. Field B4 - Marinya 1995 wheat

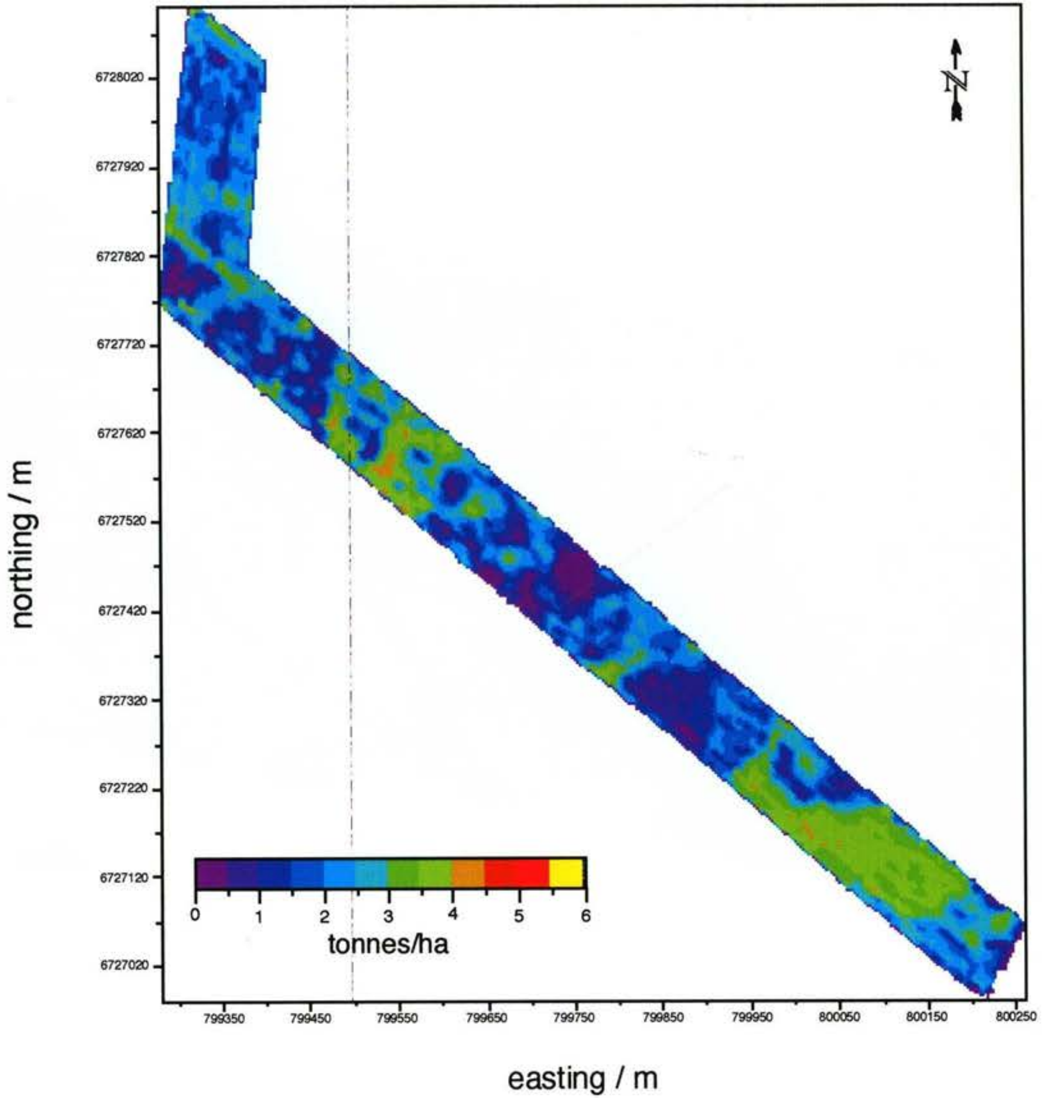

Figure B-6. Field N3 - Marinya 1995 wheat

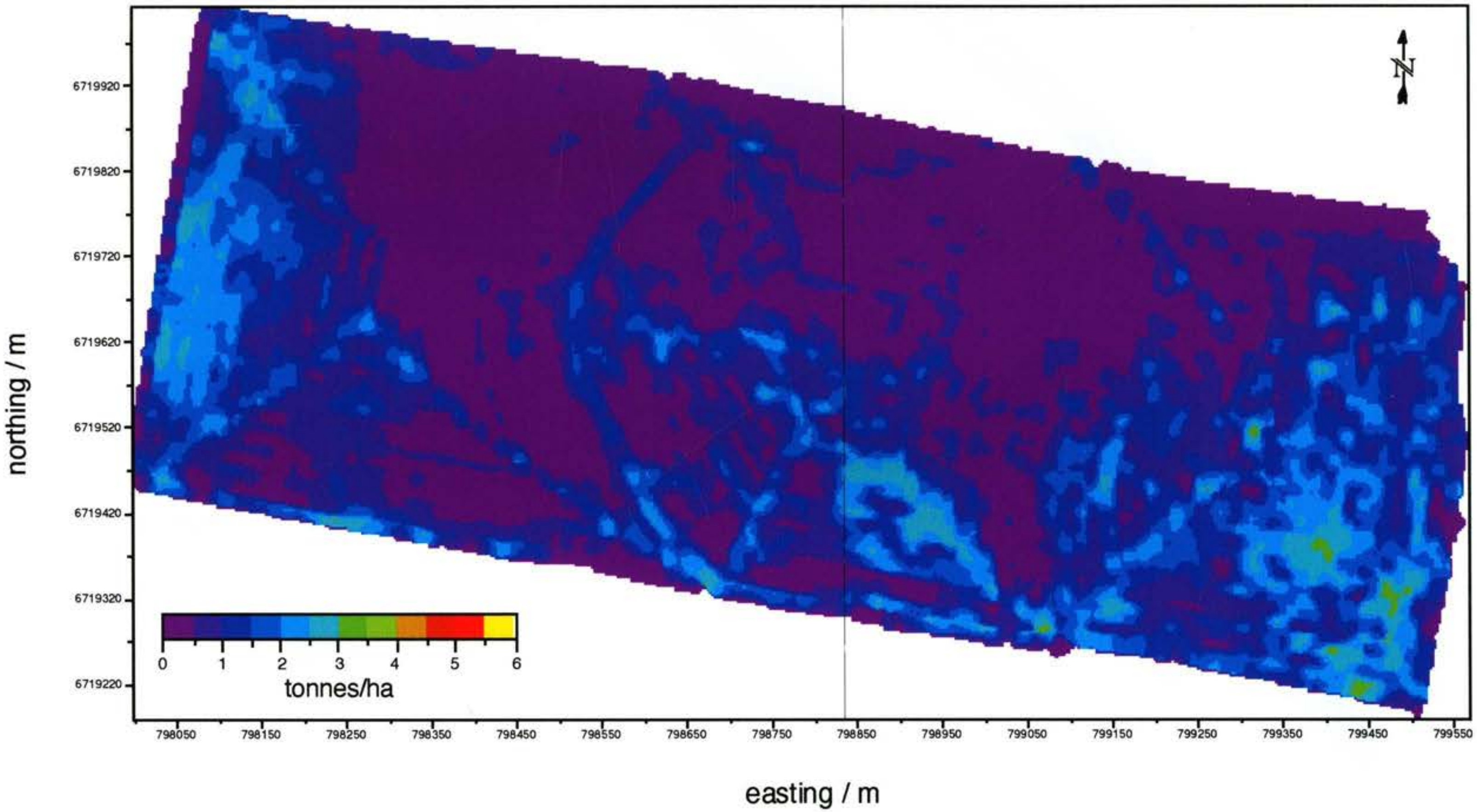

Figure B-7. Maidens 1995 wheat (10m radius moving average)

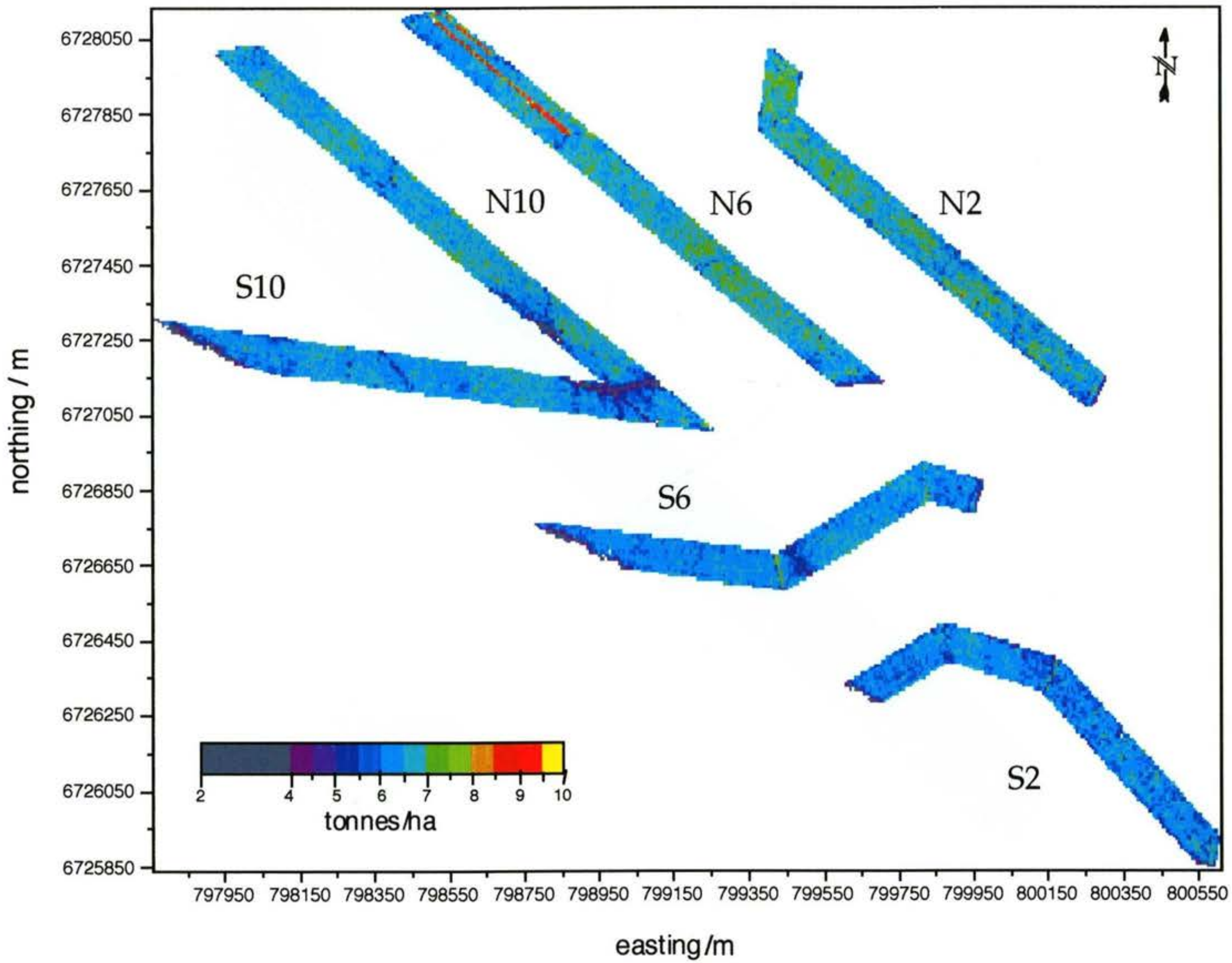

Figure B-8. Marinya 1996 sorghum yield overview.

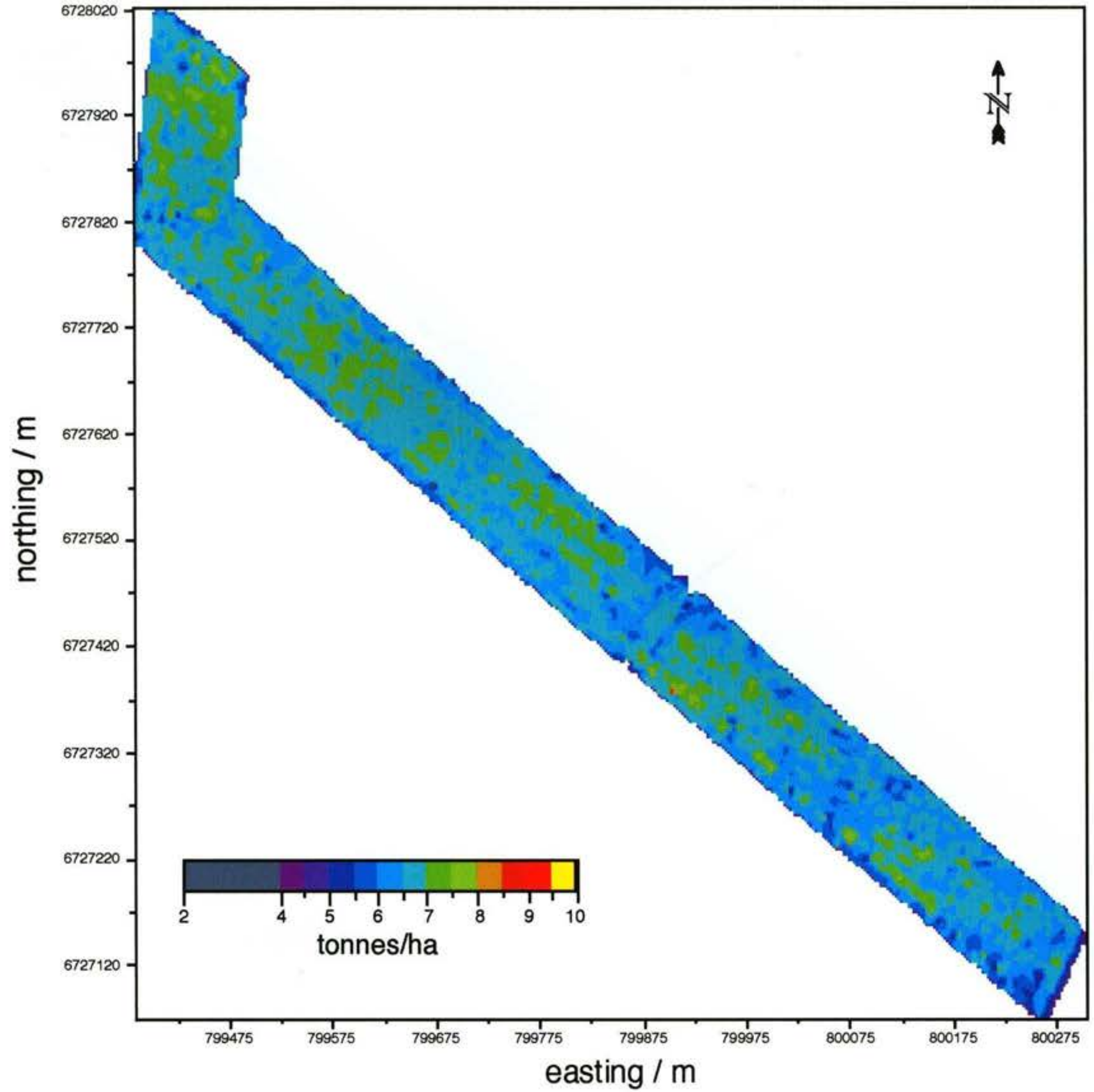

Figure B-9. Field N2 -Marinya 1996 sorghum .

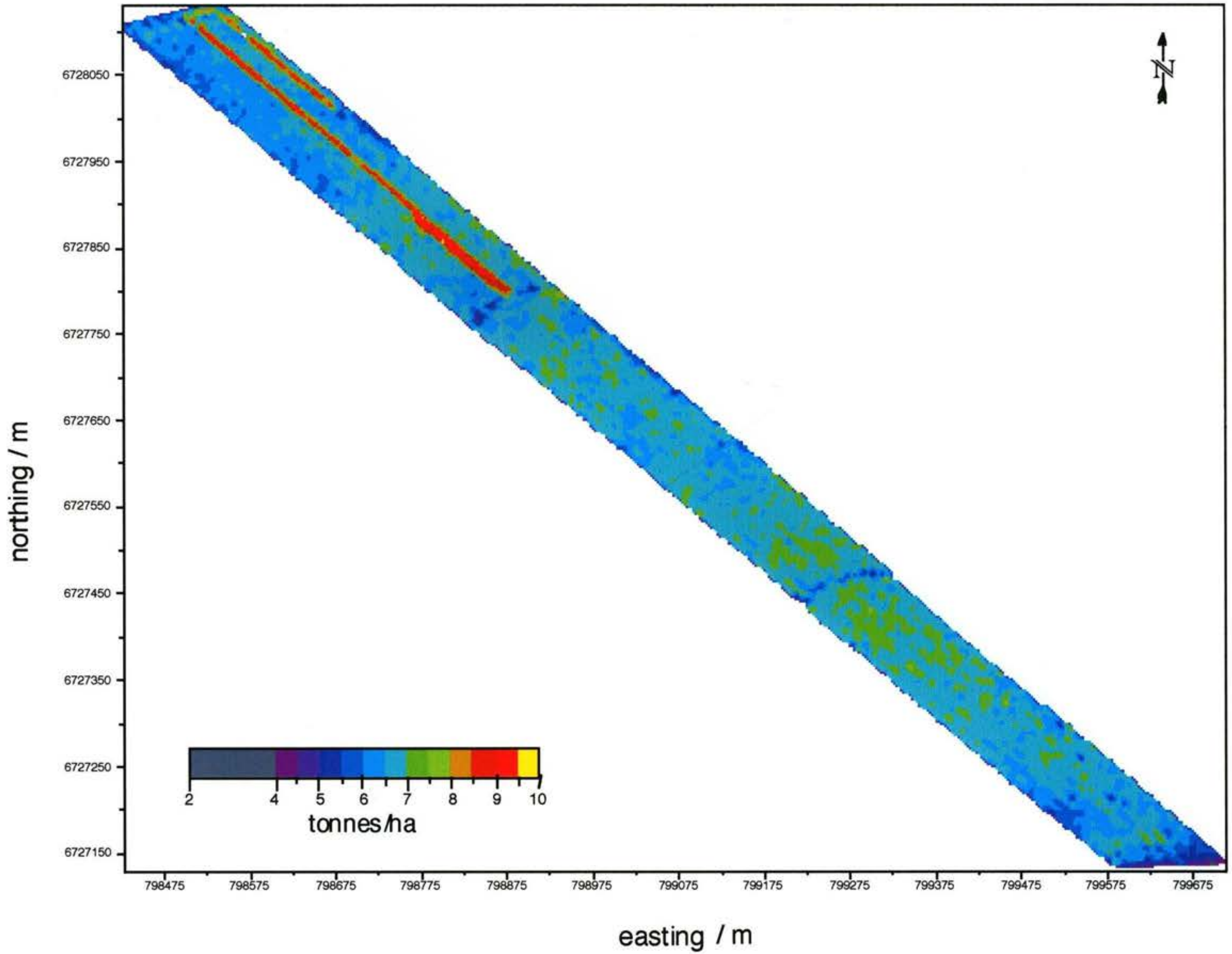

Figure B-10. Field N6 - Marinya 1996 sorghum.

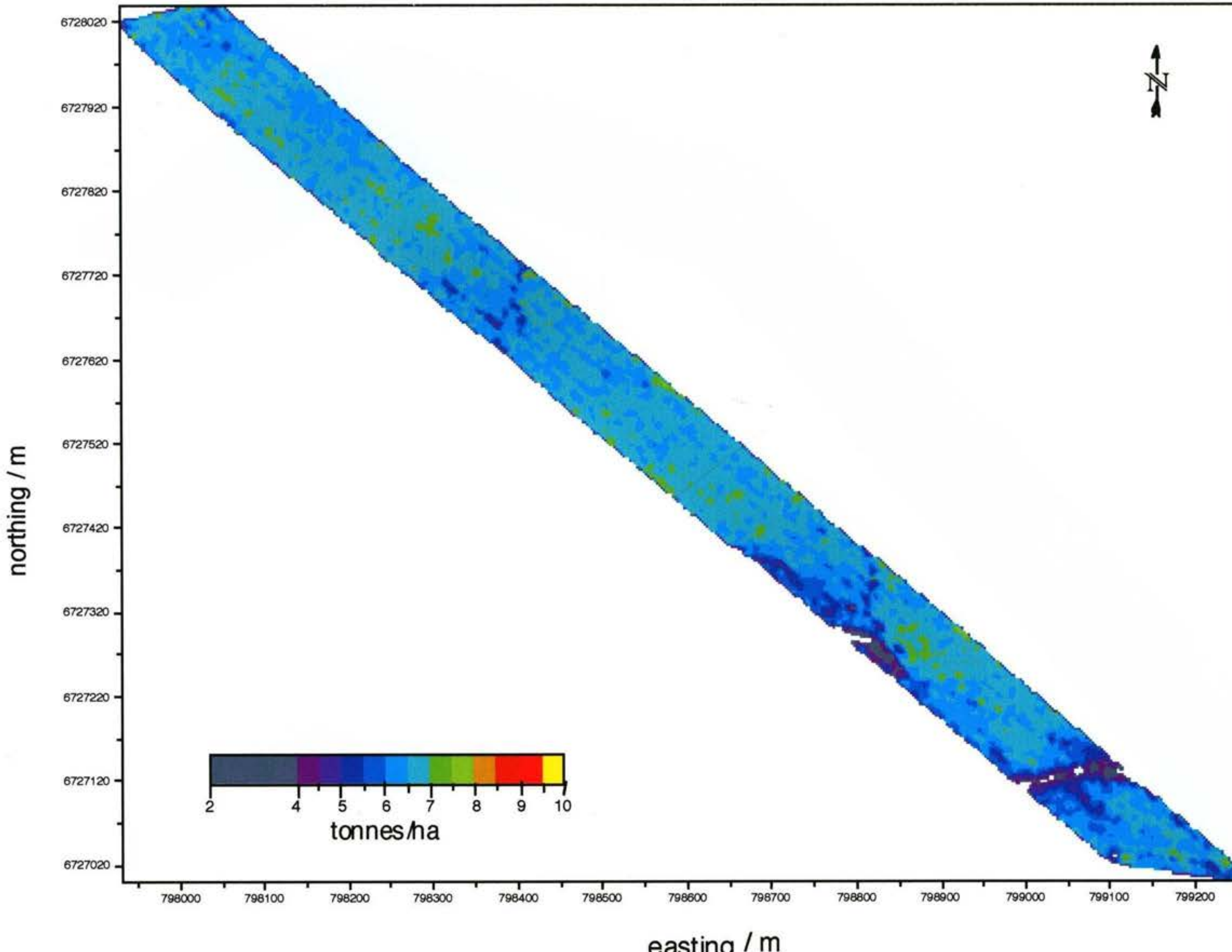

Figure B-11. Field N10 - Marinya 1996 sorghum.

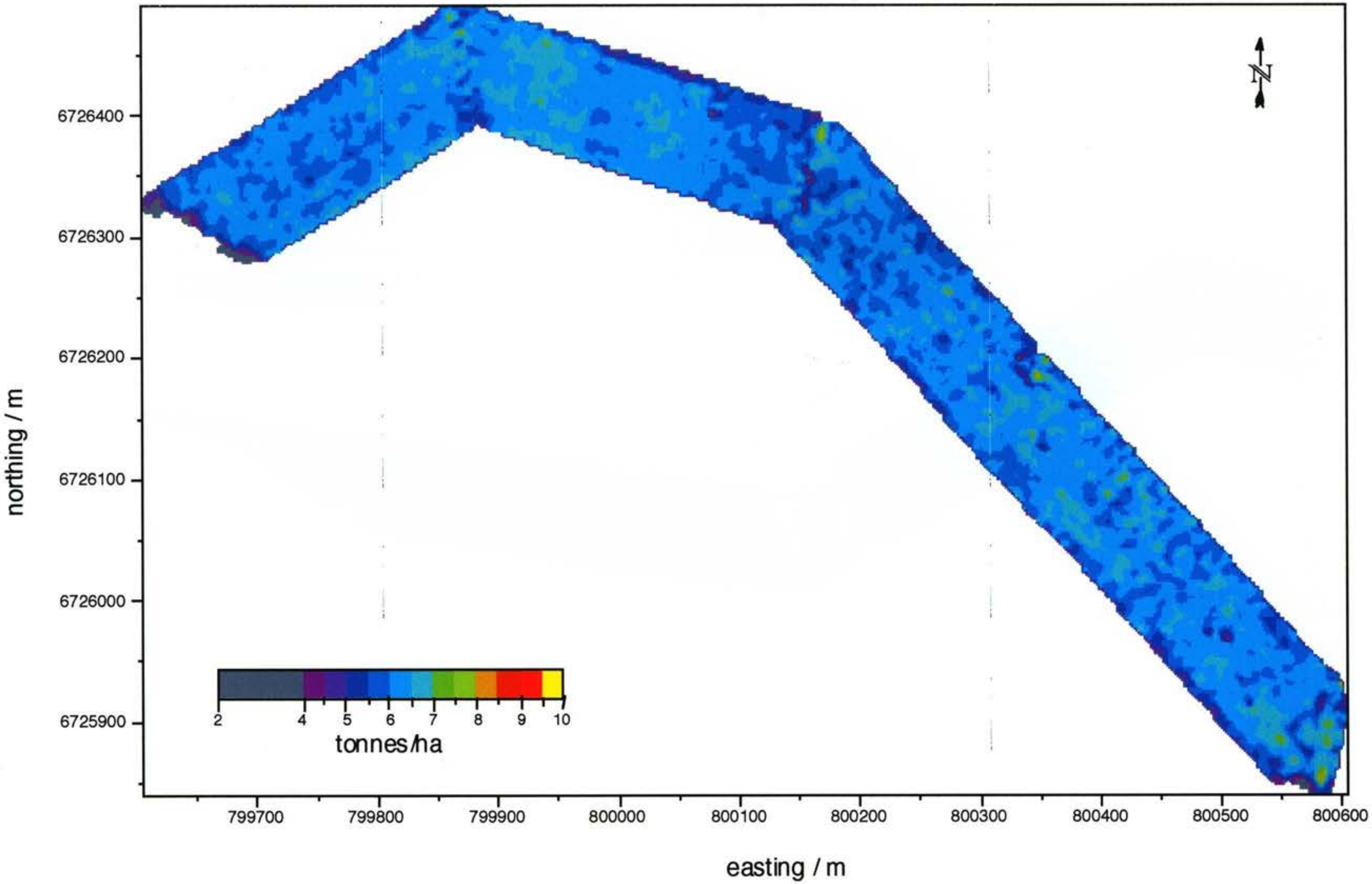

Figure B-12. Field S2 - Marinya 1996 sorghum.

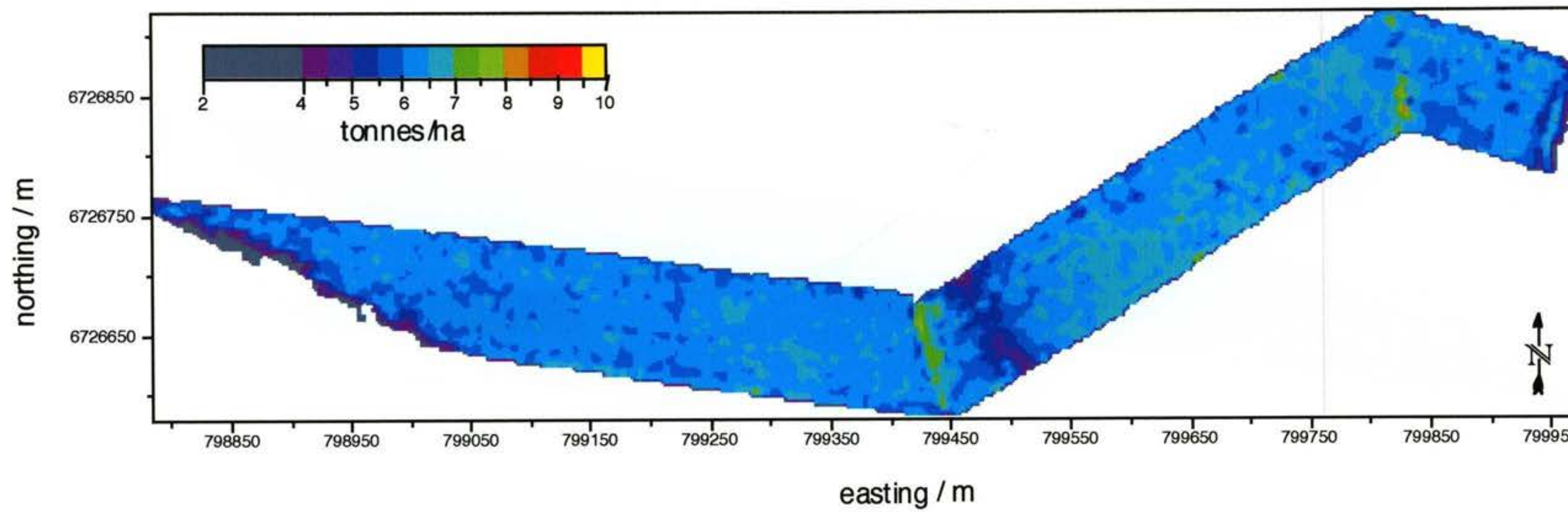

Figure B-13. Field S6 - Marinya 1996 sorghum.

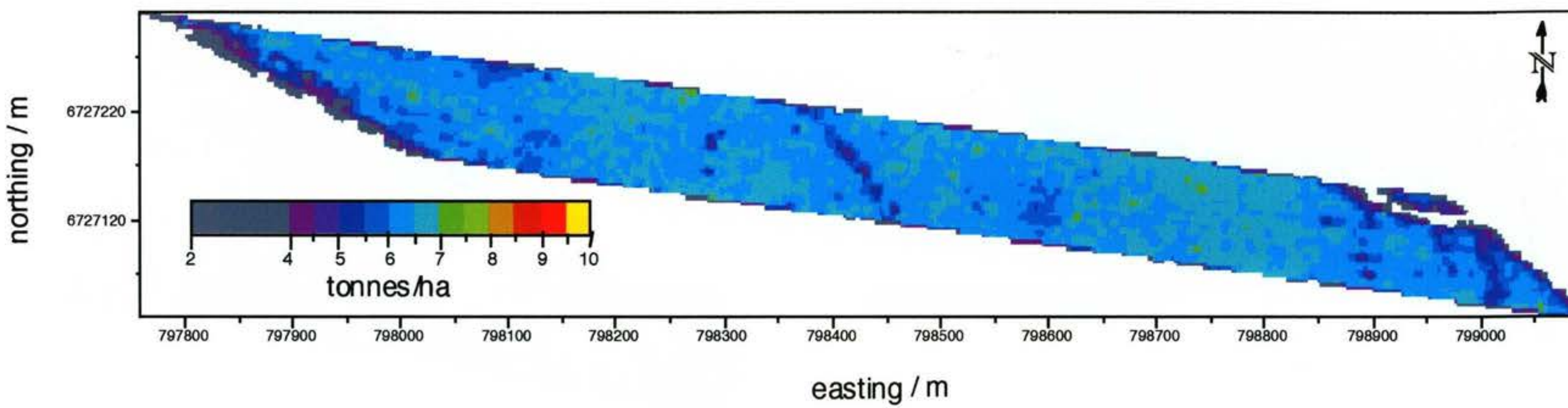

Figure B-14. Field S10 - Marinya 1996 sorghum.

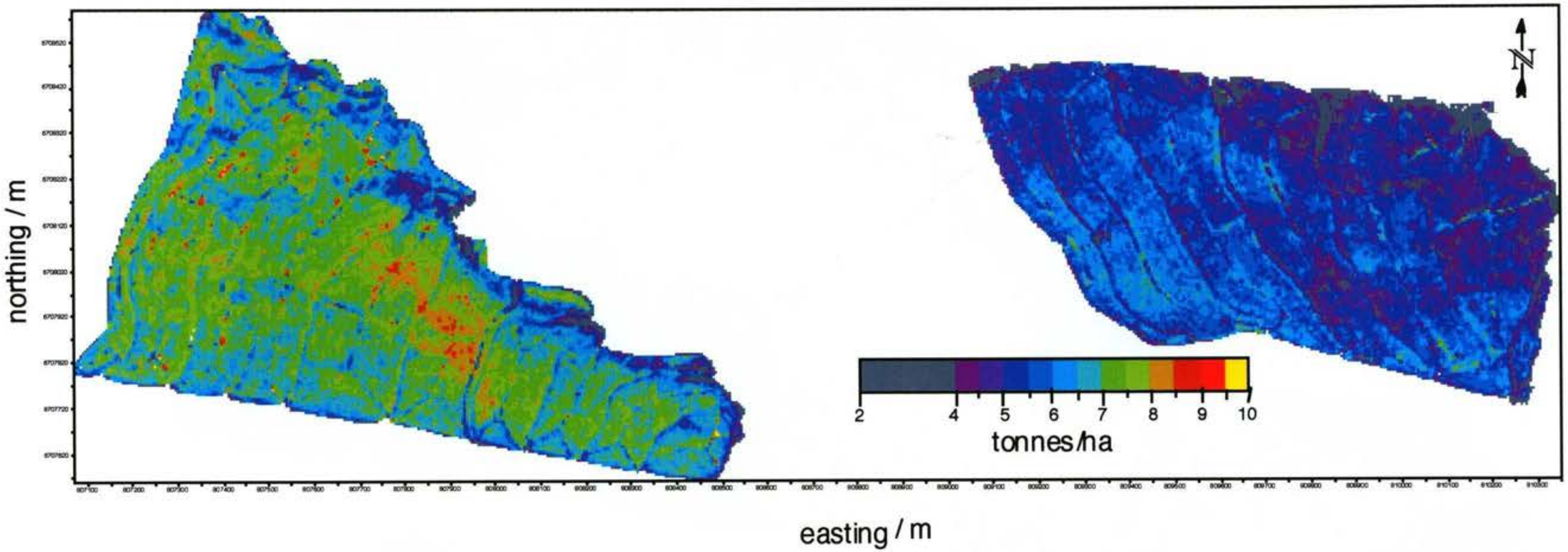

Figure B-15. Romaka 1996 sorghum yield overview.

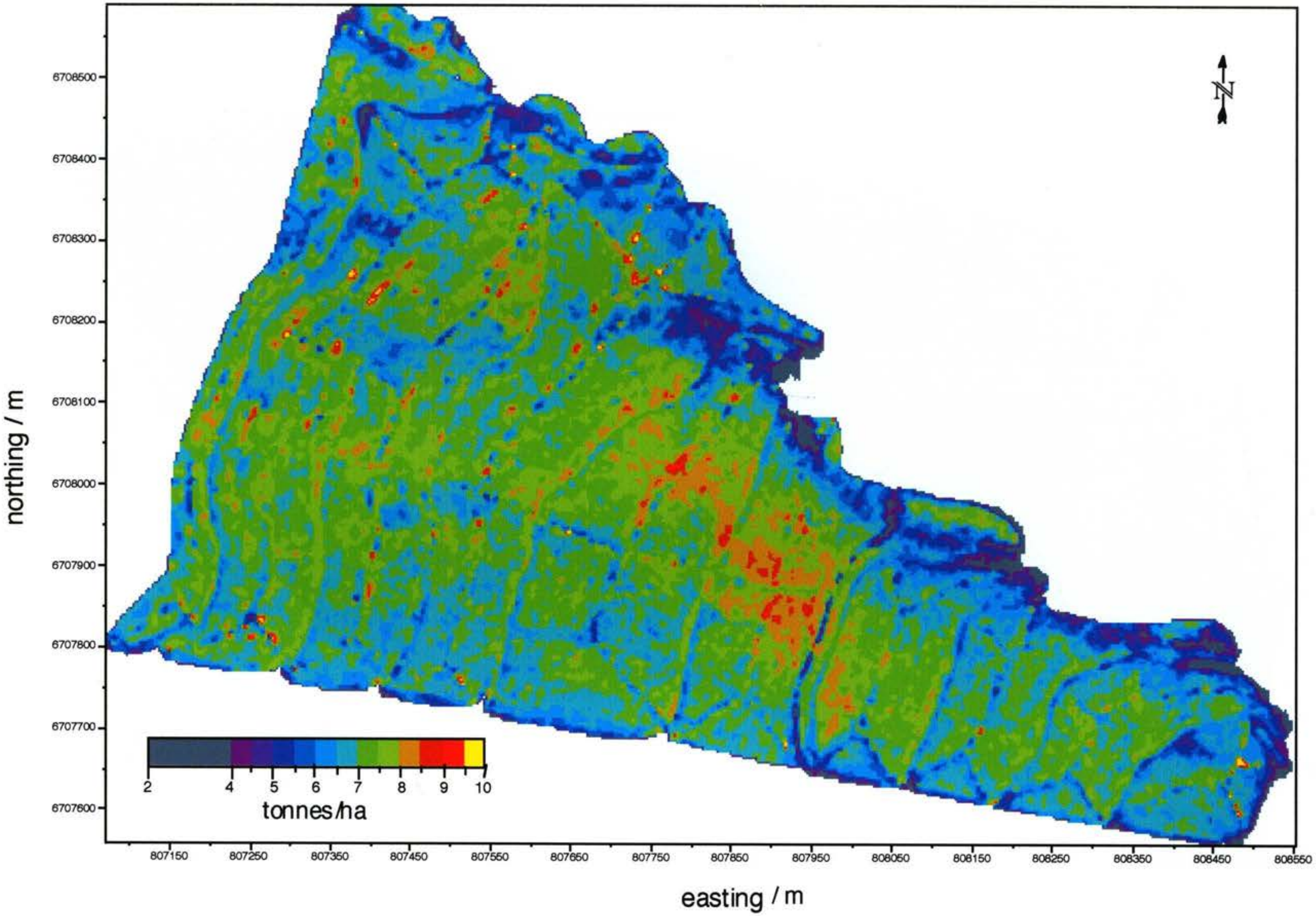

Figure B-16. Creek Field - Romaka 1996 sorghum.

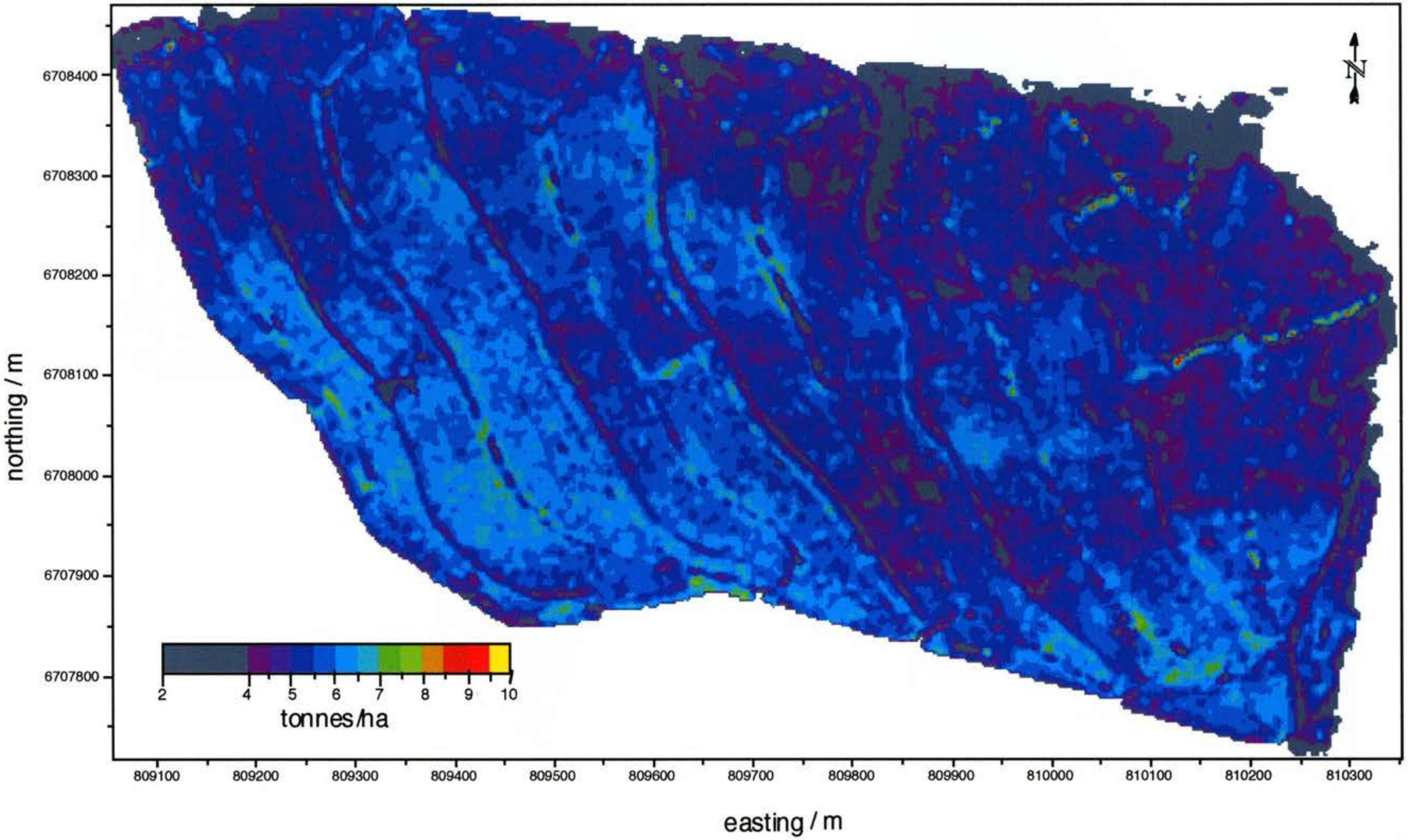

Figure B-17. Pine Field - Romaka 1996 sorghum.

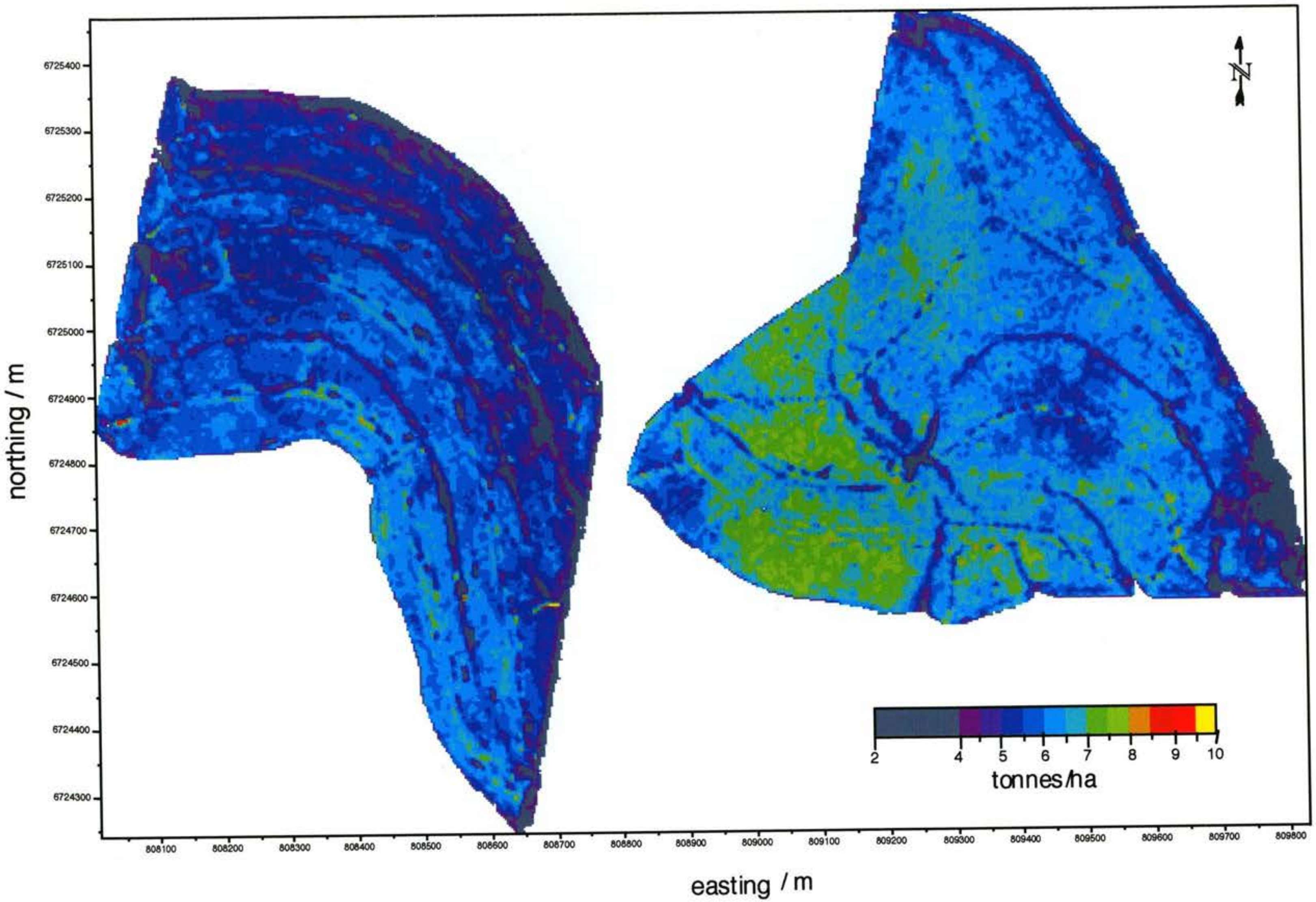

Figure B-18. Cabro 1996 sorghum yield overview.

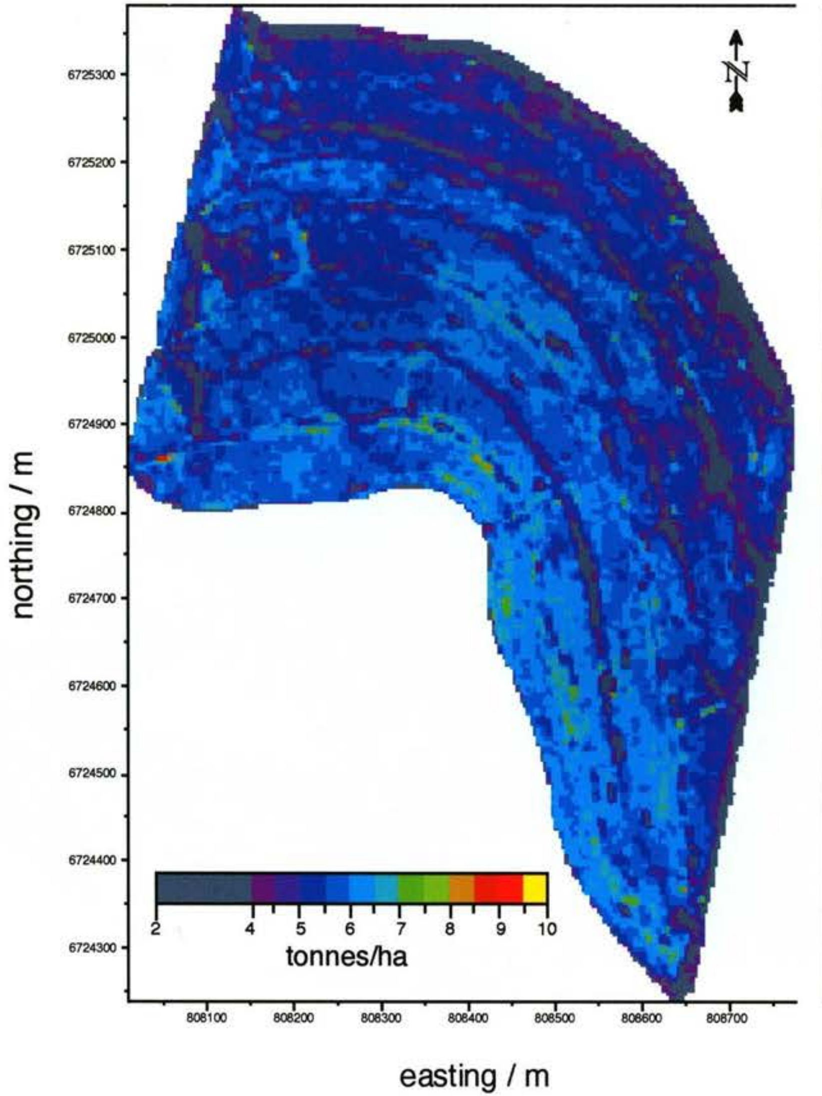

Figure B-19. Cabro West Field - Cabro 1996 sorghum.

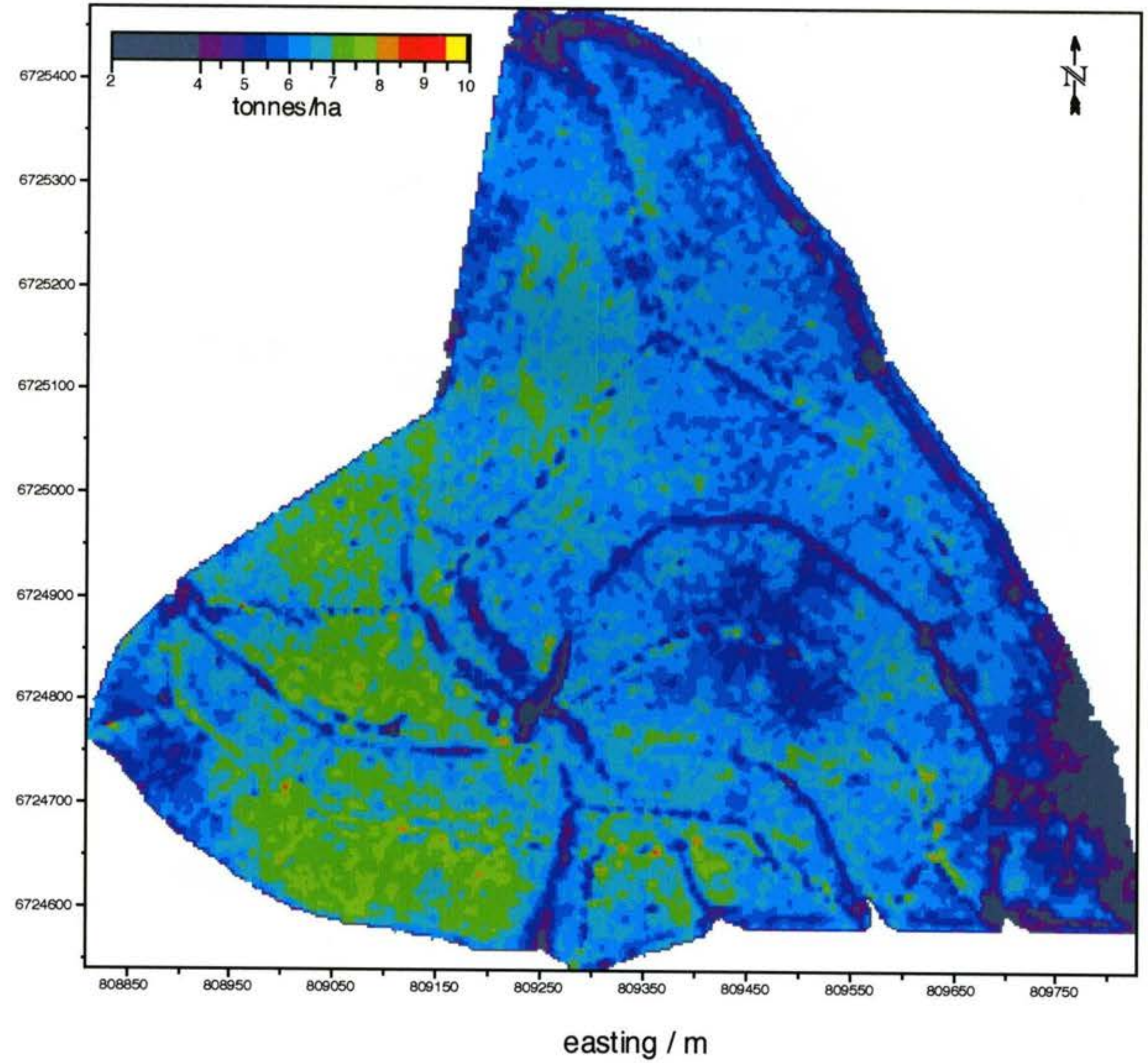

Figure B-20. Cabro East Field - Cabro 1996 sorghum.

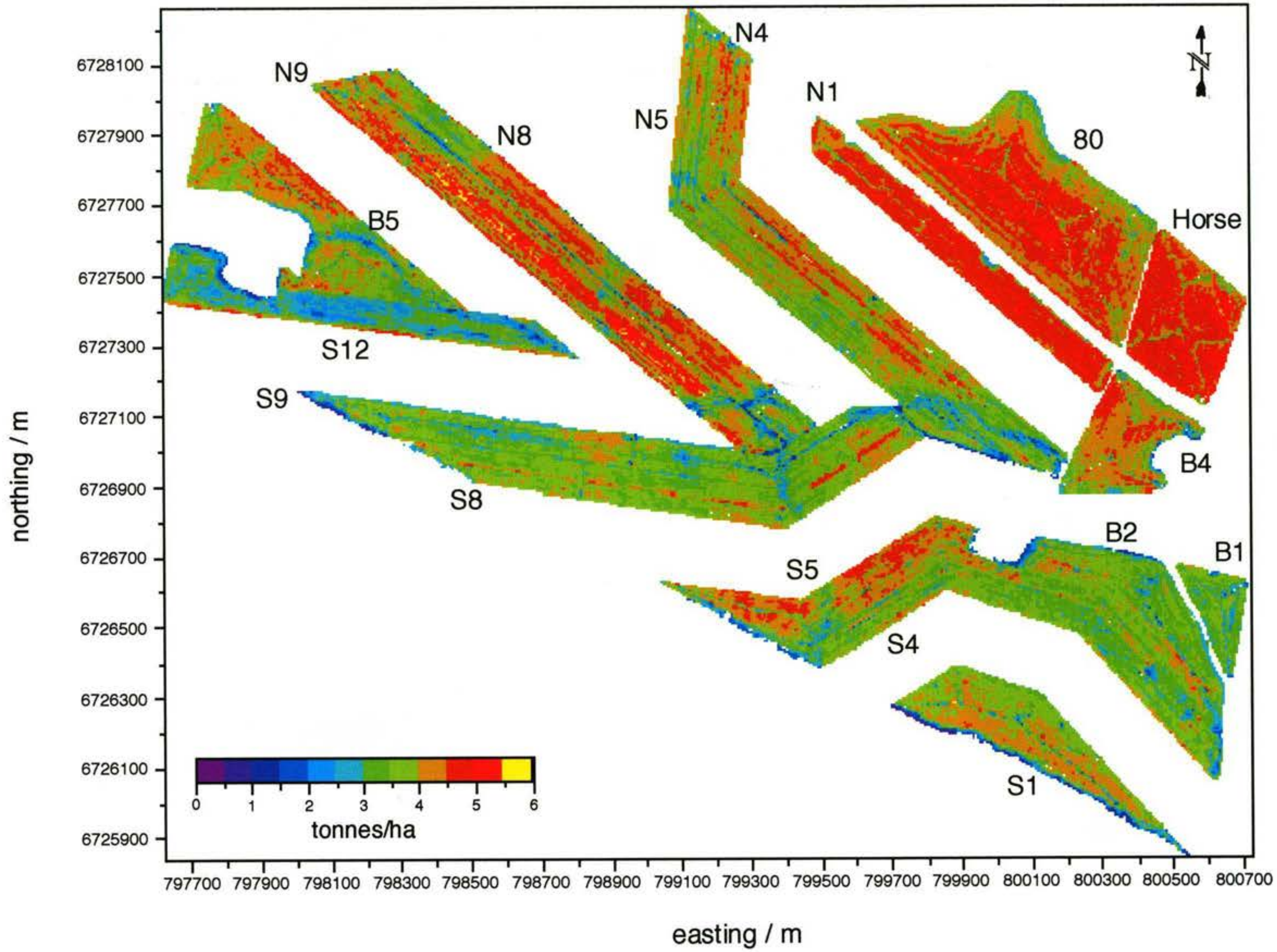

Figure B-21. Marinya 1996 wheat yield overview.

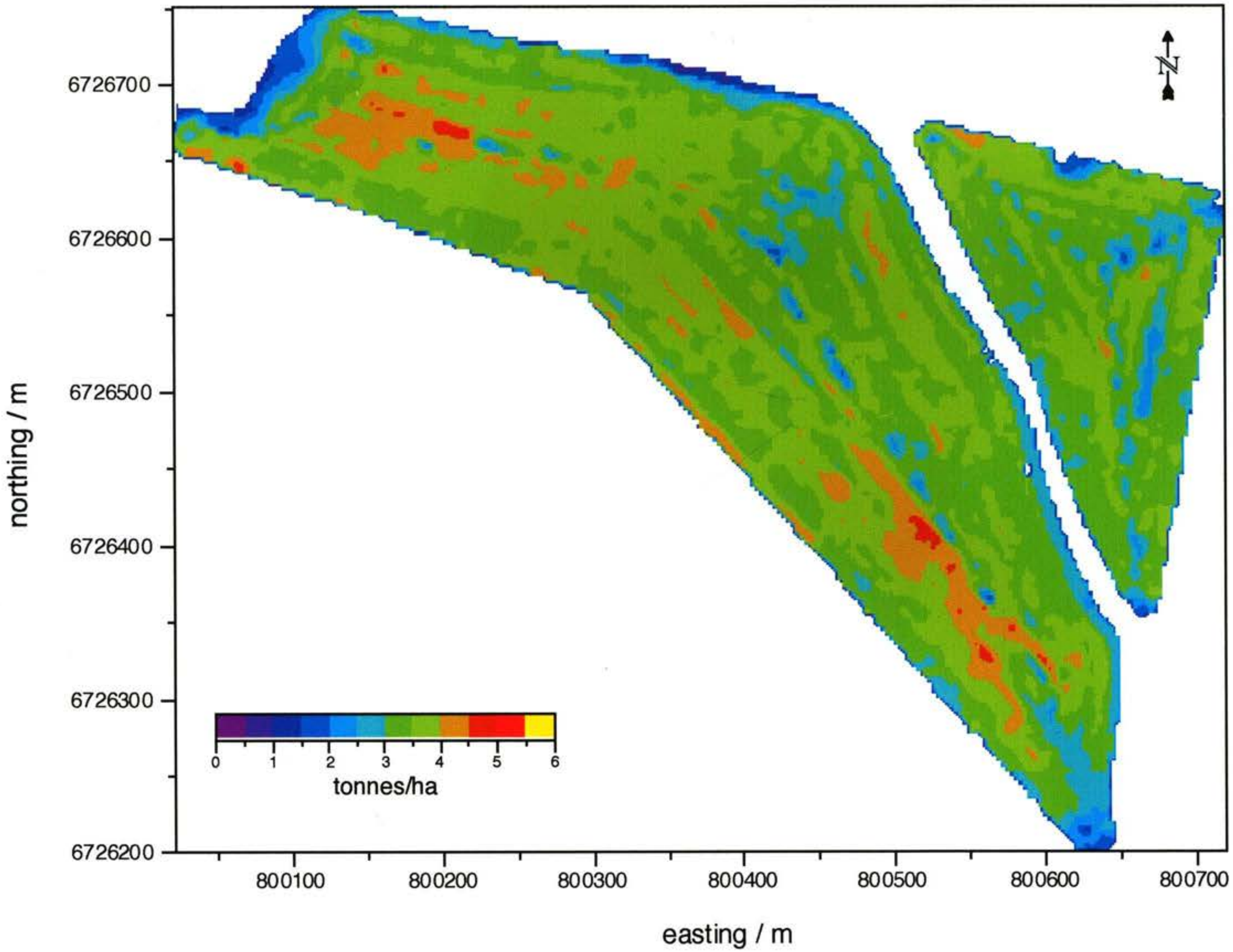

Figure B-22. Field B1 & B2 - Marinya 1996 wheat.

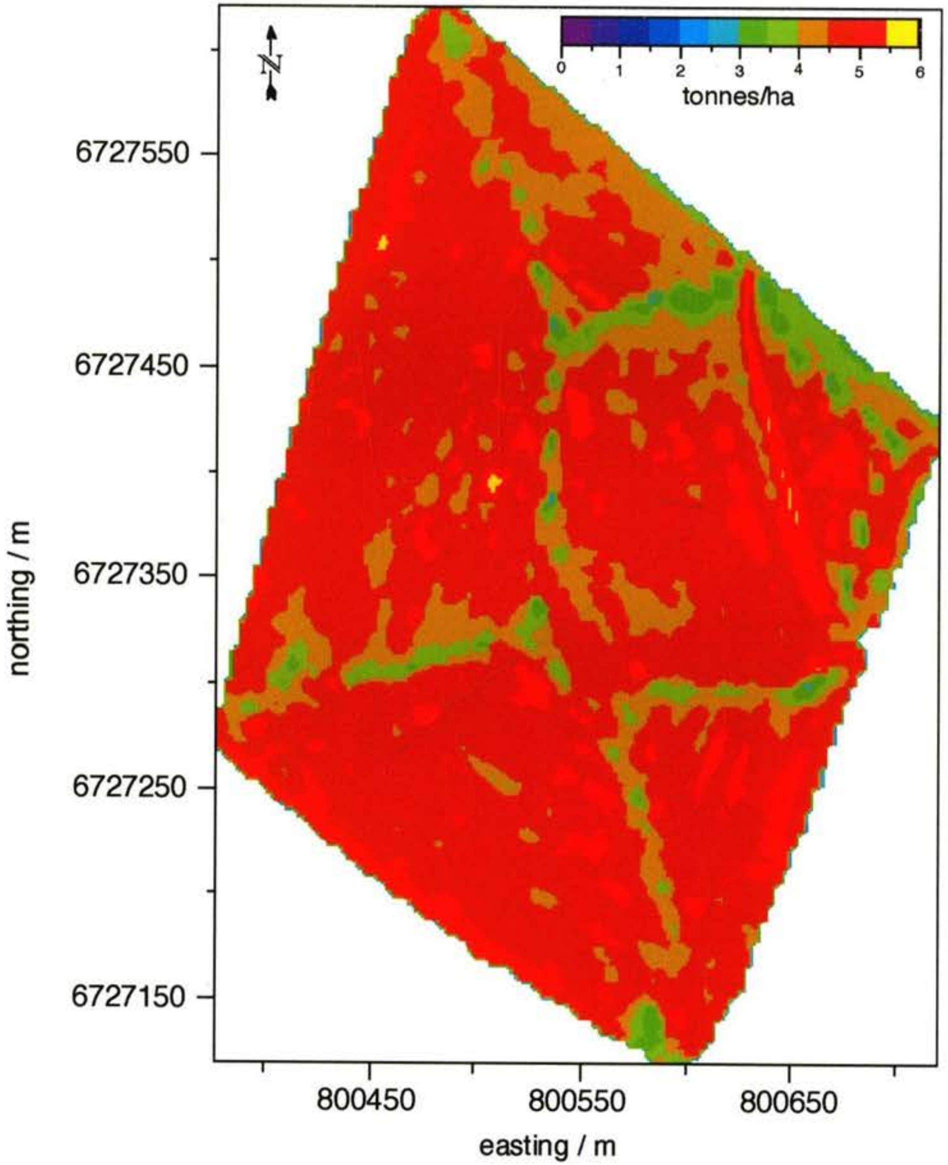

Figure B-23. Horse Field - Marinya 1996 wheat.

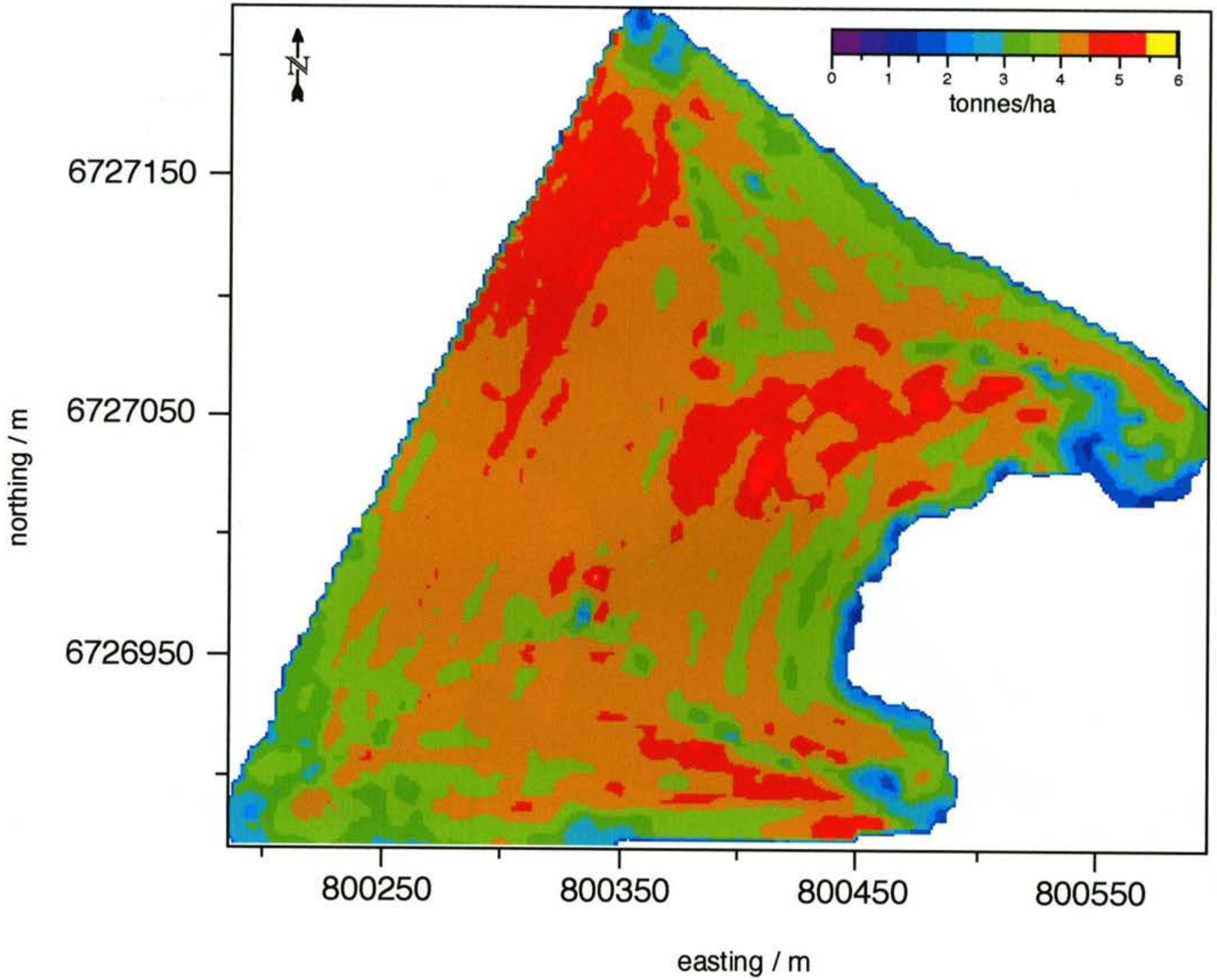

Figure B-24. Field B4 - Marinya 1996 wheat.

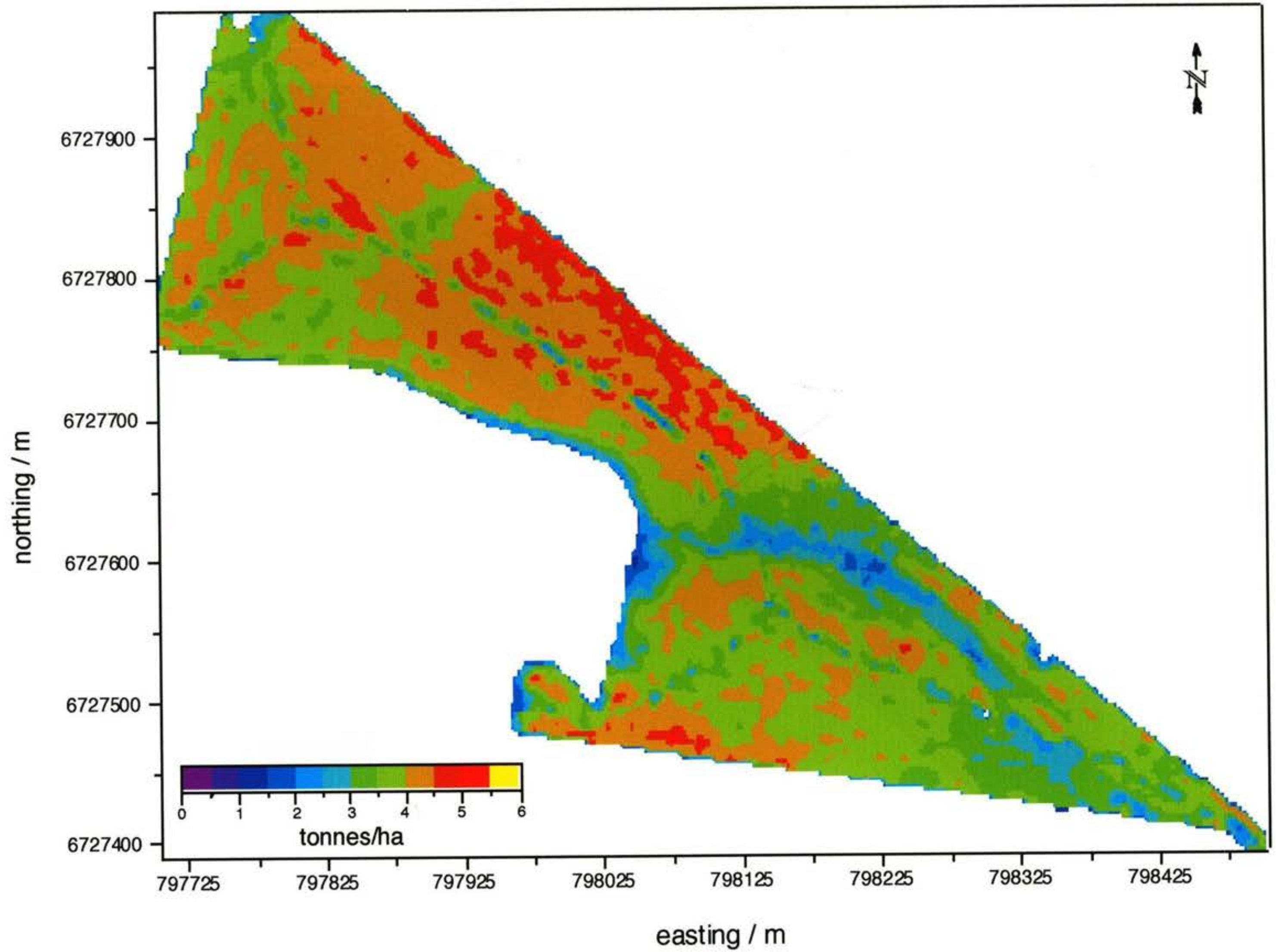

Figure B-25. Field B5 - Marinya 1996 wheat.

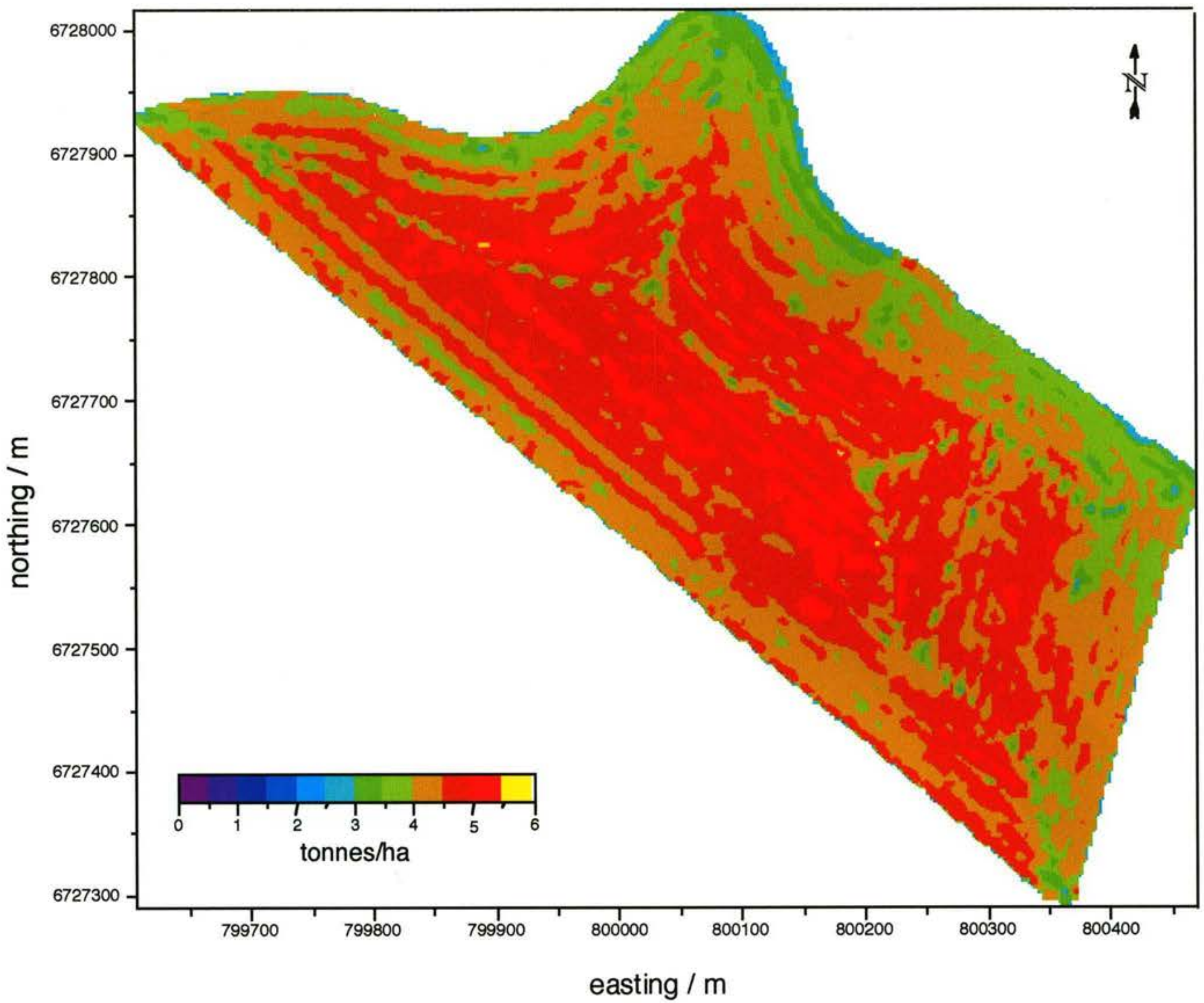

Figure B-26. Field 80 - Marinya 1996 wheat.

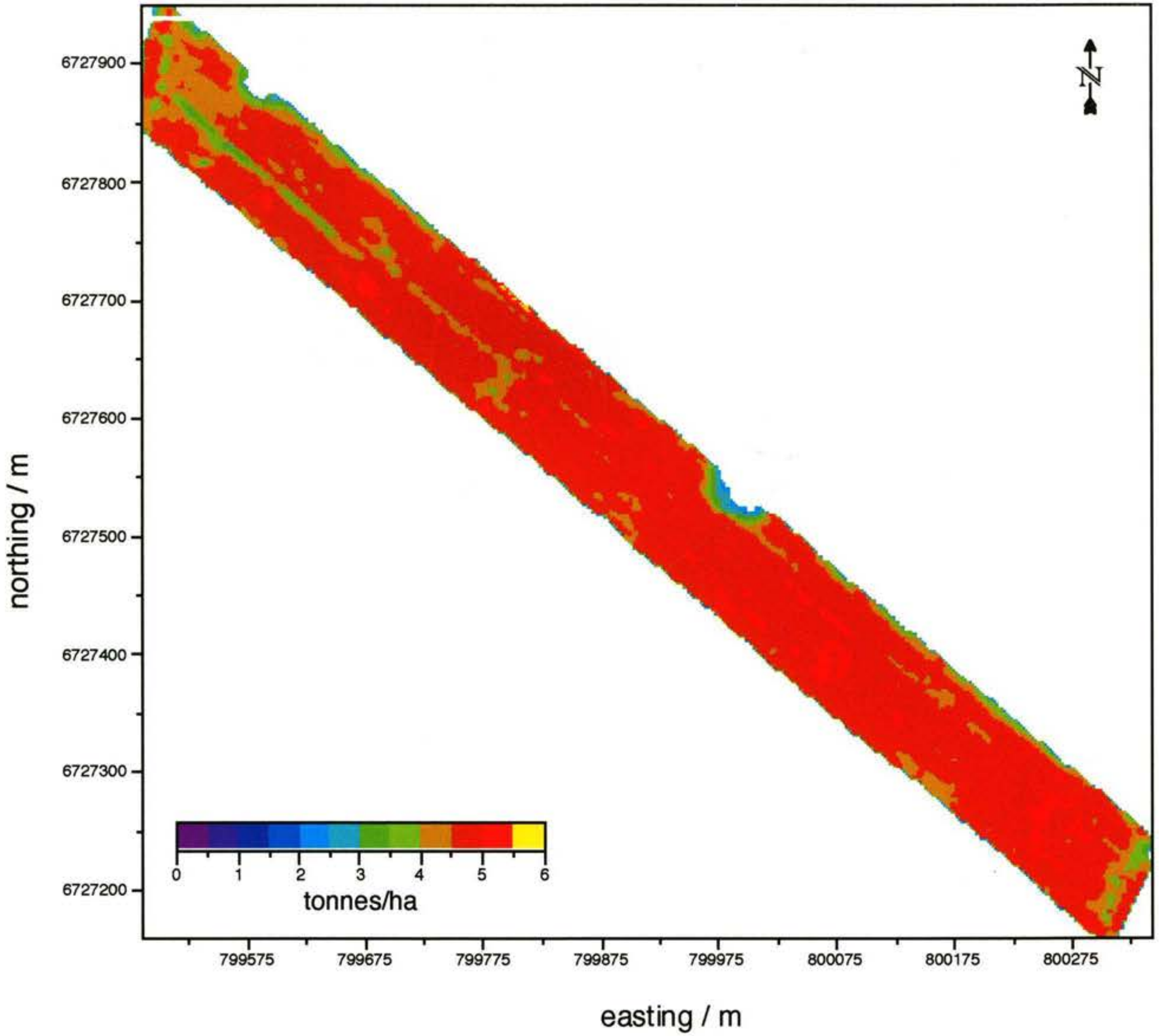

Figure B-27. Field N1 - Marinya 1996 wheat.

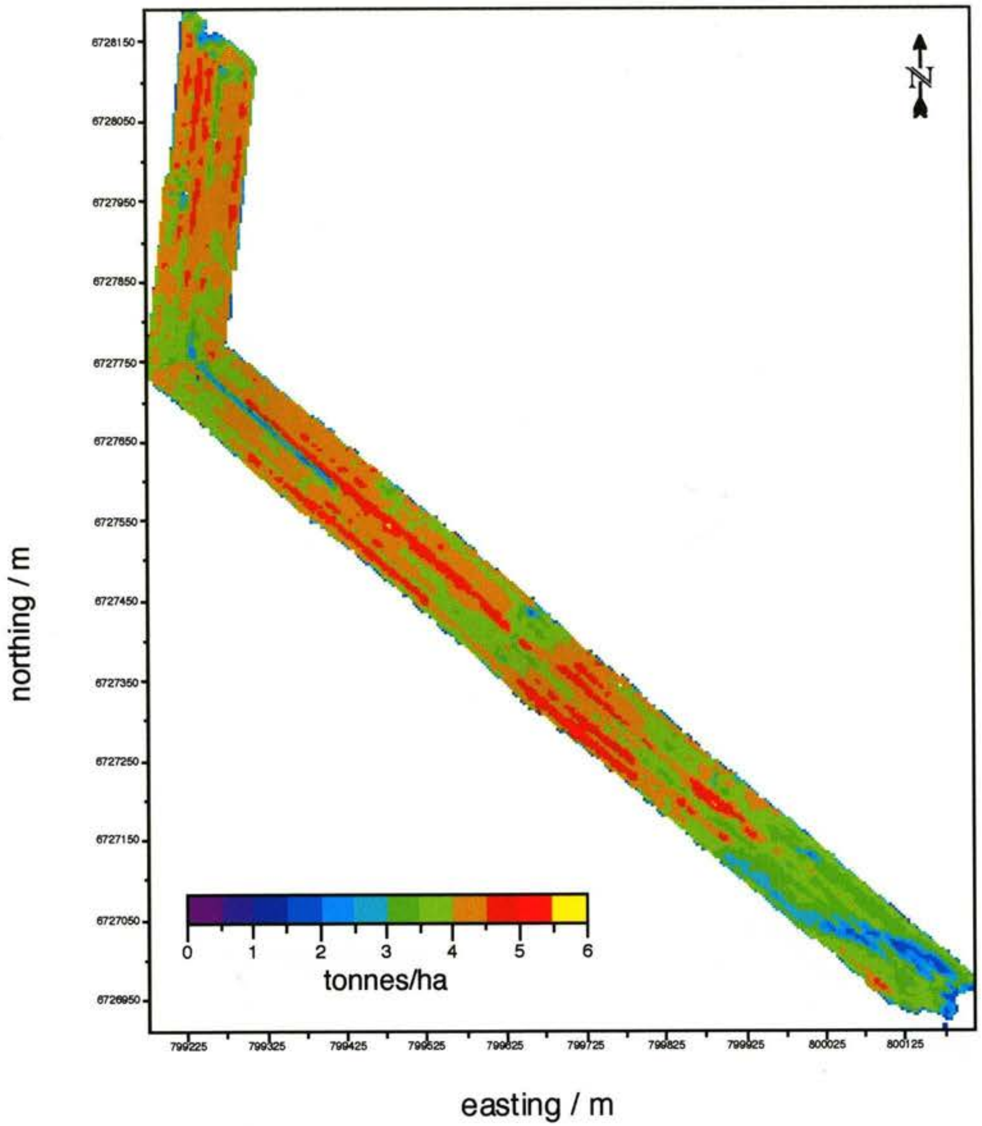

Figure B-28. Field N4 - Marinya 1996 wheat.

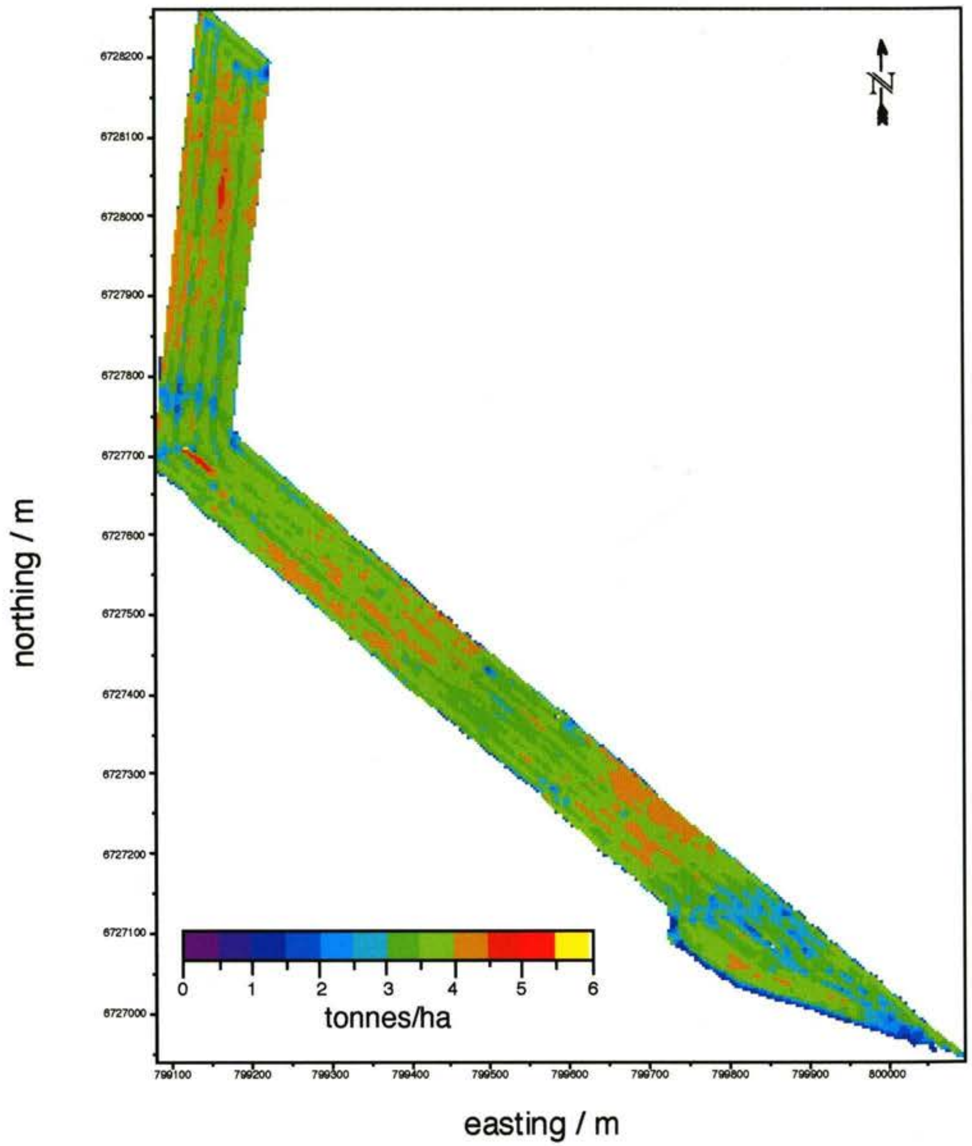

Figure B-29. Field N5 - Marinya 1996 wheat.

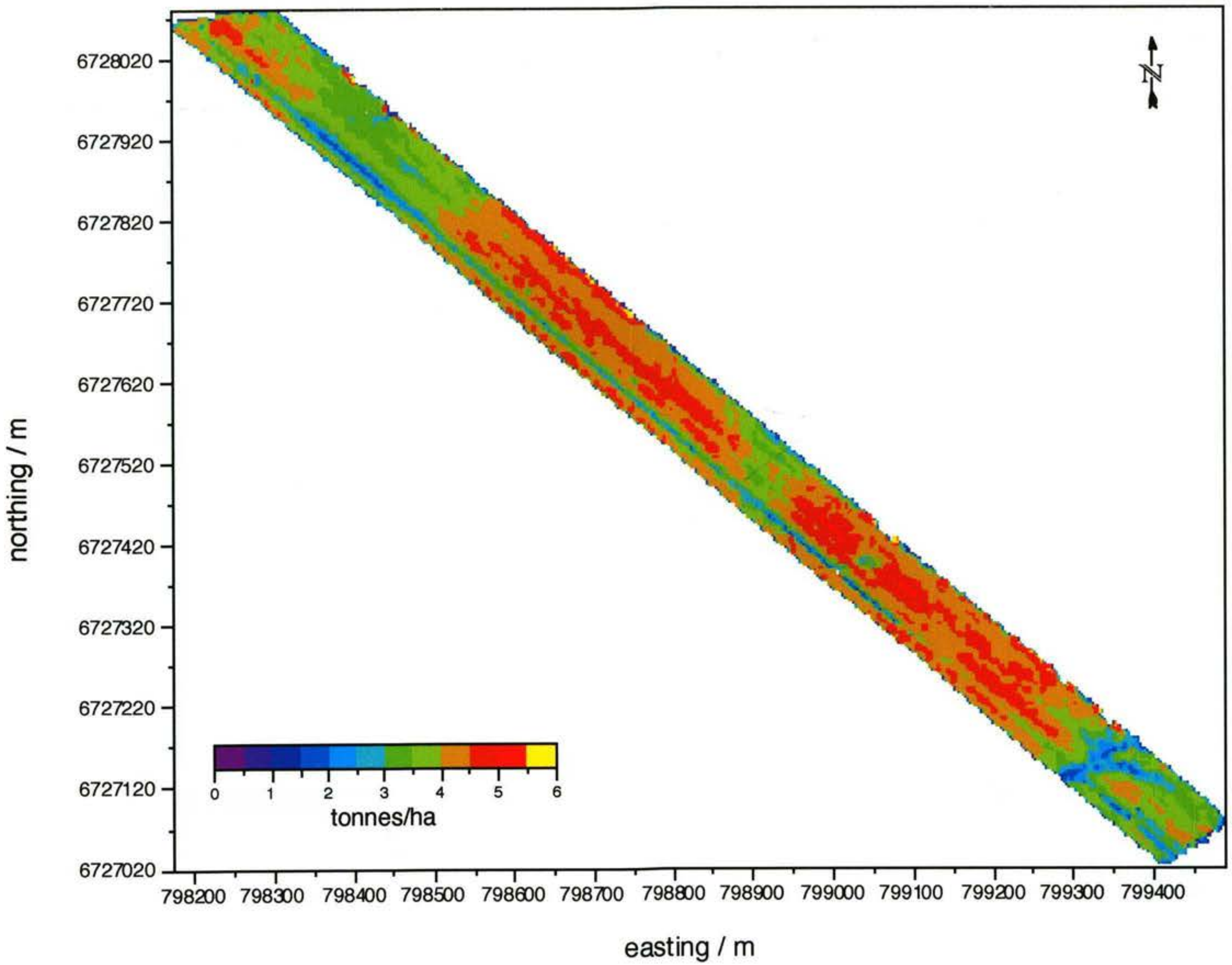

Figure B-30. Field N8 - Marinya 1996 wheat.

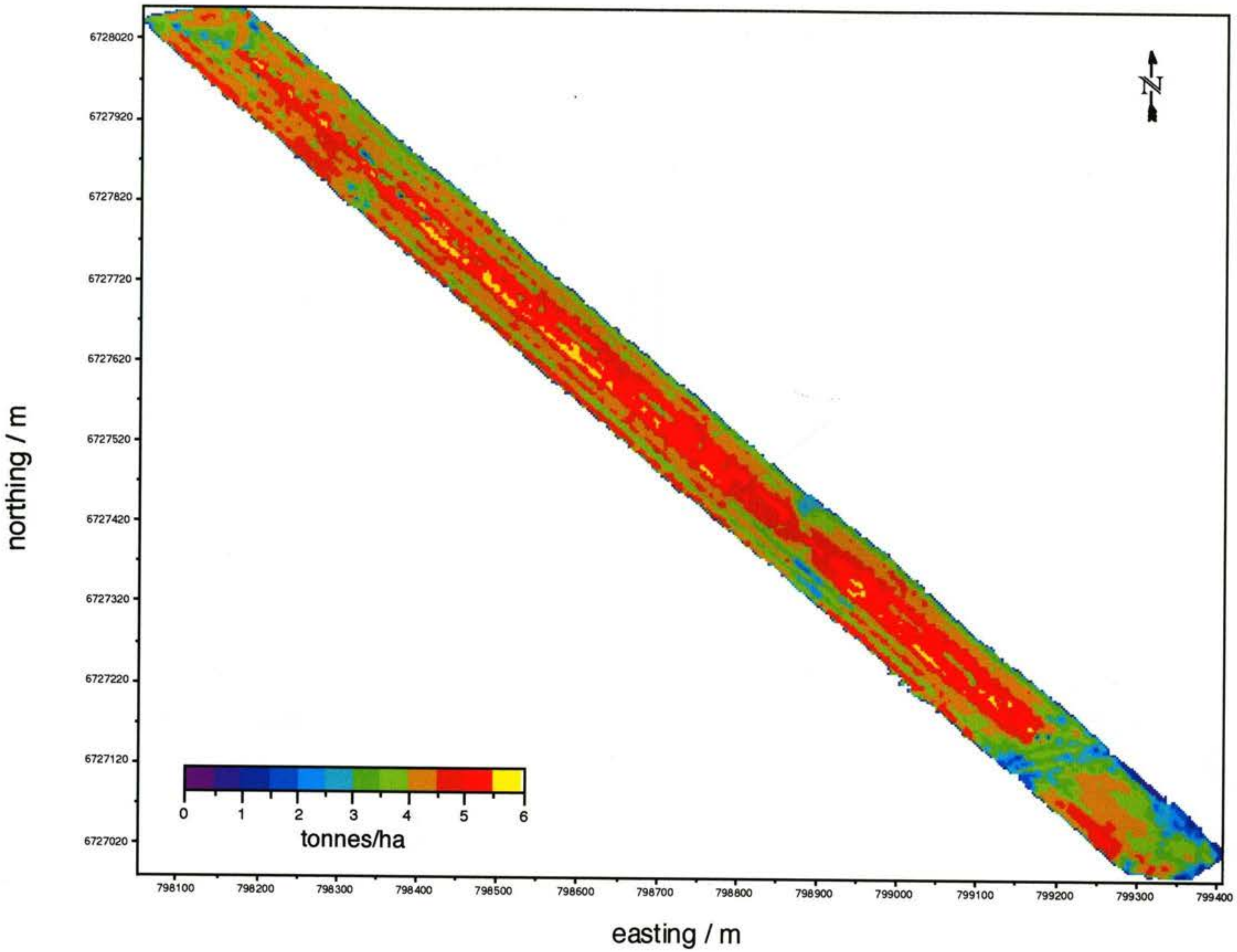

Figure B-31. Field N9 - Marinya 1996 wheat.

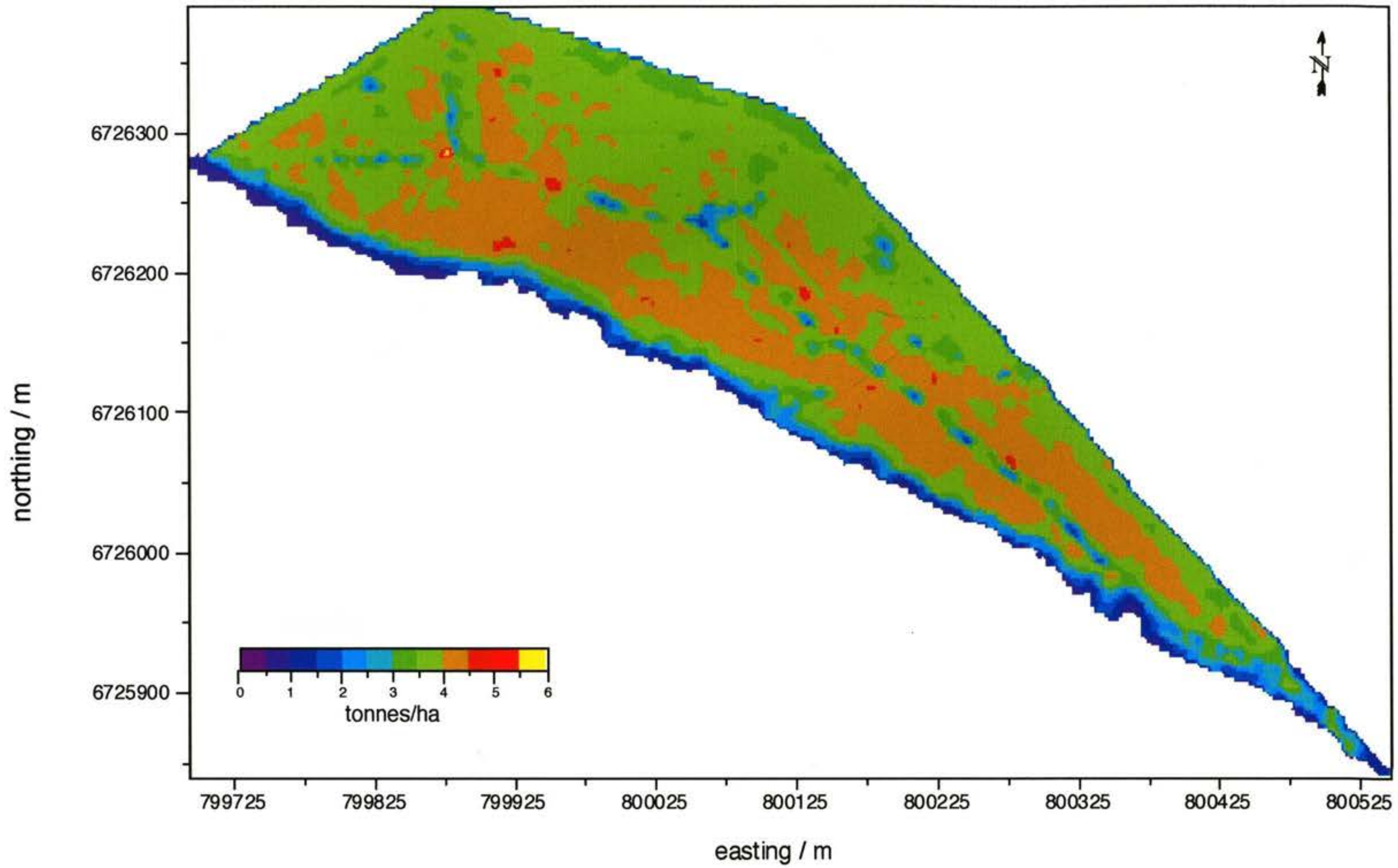

Figure B-32. Field S1 - Marinya 1996 wheat.

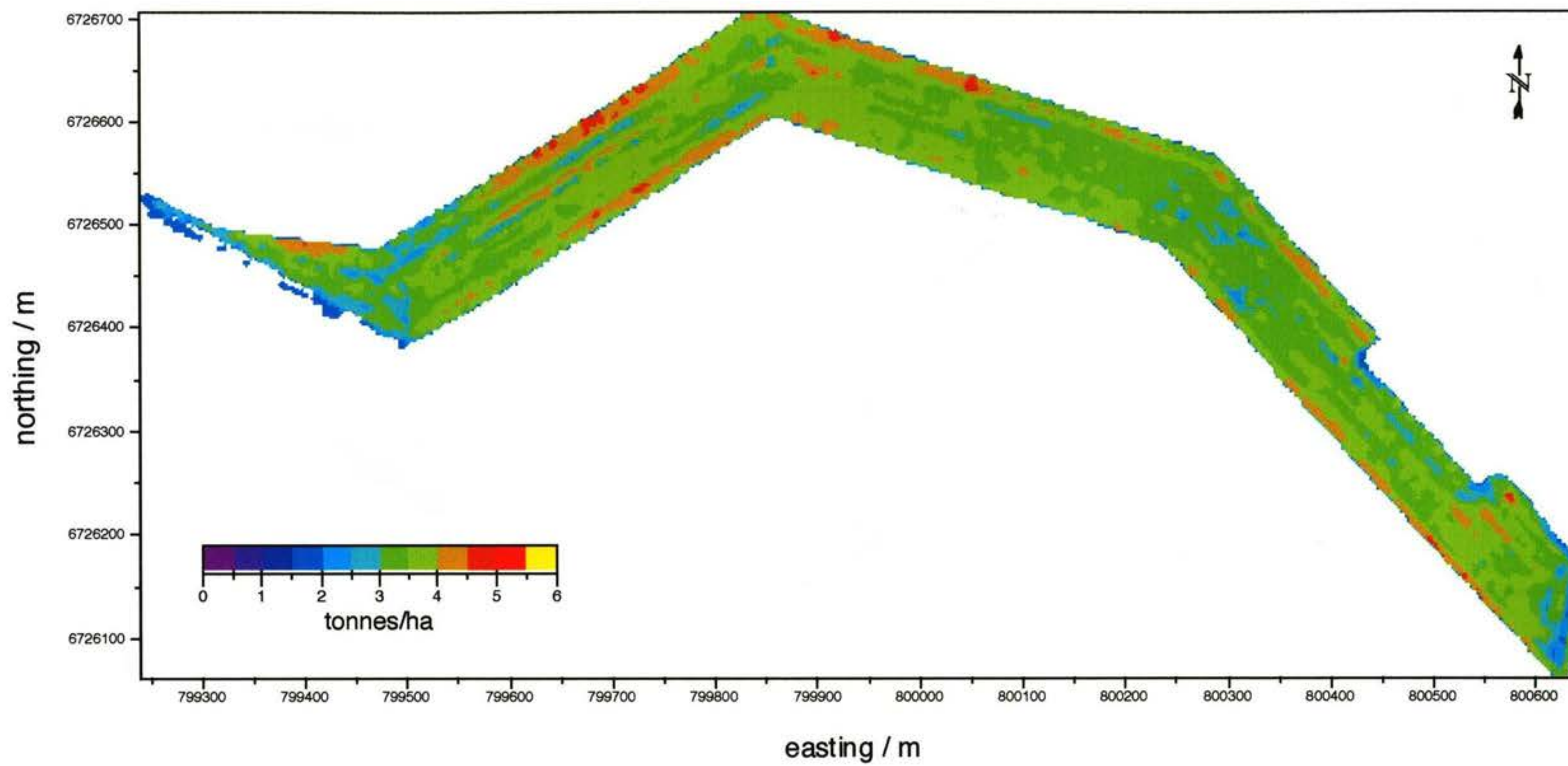

Figure B-33. Field S4 - Marinya 1996 wheat.

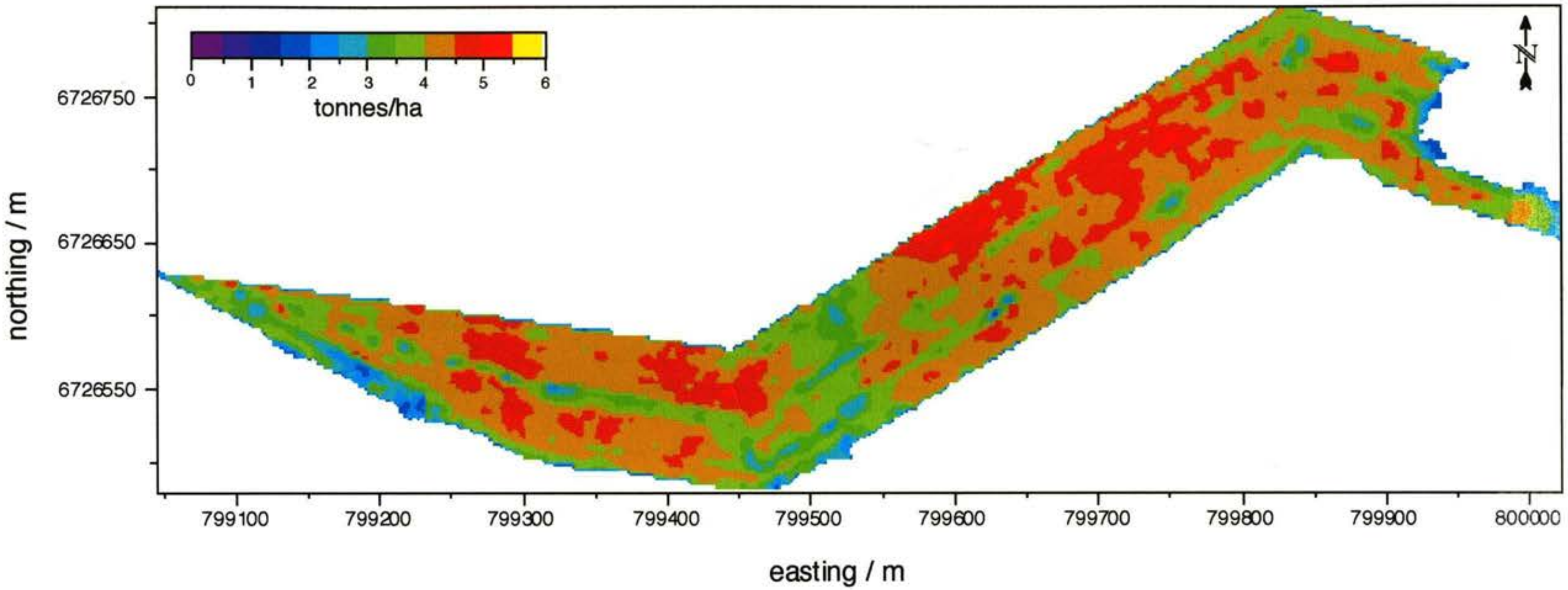

Figure B-34. Field S5 - Marinya 1996 wheat.

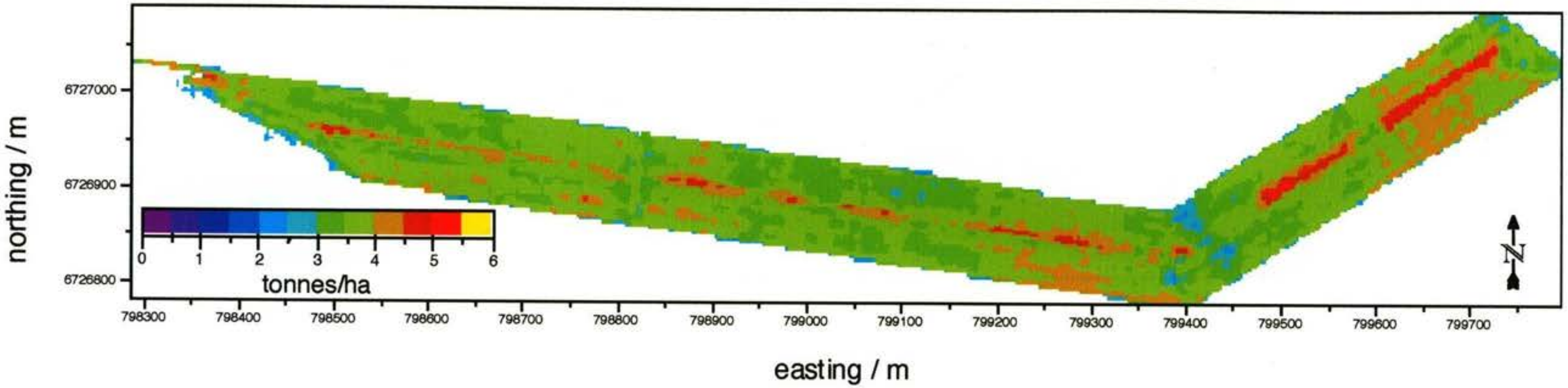

Figure B-35. Field S8 - Marinya 1996 wheat.

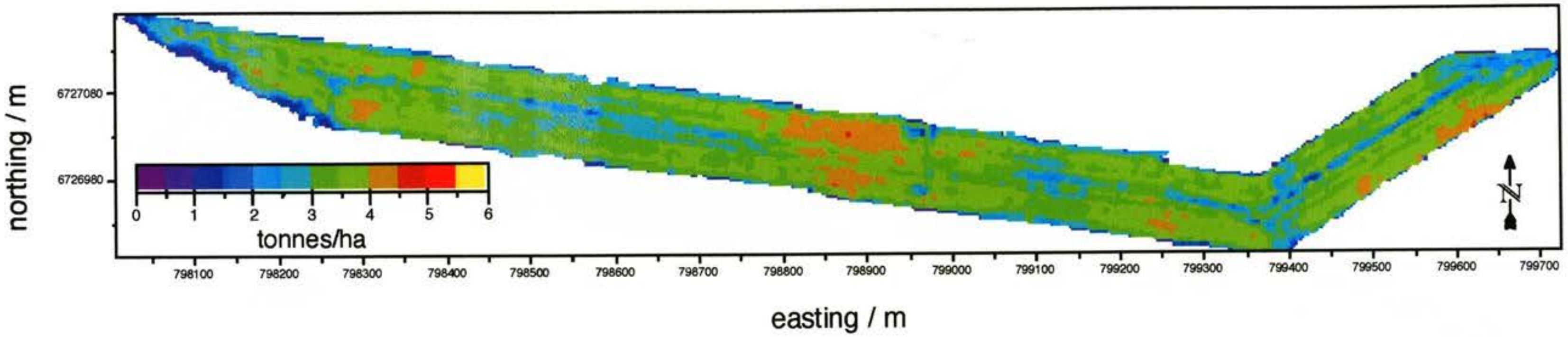

Figure B-36. Field S9 - Marinya 1996 wheat.

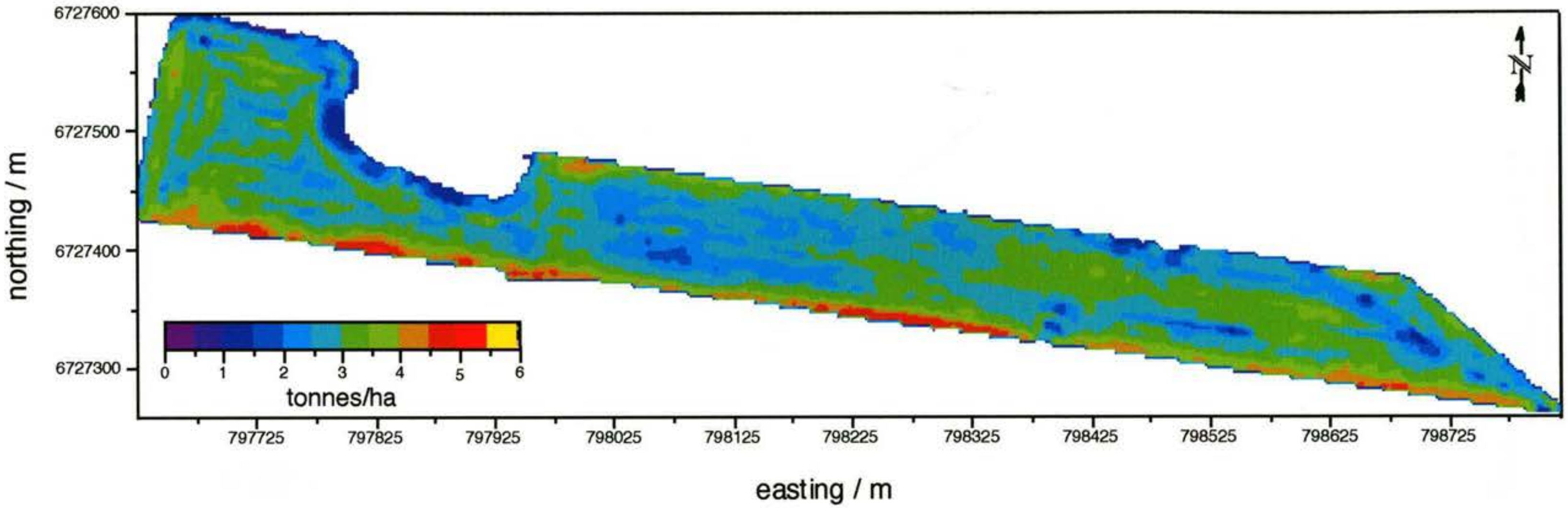

Figure B-37. Field S12 - Marinya 1996 wheat.

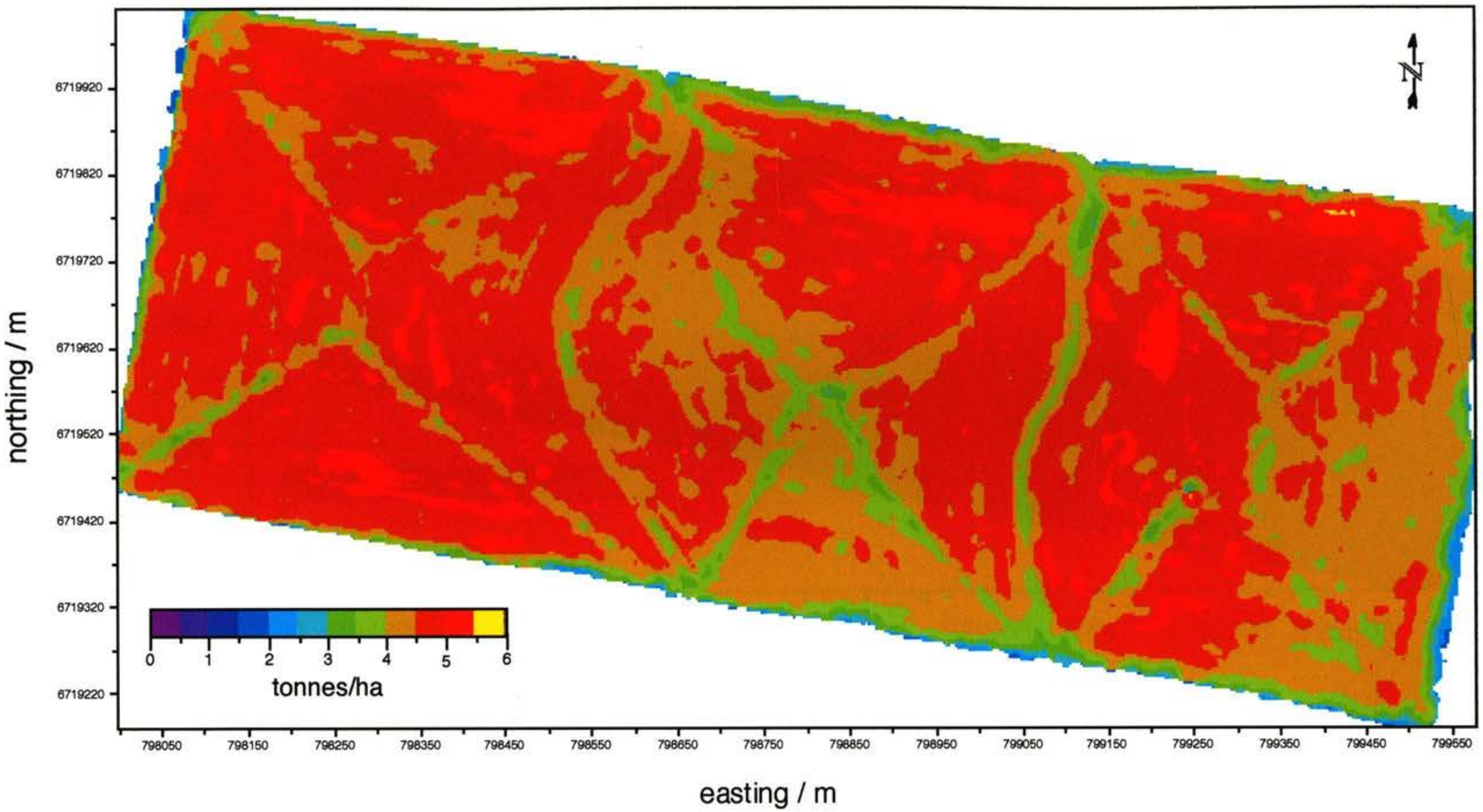

Figure B-38. Maidens 1996 wheat (10m radius moving average).

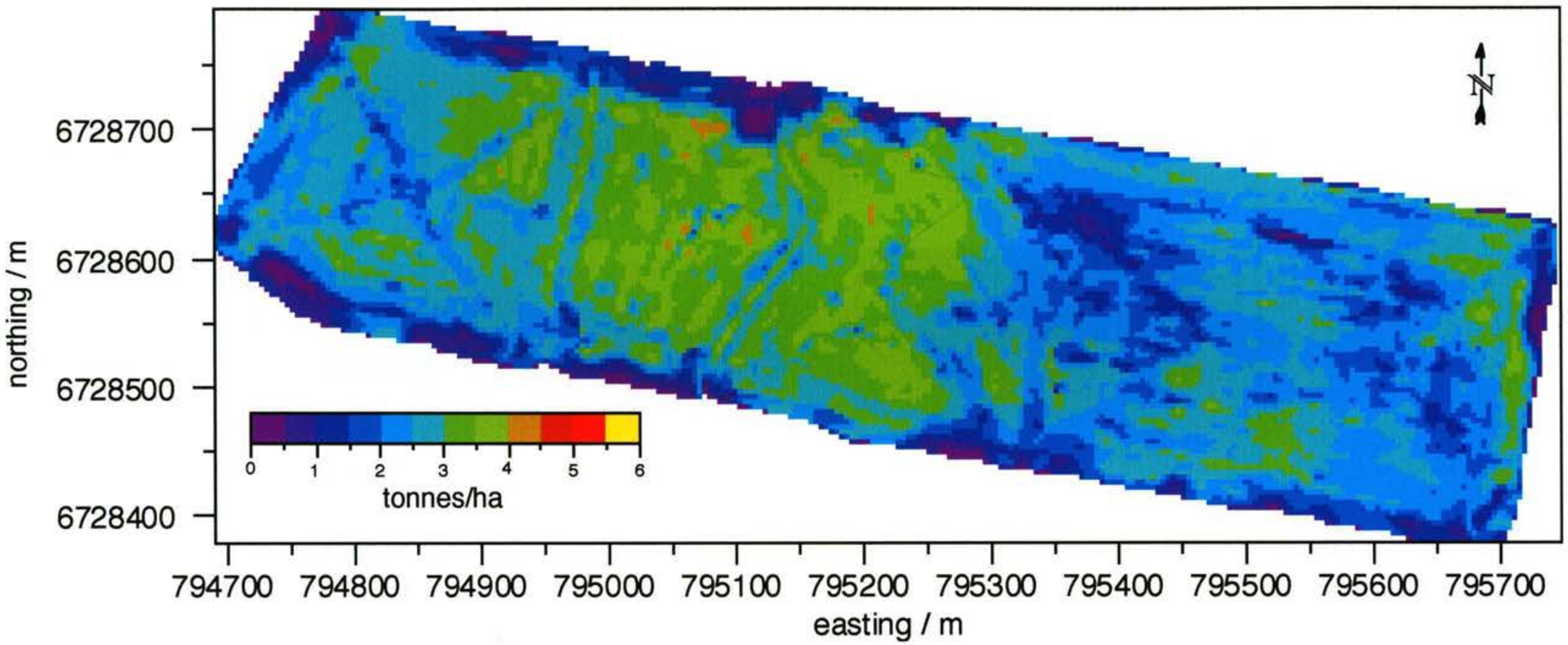

Figure B-39. Bommera 1996 wheat.

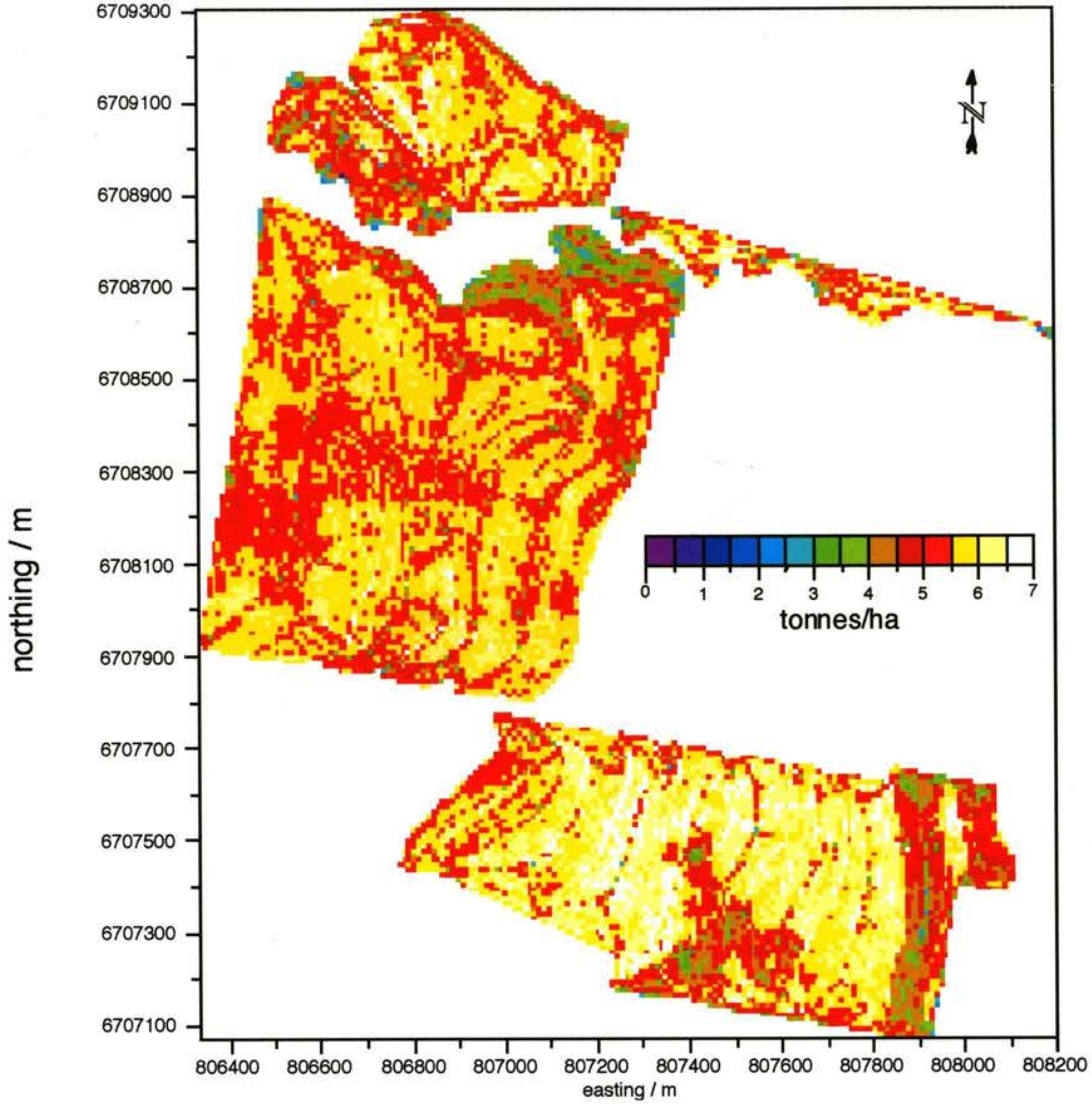

Figure B-40. Romaka 1996 wheat yield overview.

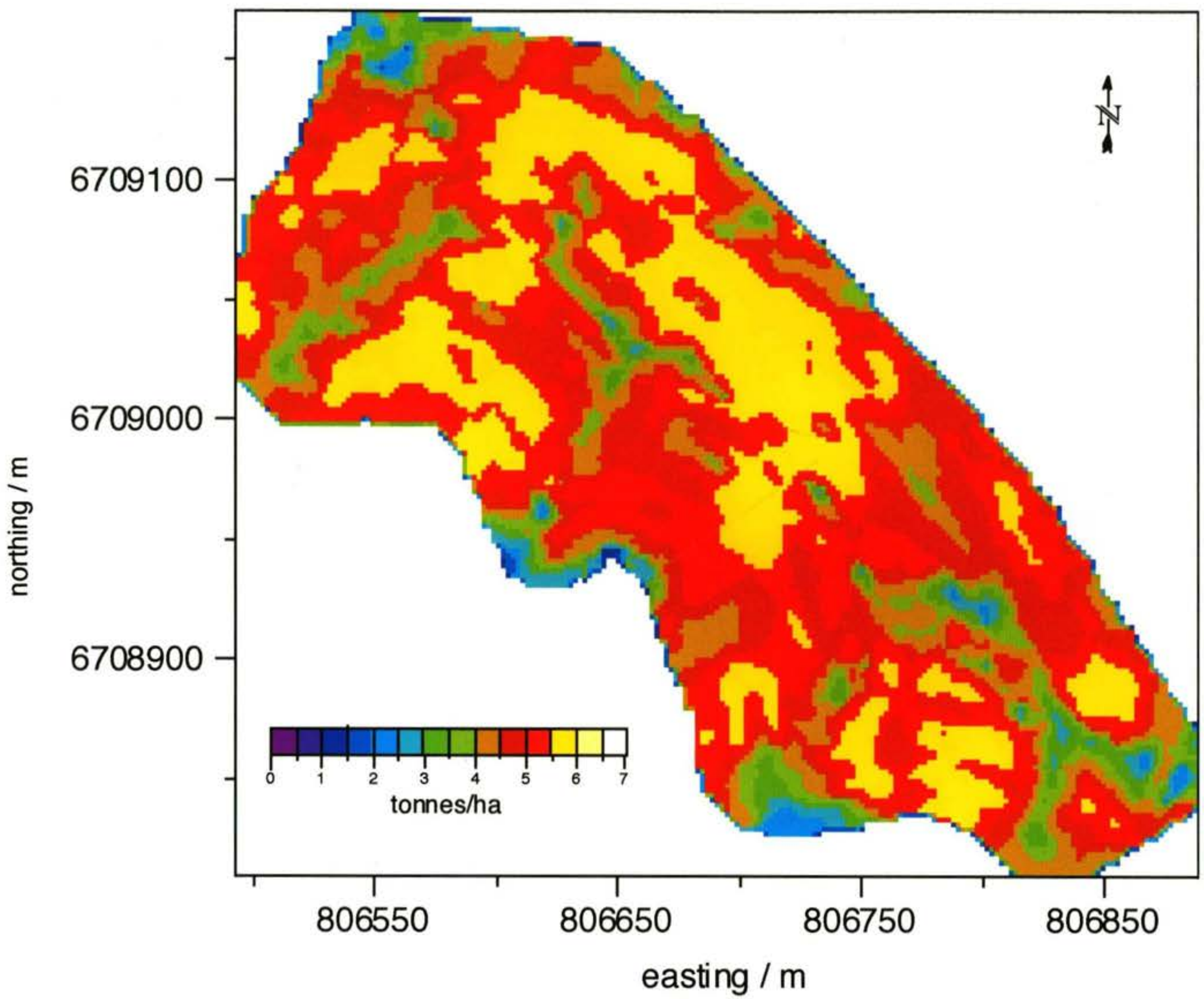

Figure B-41. Bull Field - Romaka 1996 wheat.

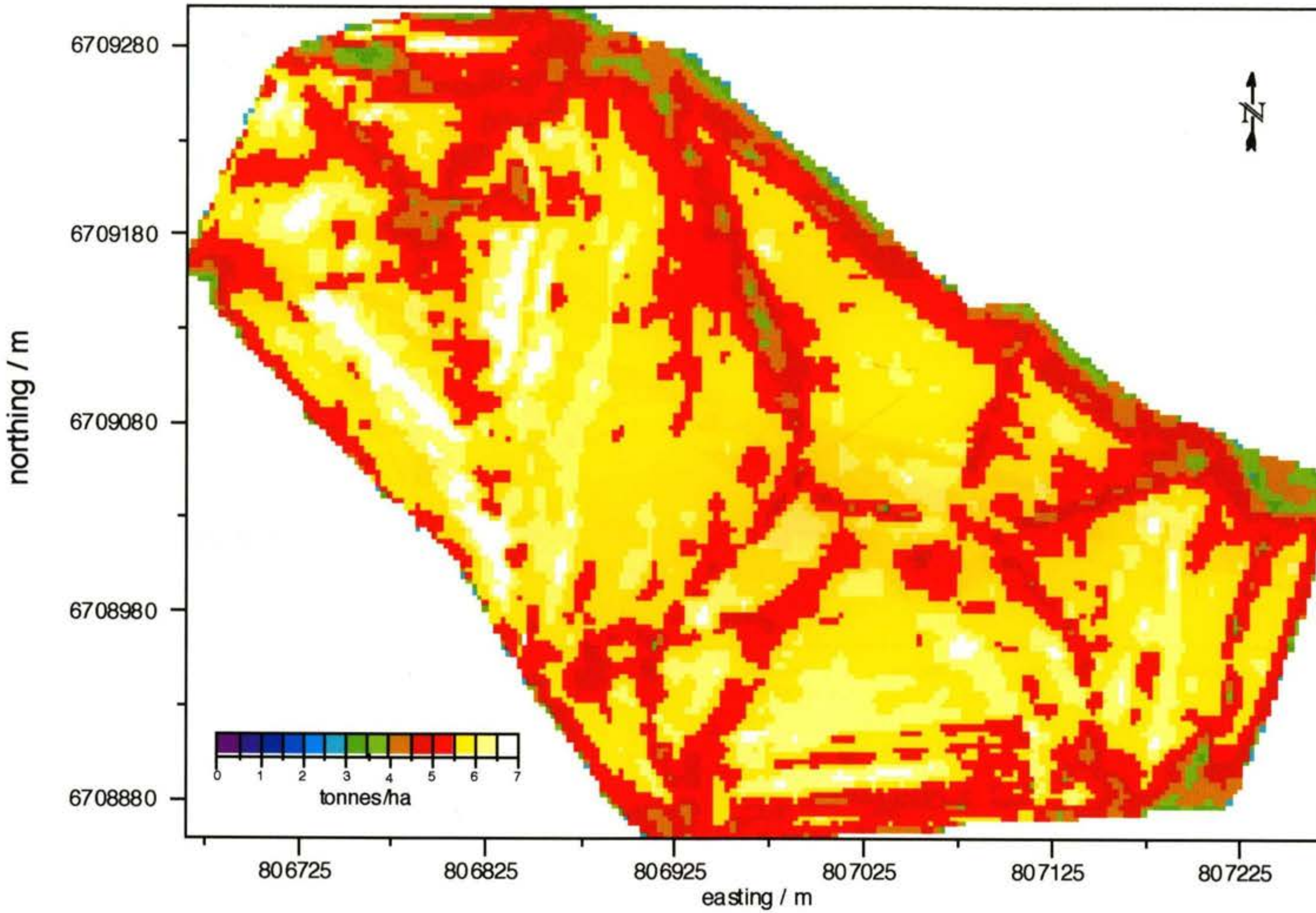

Figure B-42. South Dam Field - Romaka 1996 wheat.

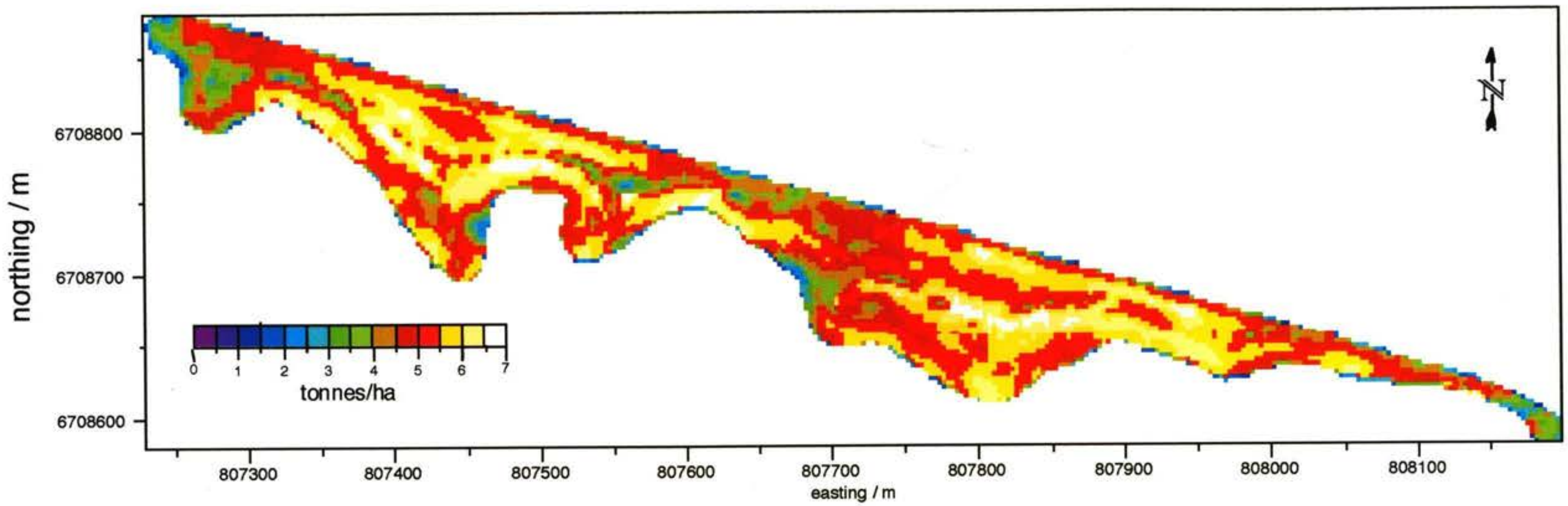

Figure B-43. Skurr Field - Romaka 1996 wheat.

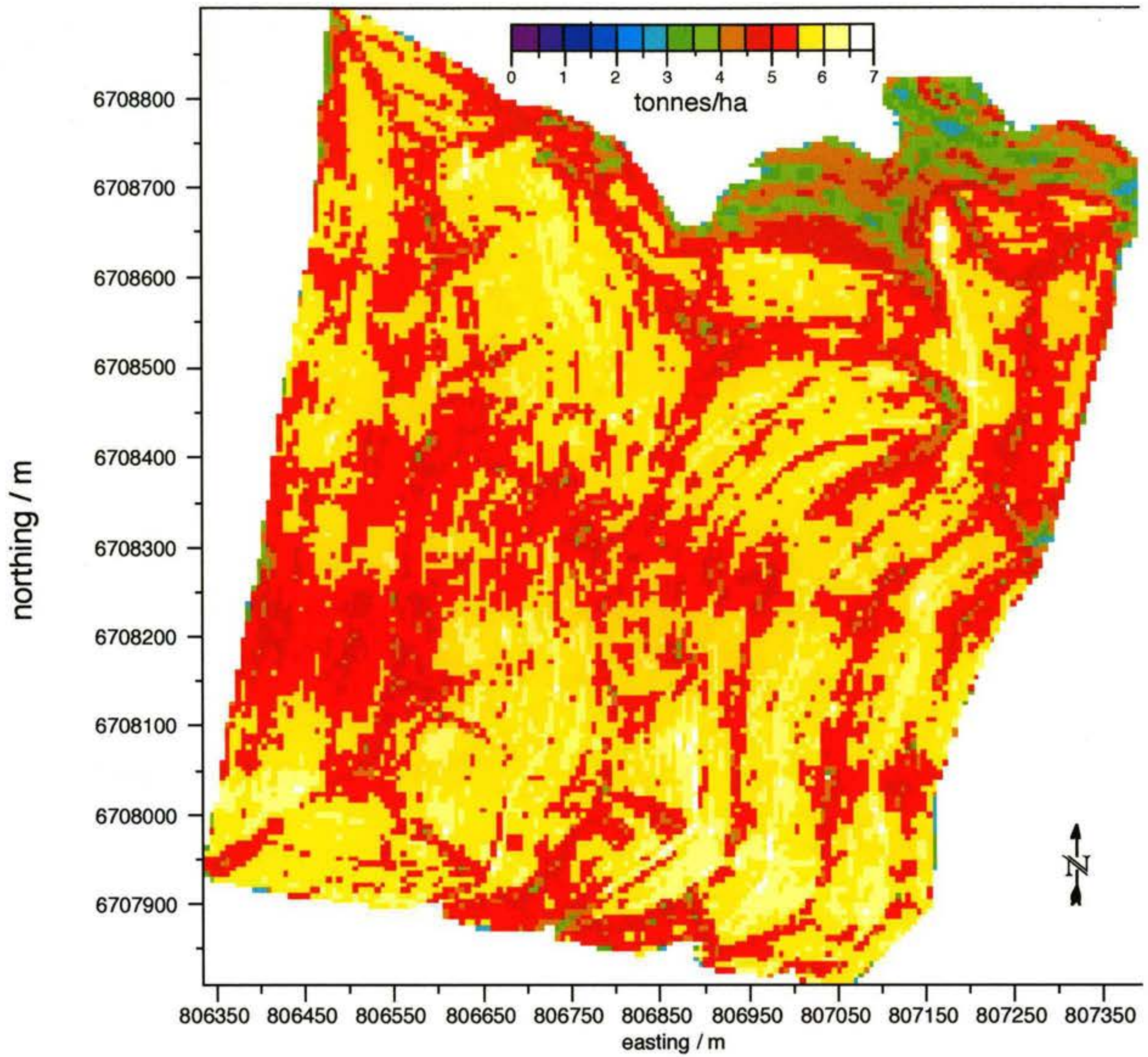

Figure B-44. Creek Field - Romaka 1996 wheat.

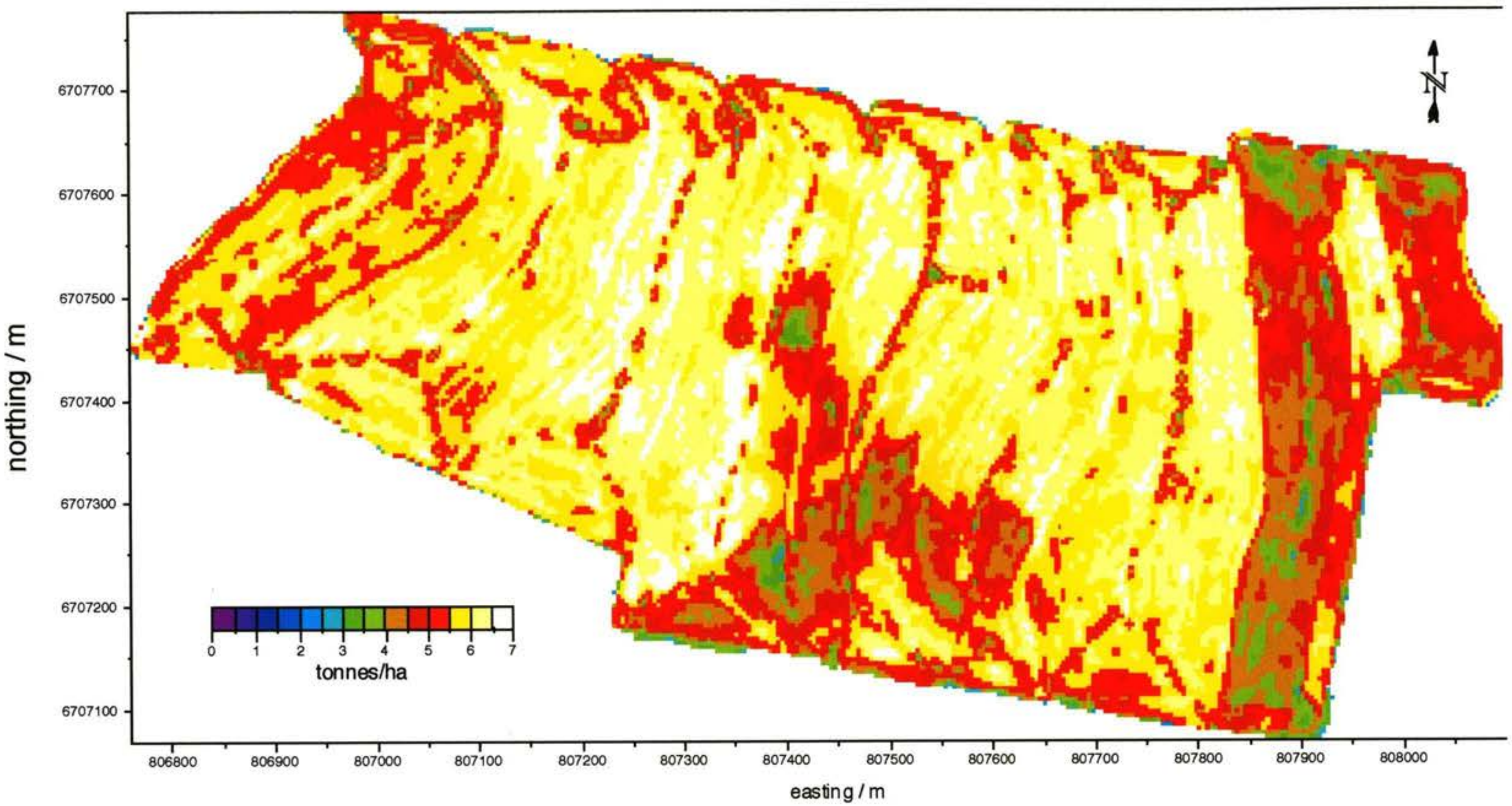

Figure B-45. Lease Field - Romaka 1996 wheat.

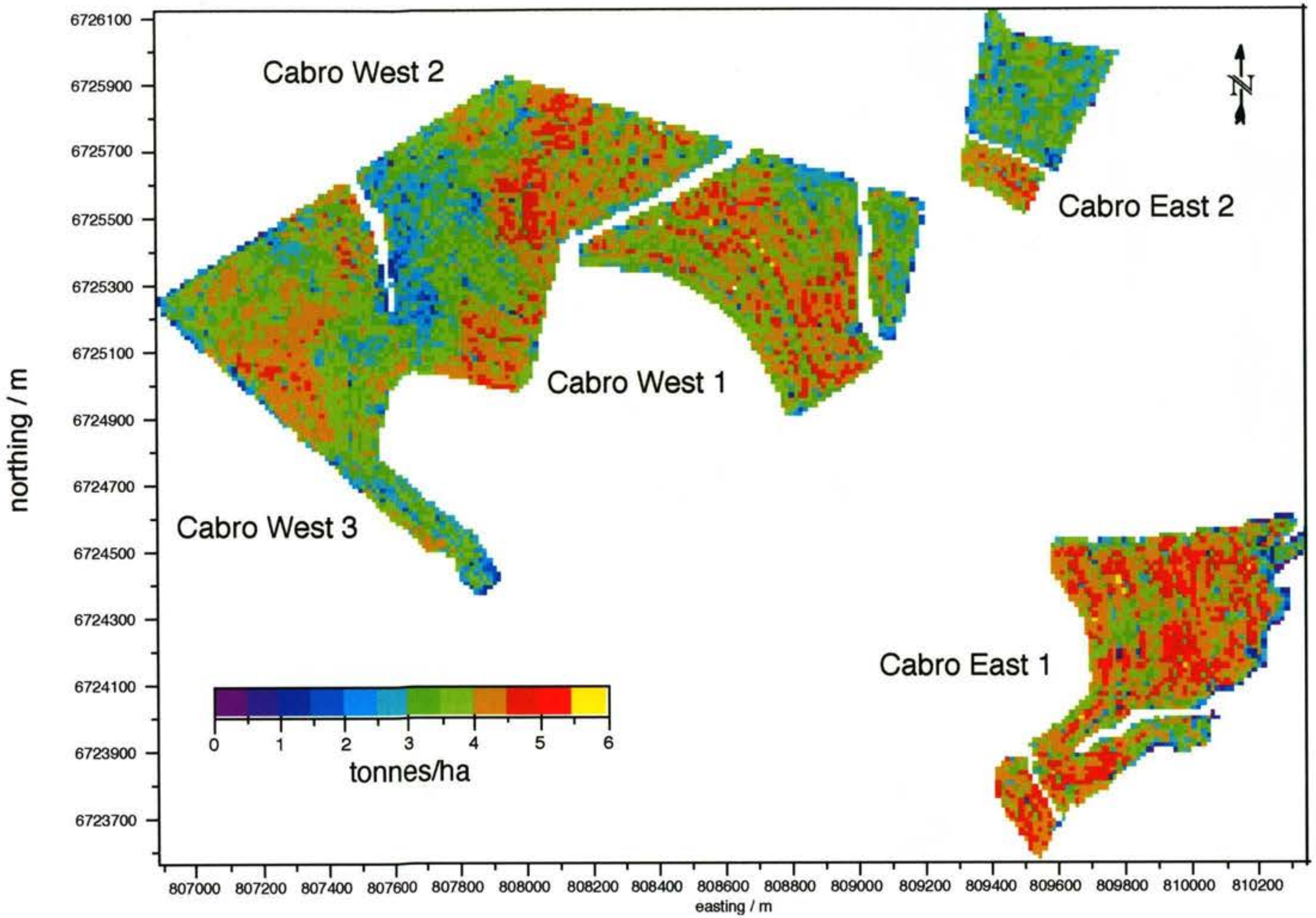

Figure B-46. Cabro 1996 wheat yield overview.

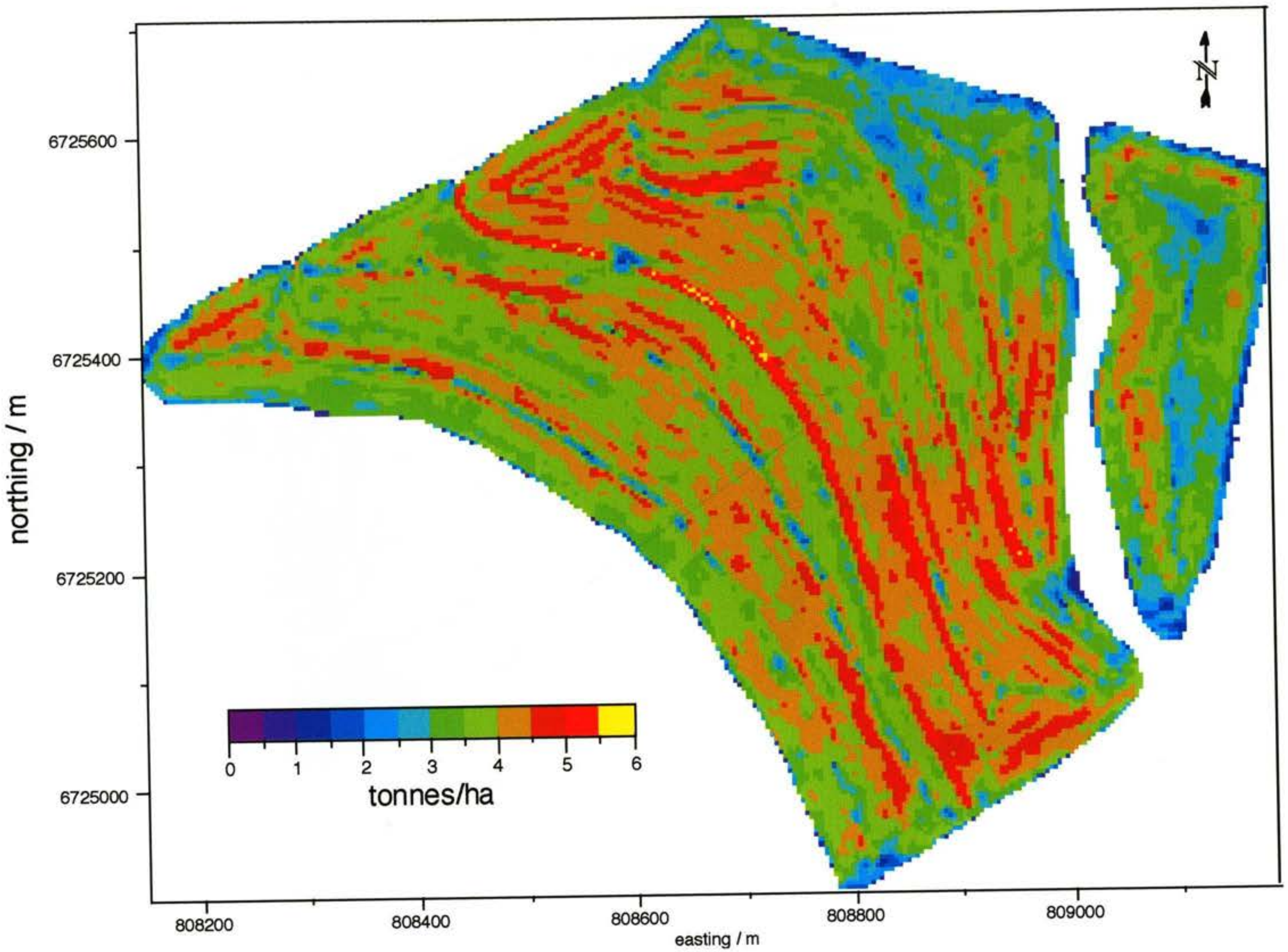

Figure B-47. Cabro West 1 - Cabro 1996 wheat.

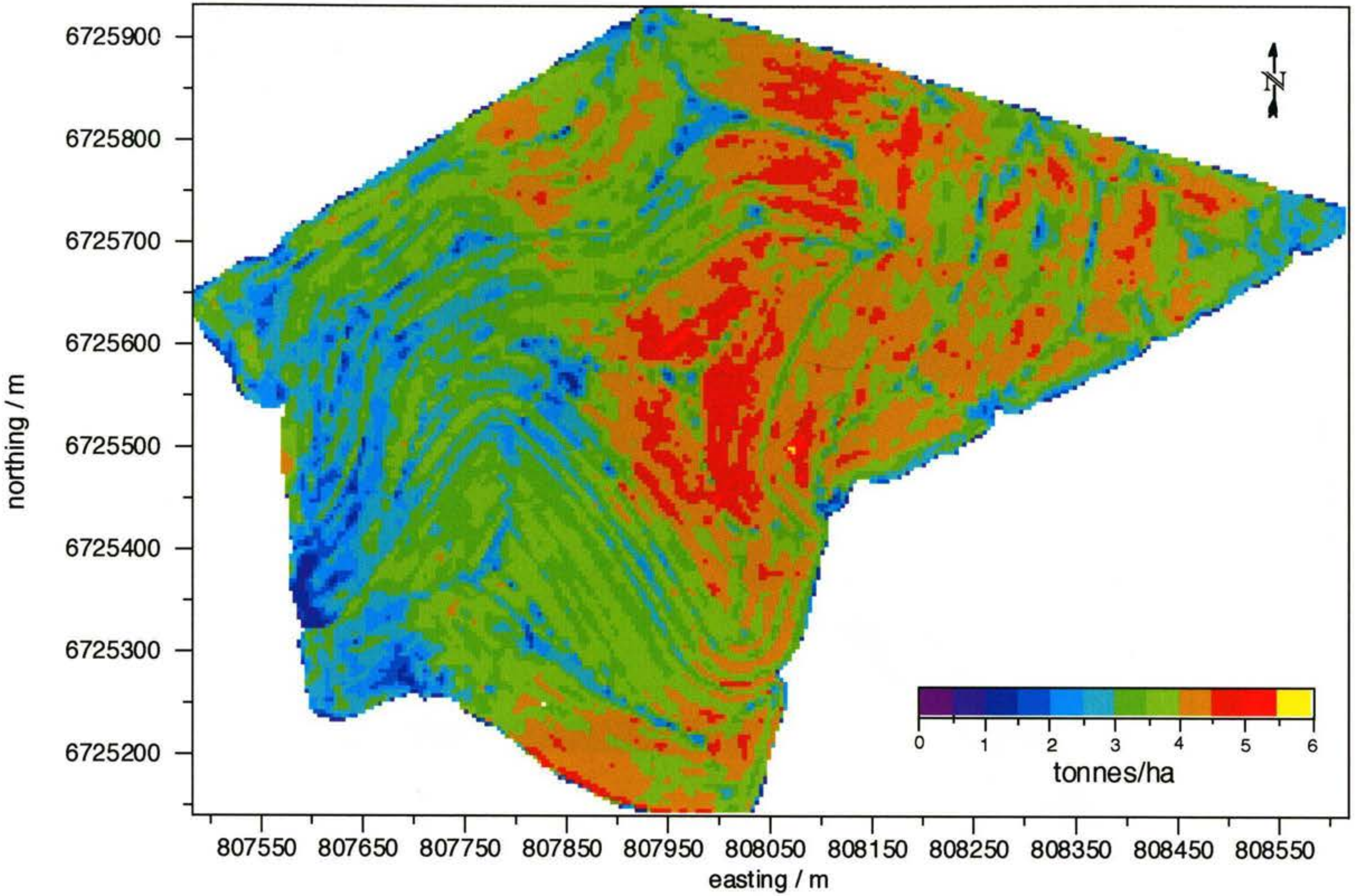

Figure B-48. Cabro West 2 - Cabro 1996 wheat.

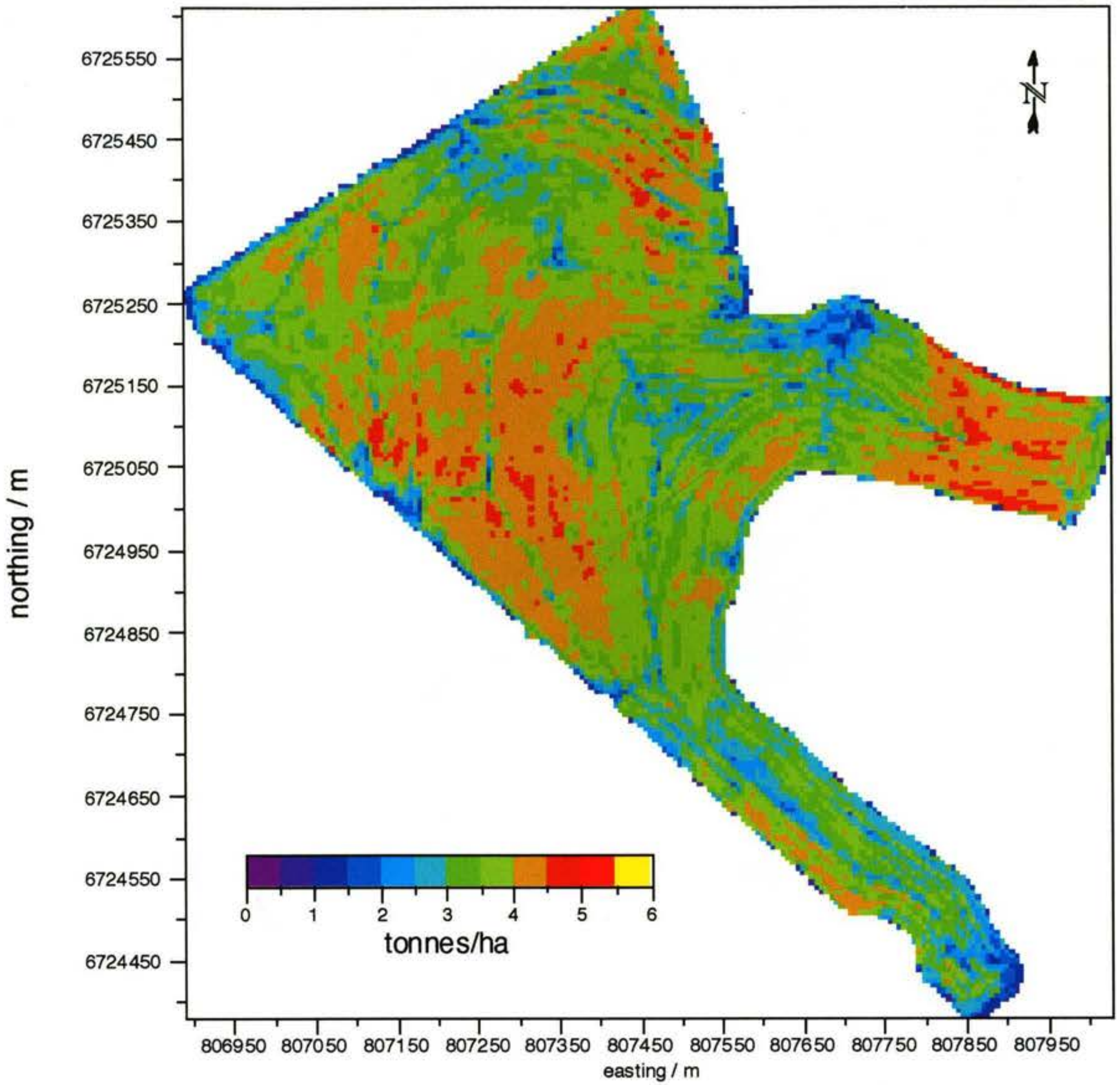

Figure B-49. Cabro West 3 - Cabro 1996 wheat.

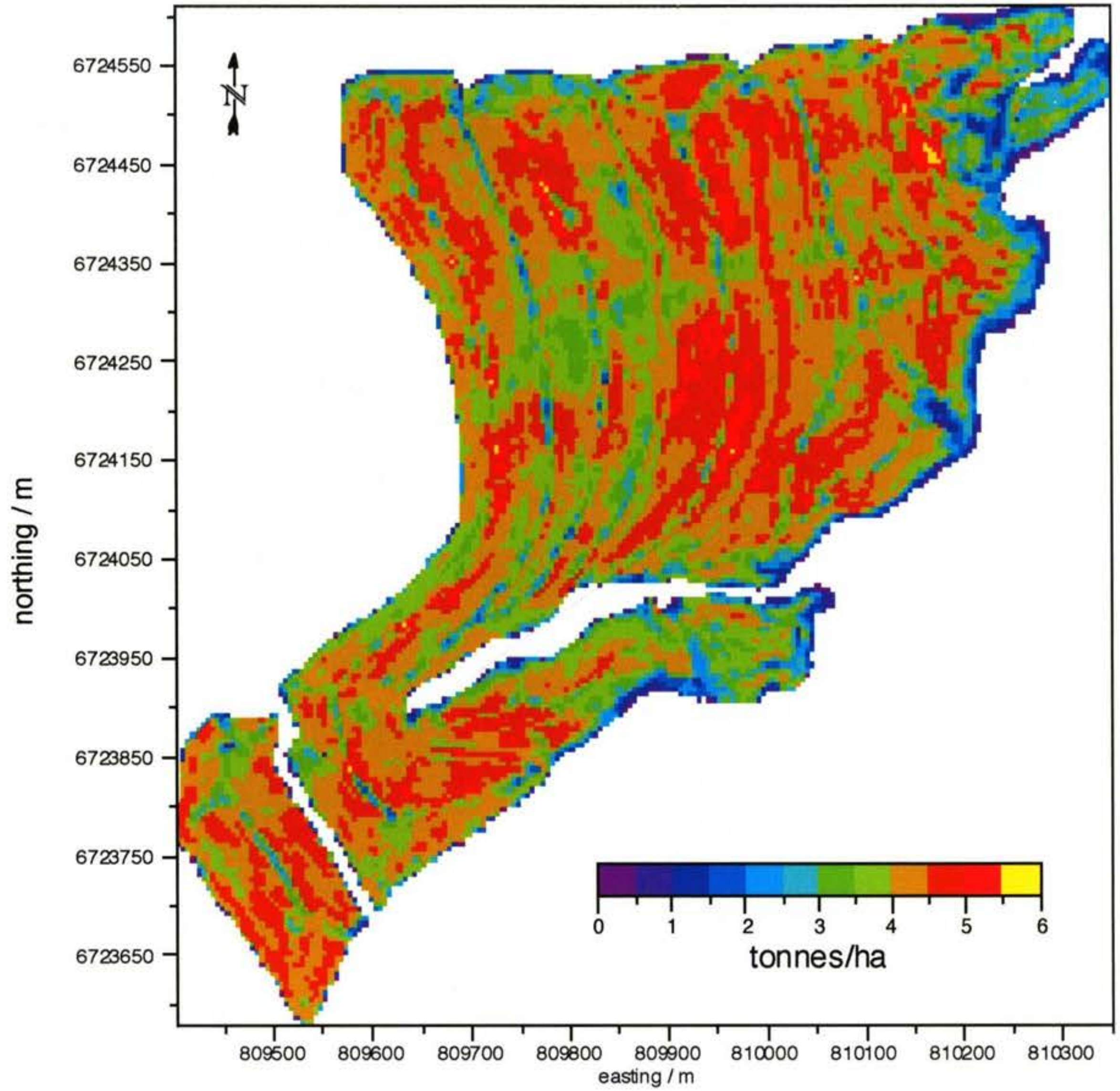

Figure B-50. Cabro East 1 - Cabro 1996 wheat.

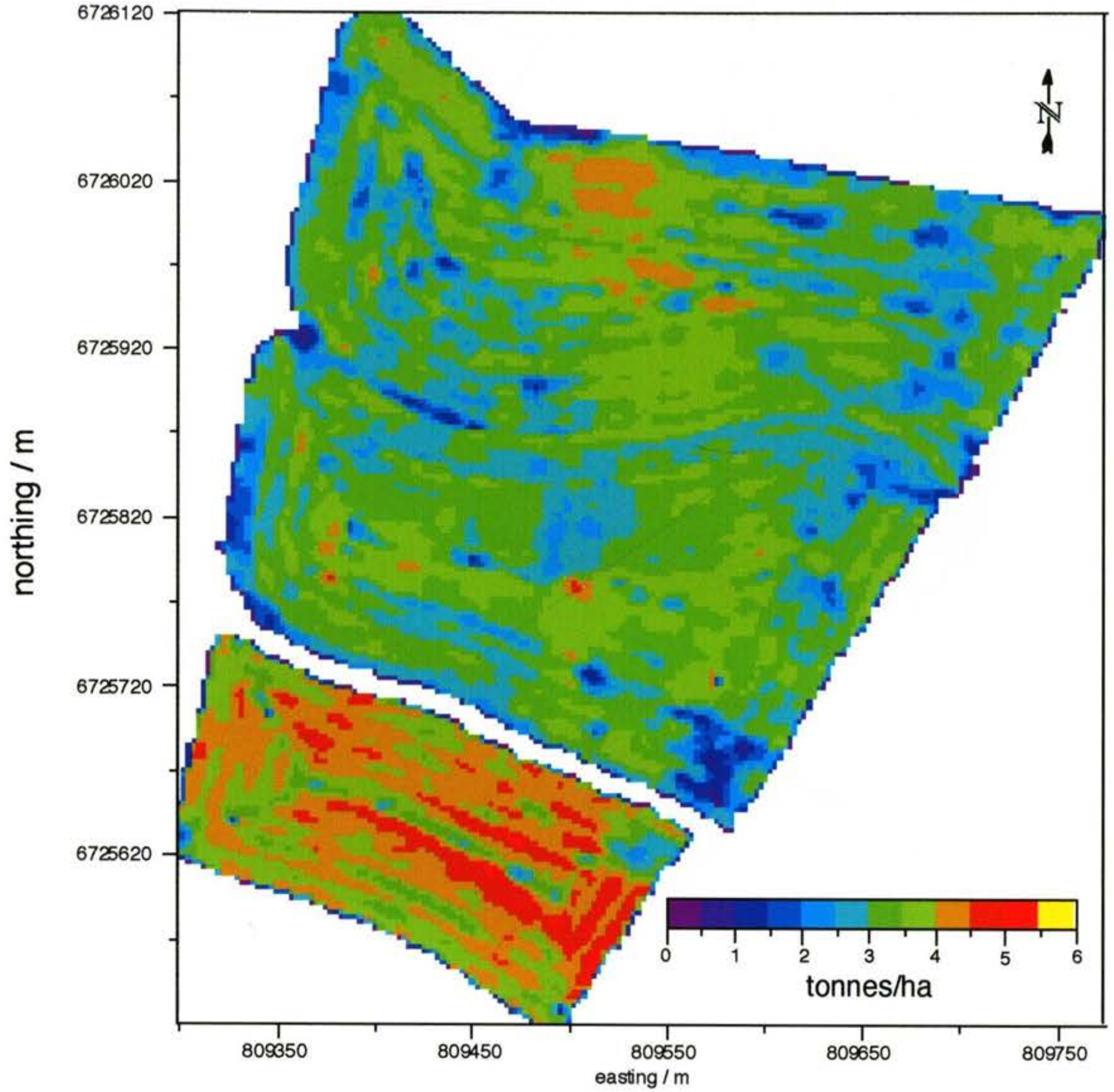

Figure B-51. Cabro East 2 - Cabro 1996 wheat.

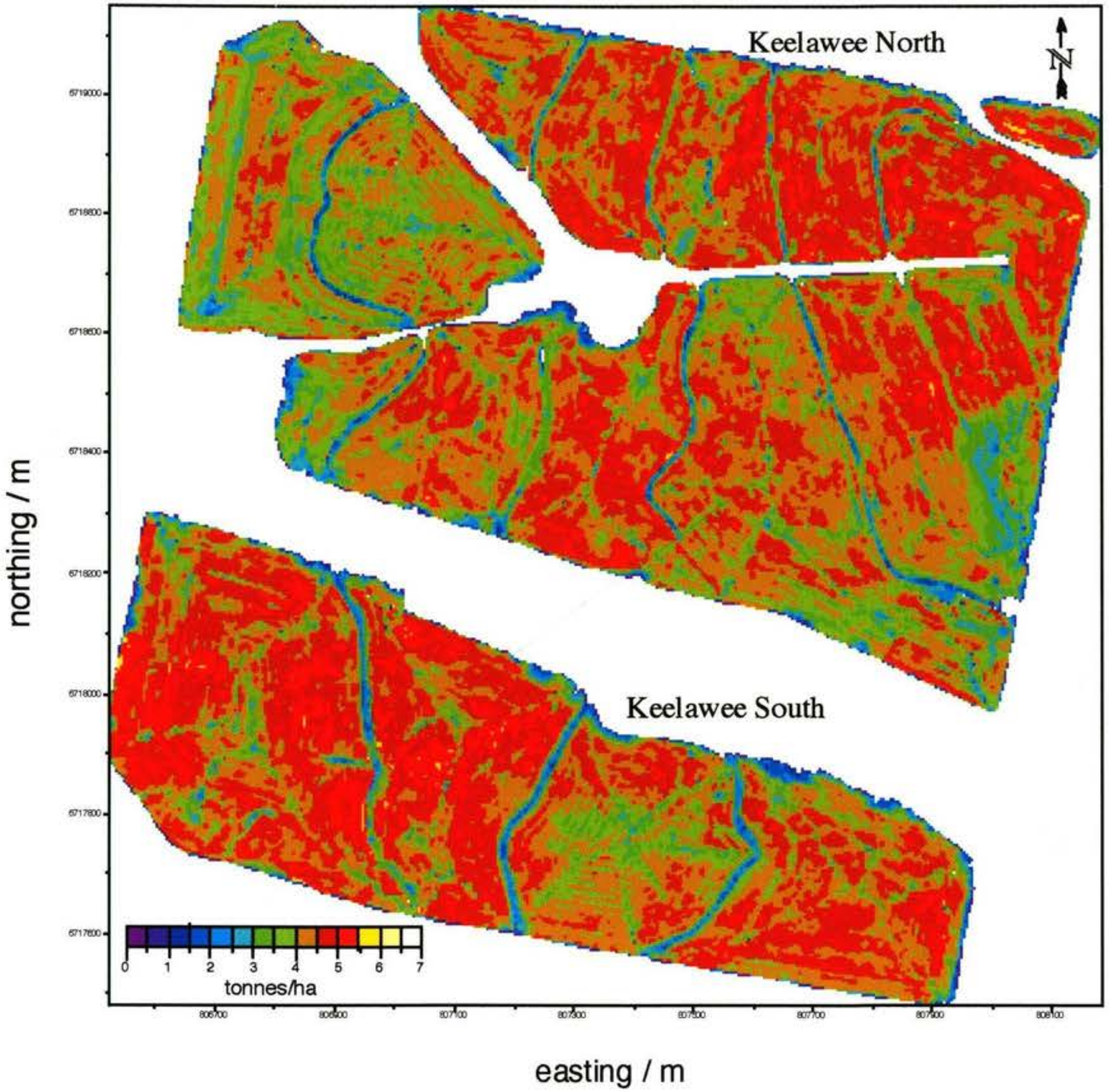

Figure B-52. Keelawee 1997 wheat yield overview.

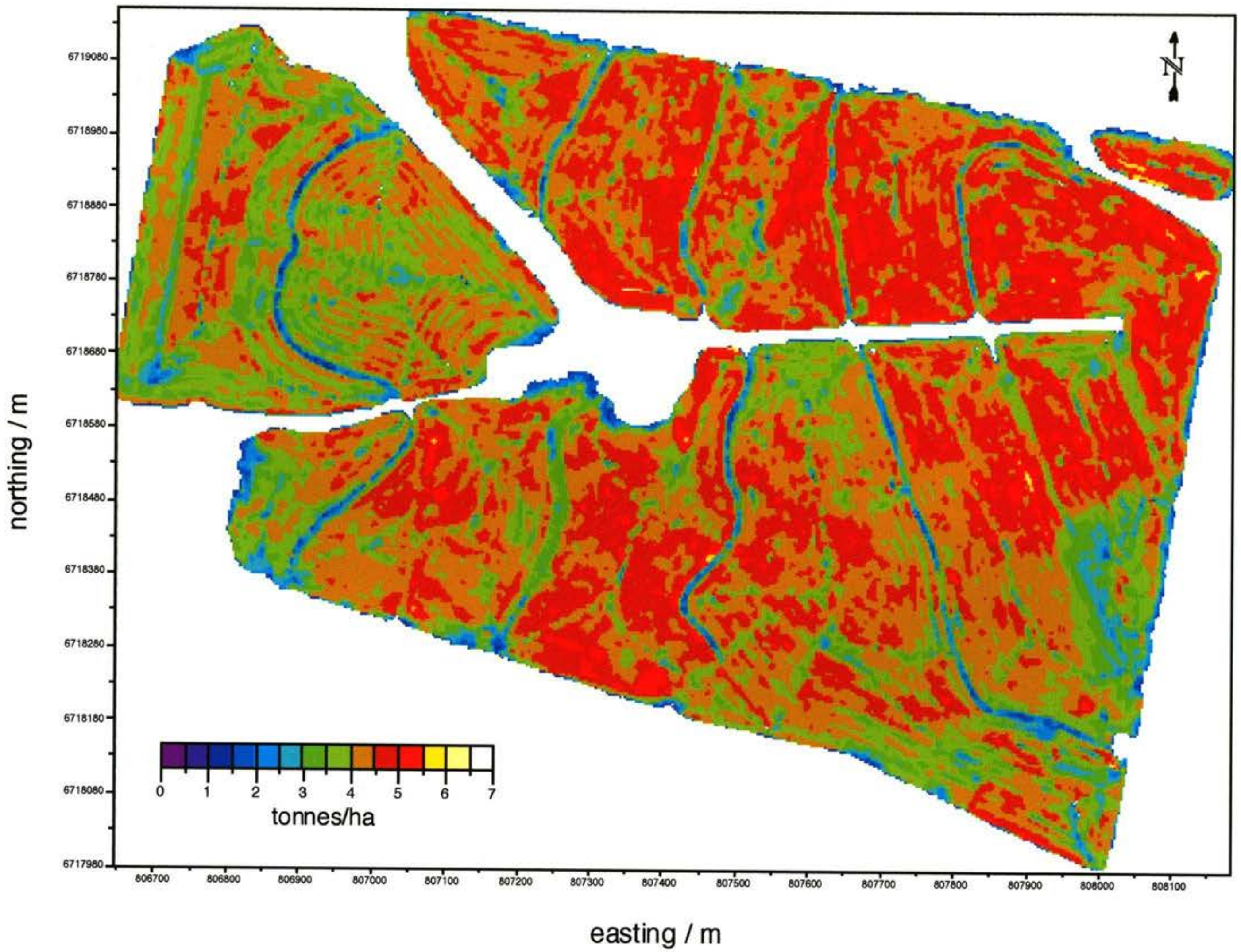

Figure B-53. Keelawee North Field - Keelawee 1996 wheat.

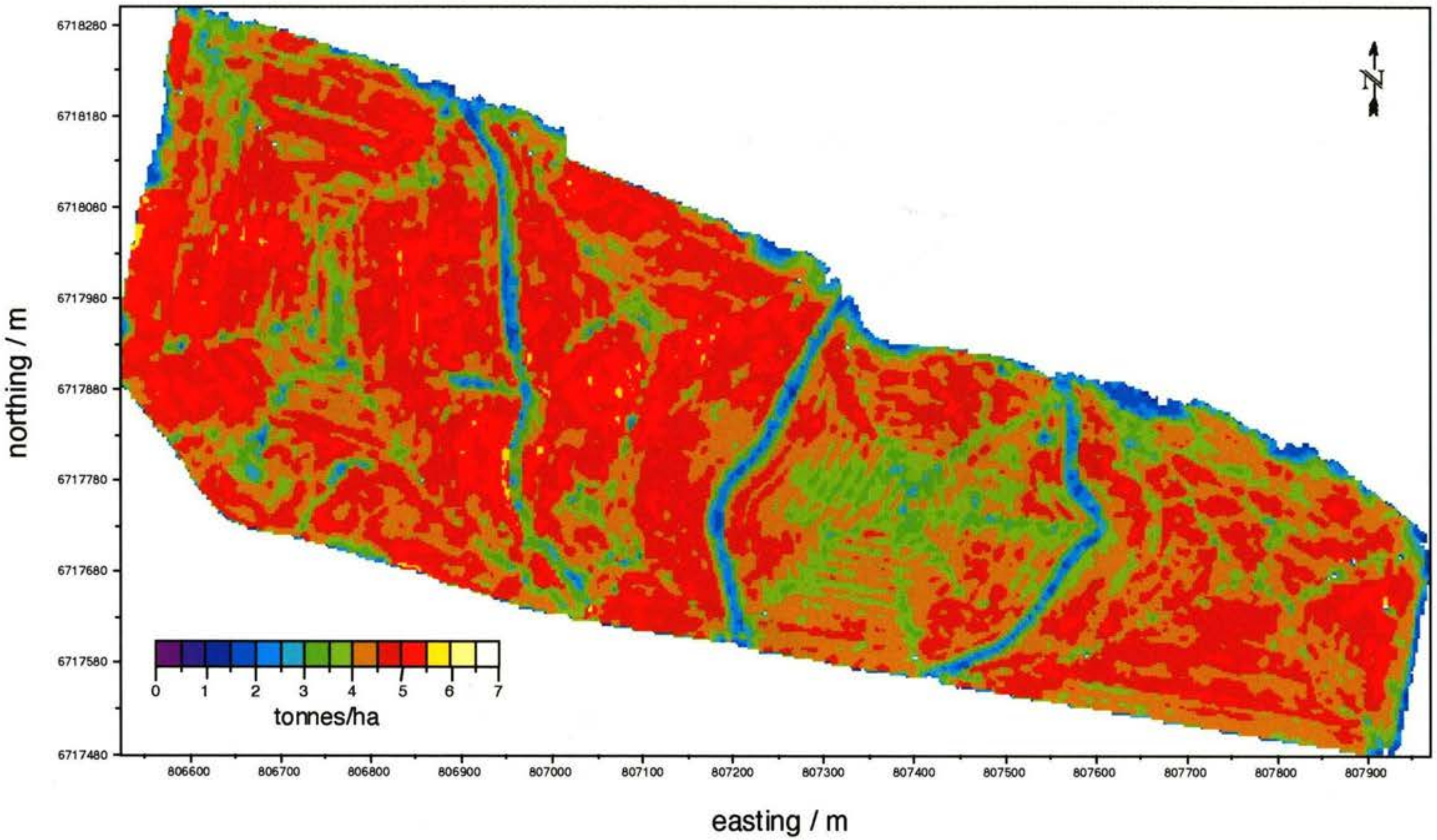

Figure B-54. Keelawee South Field - Keelawee 1996 wheat.

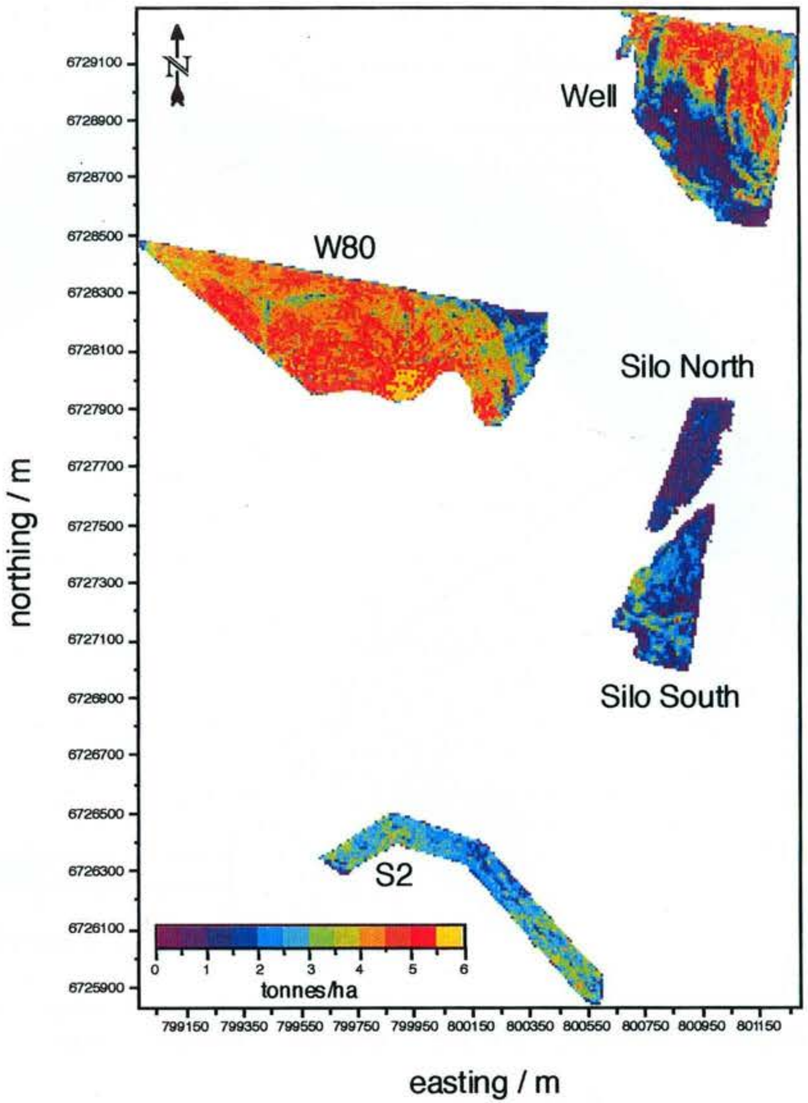

Figure B-55. Marinya 1997 sorghum yield overview.

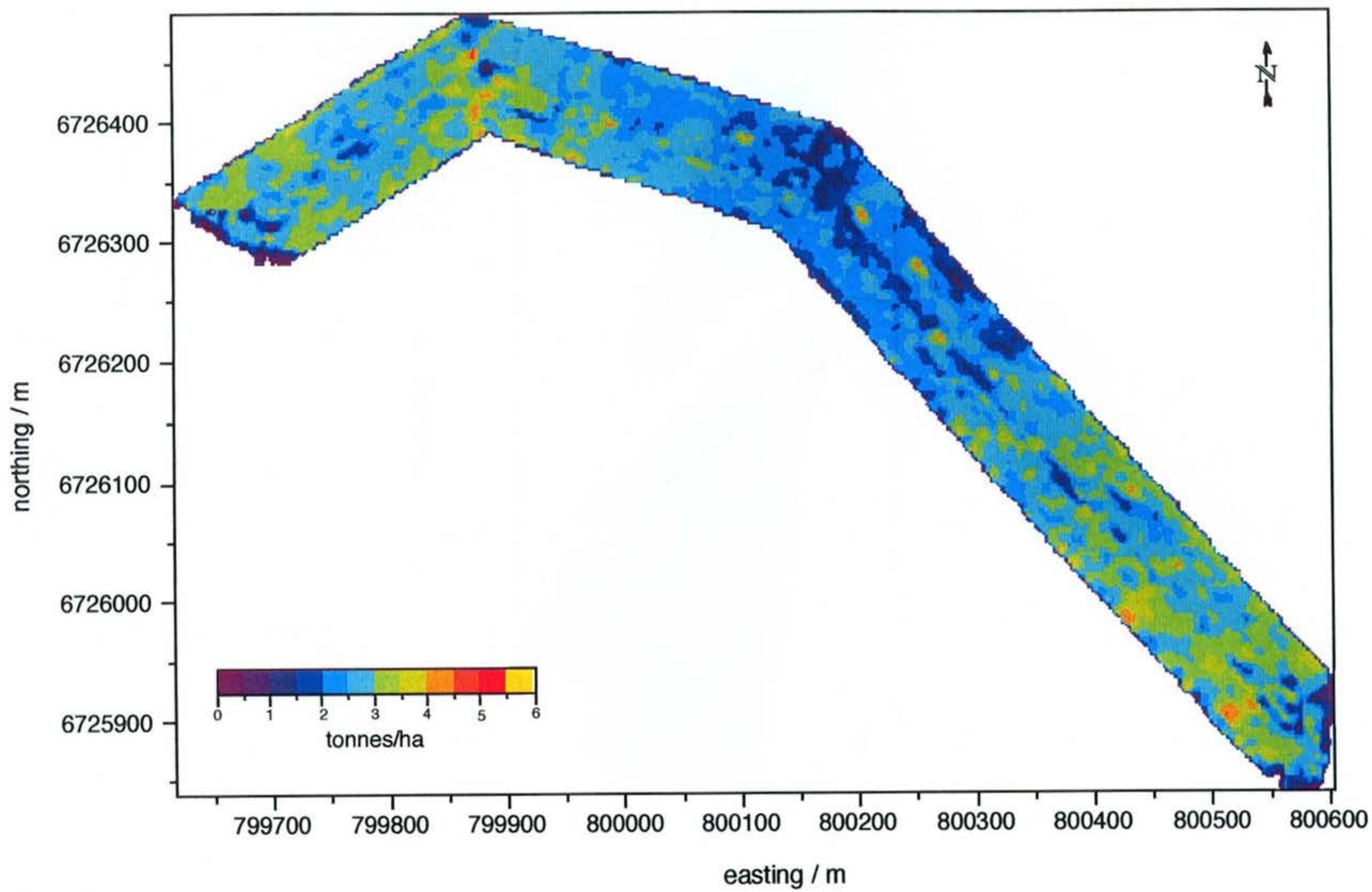

Figure B-56. Field S2 - Marinya 1997 sorghum.

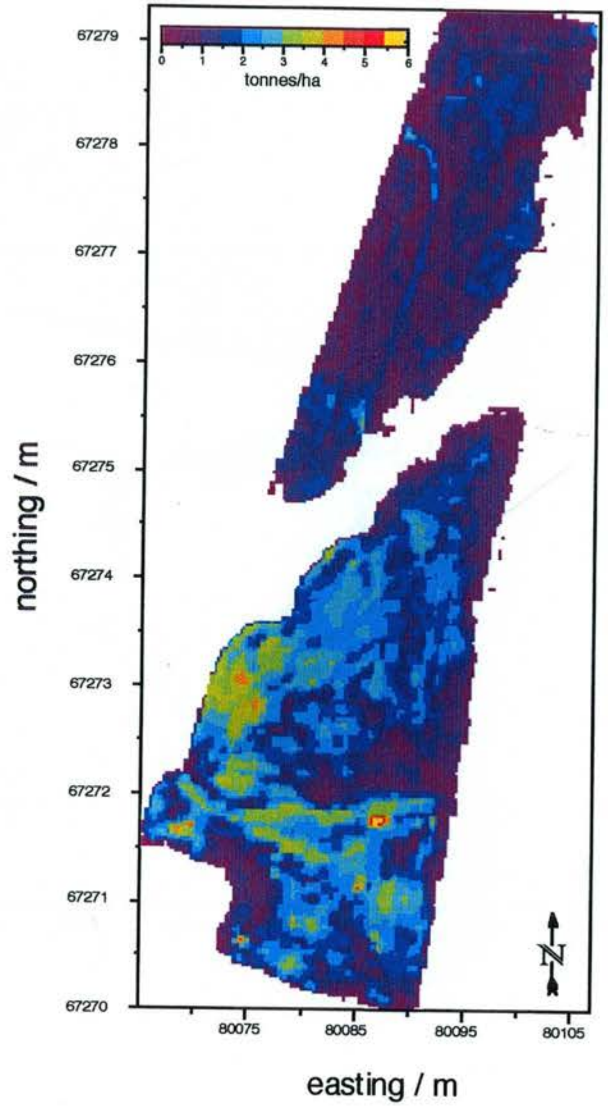

Figure B-57. Silo South & North Fields - Marinya 1997 sorghum.

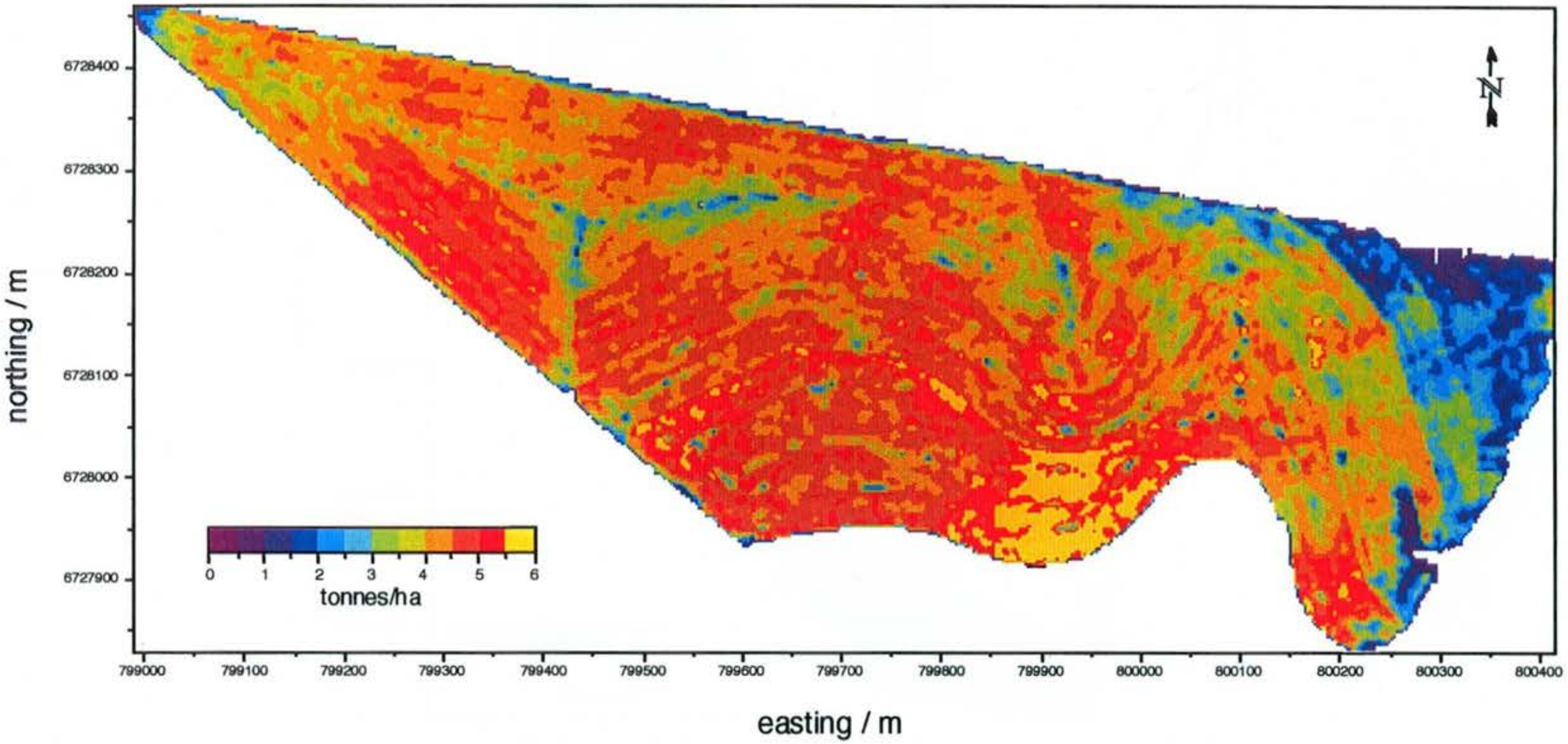

Figure B-58. Field W80 - Marinya 1997 sorghum.

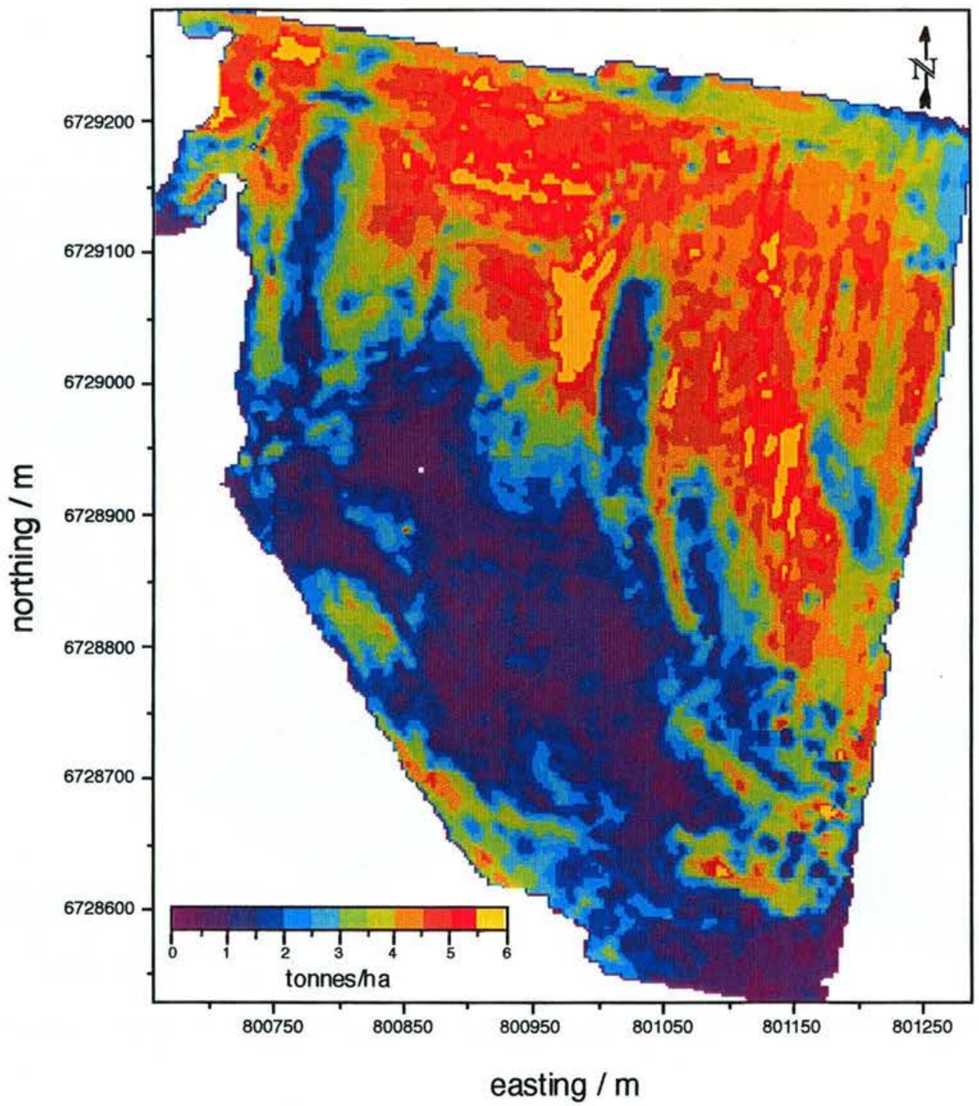

Figure B-59. Well Field - Marinya 1997 sorghum.

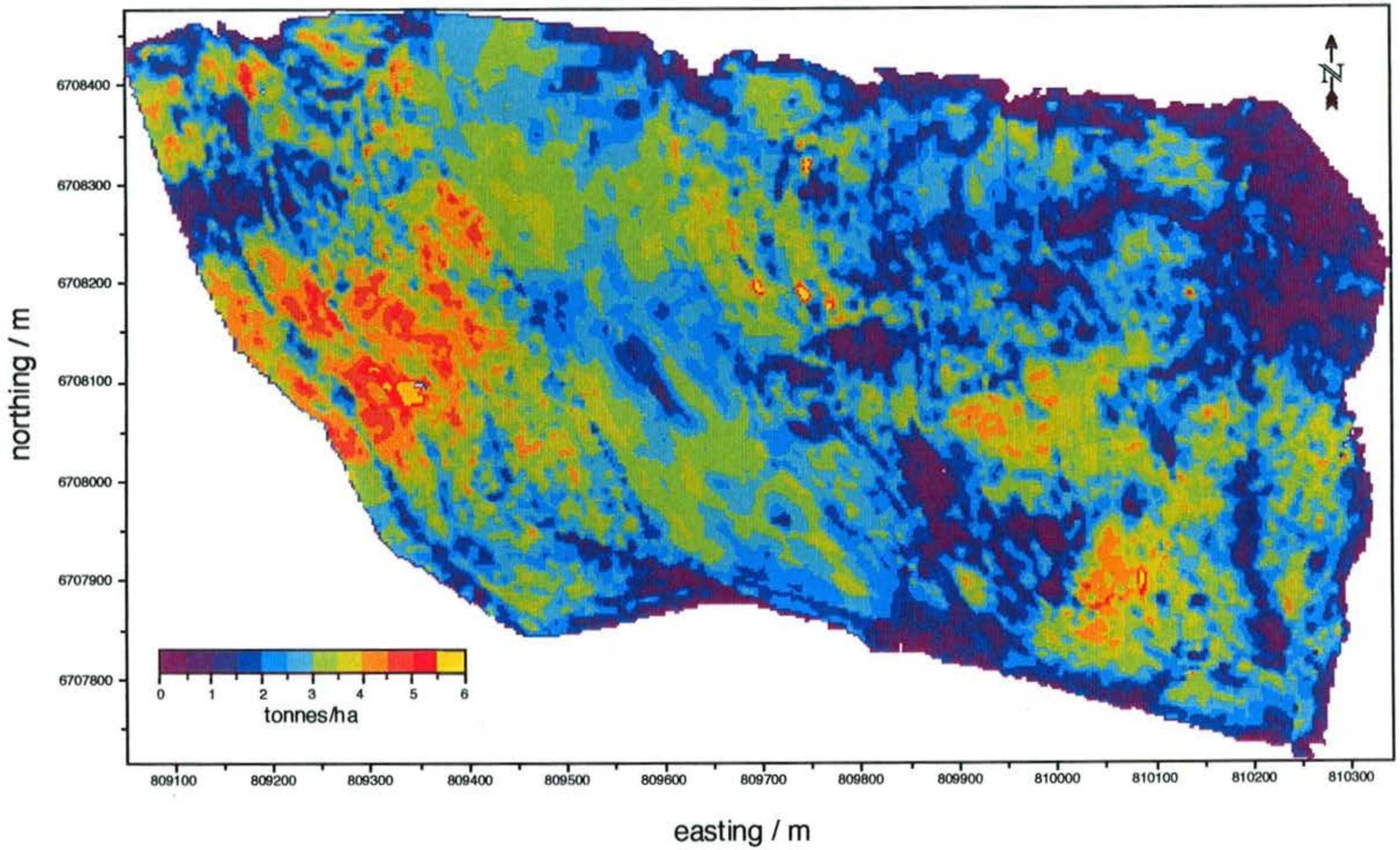

Figure B-60. Pine Field - Romaka 1997 sorghum.