Chapter 8
Spatial Variation and Site-Specific Management Zones

R. Khosla, D.G. Westfall, R.M. Reich, J.S. Mahal and W.J. Gangloff

Abstract Many approaches have been proposed over the last two decades for managing the spatial variation of soil and crops. In this chapter we discuss the importance of quantifying and managing spatial variation in crop production fields to implement site-specific crop management. We outline the challenges that soil and crop scientists have addressed since the inception of precision agriculture (PA) in terms of managing soil spatial variation, and the development of simple, stable and inexpensive techniques for quantifying and managing it with tools such as site-specific management zones. This chapter summarizes and cites the work of several scientists who have worked in the area of development and evaluation of site-specific management zones from around the world. Geostatistics is being applied increasingly in PA because of the need for accurate maps on which to base site-specific management. For soil and crop properties that require costly sampling and analysis, there are often insufficient data for geostatistical analyses and this chapter shows how management zones can provide an interim solution to more comprehensive site-specific management. Physical and chemical soil properties have been the most widely used properties for delineating management zones, however, intensive data from remote and proximal sensors are being used increasingly. The case study describes methods of delineating and evaluating management zones.

Keywords Management zones · Delineation · Site-specific crop management · Physical and chemical soil properties · GIS data layers · Bare soil imagery · Yield

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8.1 Introduction

Spatial variation in soil properties exists within fields, farms and across landscapes. Although spatial variation in agricultural fields has received considerable attention recently, its importance and impact on crop management has been discussed for over a century. Mercer and Hall (1911) examined the variation in crop yields in small plots in fields at Rothamsted Research, Harpenden, England. Later Waynick and Sharp (1919) reported variation in soil nitrogen and carbon in field trials in a series of studies and its impact on the accuracy of field trials. They found that the differences between samples taken at shorter intervals were significantly less than those for the population as a whole (Waynick and Sharp 1919). Several studies since then have shown that soil properties, as well as many natural resource properties, vary continuously in space (Haradine 1949; Hammond et al. 1958; Peterson and Calvin 1986; Cipra et al. 1972; Vieira et al. 1982). Likewise, crop producers and farm managers have observed spatial and temporal variability in their fields for a long time. Until recently, they did not have access to appropriate tools and technology to manage the variation. Since variation in soil properties greatly influences crop productivity across a field, it was evident early on that successful implementation of precision agriculture technologies for managing agricultural fields would require the spatial variation to be quantified accurately.

Geostatistical techniques have been adopted with some enthusiasm in PA because of their suitability for quantifying and predicting the spatial variation of soil, crop and landscape properties (see Chapter 1 for some of the background). Natural systems in the environment usually show structured or periodic variation in time or space (i.e. spatial or temporal dependence, see Chapter 5). This is particularly true for soil systems where patterns develop as a result of variation in topography, parent material, climate and biology. The consequence of spatial dependence is that samples separated by small distances tend to be more similar than those further apart. Classical statistical procedures on the other hand assume that data are spatially independent. Geostatistics is a collection of statistical methods that have been used for some time in the geosciences. The basis of the methods is to describe and model spatial dependence or autocorrelation among sample data, and to use this information for various types of spatial prediction. There is some overlap with GIS (geographic information systems) and spatial statistics more generally.

There are two major components of a geostatistical analysis: modelling spatial dependence in the form of a correlogram or variogram, and predicting variable values at unsampled locations with techniques such as kriging or cokriging (see Chapters 1 and 7, in particular for more theoretical background to these techniques). Geostatistics can provide accurate maps for the successful implementation of variable-rate prescription for site-specific nutrient management and other applications in precision agriculture, such as irrigation.

If the objective is to quantify the spatial variation in a given field, the sample design used to obtain data is important. Geostatistics places a different emphasis on the approach to sampling from that used in conventional statistics (see Chapters 2 and 3). Classical methods of sampling based on randomization of the sampling positions aim to avoid spatial correlation because of the assumptions that underpin many conventional statistical techniques. In geostatistics, the aim of sampling is to ensure that the data will be spatially correlated and randomization is no longer a requirement. Randomization in geostatistics is a feature of the model rather than a property of the phenomenon of interest. Furthermore, geostatistics changes the emphasis from the estimation of regional averages in classical statistics to the local estimation of spatially distributed variables using techniques such as kriging and cokriging.

The costs of obtaining enough data for geostatistical analysis often preclude its application and there is a need for an alternative approach to site-specific management that does not necessarily depend on spatially dependent information about the soil. In the last decade there has been considerable research in PA on the delineation of zones for crop management. They enable site-specific crop management without the high costs associated with sampling and analysis for geostatistical analyses. The basis for delineating management zones is to identify soil and crop properties that: (i) are easy and or inexpensive to measure; (ii) are temporally stable (do not change in the short term, i.e. year to year) and (iii) can characterize variation in crop yield accurately. The resulting zones should be simple, stable, accurate and inexpensive to identify, and enable within-field spatial variation to be managed. Zones within a field can be classified into areas that need to be managed differently (Fig. 8.7), and this is the main focus of this chapter.

8.2 Quantifying Spatial Variation in Soil and Crop Properties

To interpolate or predict spatially a continuous or discrete variable, it is important to know how it changes throughout the area of interest. For example, if the variable is distributed randomly, then the best local estimate would be the global mean. If, as is usually the case, the variable shows some spatial structure, for example patches of soil with large or small organic matter (OM) contents, it should be possible to describe this change quantitatively. To describe the variation requires a suitable sampling design, otherwise the results of statistical analysis and or interpolation could be disappointing and sometimes misleading.

Several sampling designs have been proposed and tested to quantify the spatial variation of soil properties in PA. For example, simple random sampling, systematic sampling on a grid and stratified random sampling where a field is stratified into *m* squares. The latter has been popular and widely reported in PA, and is sometimes referred to as grid sampling as is systematic sampling (Thom et al. 2003). The scale at which sampling is done commercially for soil surveys by agricultural service providers is at about one sample per hectare or more due to economic constraints (Landwise Inc. 2006; Thom et al. 2003; Rehm et al. 2001; Pachepsky 1998). However, an important consideration when designing a survey for spatial interpolation is the scale of variation of the property at the level of investigation, i.e. the field for PA. The main limitation of using such large separating distances between sample locations is that the scales of variation associated with soil and crop variables are much smaller (Gangloff 2004). For example, if one soil sample per hectare is taken in a field where variation is over distances of say 30–40 m, the sampling design will not resolve the variation adequately for interpolation. It should be noted that any method of interpolation, geostatistical or otherwise requires data that are spatially correlated or dependent.

Mueller et al. (2001) concluded that a commercial sampling approach on a grid of 100×100 m (1 ha) was inadequate for developing sound soil nutrient maps, whereas Franzen and Peck (1995) found that distance of 65-m (0.42 ha) between samples was necessary. Hammond (1993) also found that a 60×60 m (0.36 ha) grid was adequate for developing nutrient concentration maps. Gangloff (2004) investigated the spatial variation of selected soil properties using a stratified random sample with a grid of 76×76 m (0.58 ha) and a finer grid of 15×15 m (0.023 ha). Gangloff (2004) used a G-statistic (Agterberg 1984) to evaluate the 'goodness-of-prediction' from kriging selected soil properties. For the coarser grid the G-statistic was close to zero, and Gangloff (2004) concluded that the poor results were because some sample locations appeared to be anomalous making it difficult to predict accurately near to them and the interval of the coarse grid was too large. Analysis of the data on the fine grid indicated that the scale of spatial dependence for the soil properties was 20–30 m, which is much smaller than the interval of the coarse grid. In practical terms, these results suggest that the grid size used by commercial practitioners makes accurate prediction of soil properties impossible because of a lack of spatial dependence among the sample data. McBratney and Pringle (1999) in a separate study previously suggested that strata of 20- to 30-m are required for site-specific applications of agricultural inputs. While it is difficult to suggest an ideal grid size to characterize soil variation accurately, variation in soil properties appears to occur at a much finer scale than the 1 hectare strata commonly used in PA.

A coarse grid also limits the number of samples available to estimate the variogram; sample sizes generally range from 35 to 76 observations. Small sample sizes, such as these, affect the accuracy of the variogram estimated by the usual method of moments (Webster and Oliver 1992). Residual maximum likelihood (REML) (Cressie 1993) is a possible alternative when there are >50 and <100 data (see Kerry and Oliver 2007). Irrespective of the method used to estimate the variogram, if the resulting model does not describe the spatial structure of the variable adequately, any kind of interpolation of soil or crop properties to produce maps is unlikely to represent variation in the field accurately.

The difficulties associated with using geostatistical techniques to interpolate soil properties in PA mean that most commercial software used by crop consultants and other practitioners disregards the importance of spatial dependence. They rely on deterministic techniques such as inverse distance weighting for interpolation without considering that this method makes little sense without spatially dependent data. The problem is that such software can interpolate from any set of data regardless of whether they are spatially dependent, and so the resulting surfaces may or may not reflect the true variation in the population. Discussions with consultants and practitioners (personal communication) indicate that "*sampling at scales needed to attain spatial dependency is time consuming, laborious, expensive and not necessarily* *advantageous given the size of the large commercial farm equipment they work with to apply variable rate nutrients across a field*". As sampling for geostatistics (or interpolation more generally) requires skilled labour, is time consuming, labour intensive and expensive (Khosla and Alley 1999; Khosla et al. 2002), there has been a need for alternative techniques that are efficient, simple, accurate and economic (Bullock and Bullock 2000) to characterize the spatial variation in soil and crop properties accurately. This has been achieved with management zones.

8.3 Site-Specific Management Zones

The most widely cited definition of a management zone was provided by Thomas Doerge in the late 1990s. According to Doerge (1999) "Management Zones" are "*sub-regions of a field that express a homogeneous combination of yield limiting factors for which a single crop input is appropriate to attain maximum efficiency of farm inputs*". This definition became a 'mantra' for those who started developing and evaluating techniques for delineating management zones for precision nutrient management and later for precision management of other inputs also (herbicides, water, seeds, manure, etc.). Figure 8.7 shows a field classified into separate regions of low, medium and high productivity. It illustrates some of the unique features of management zones: (i) the areas of different productivity potential may or may not be contiguous and (ii) the number of zones delineated is subjective and is a function of the technique used to delineate them and the scale of variation observed in that field. The overarching idea is to characterize within-field variation, identify yield limiting factors and classify homogenous areas into zones to manage them separately to enhance production, and to improve the efficient use of inputs and economic returns (Khosla et al. 2002; Koch et al. 2004).

Based on the number of publications (>200) found in the Agricola® and other scientific databases that reported work on some aspect of management zones, coupled with the diversity of management zone techniques reported in the literature, it may appear that they have been around for decades. However, the concept of managing crop production inputs within zones is relatively new. A review of the literature indicates that Yost et al. (1982) delineated '*zones of influence*', i.e. areas of soil with similar properties based on the 'range' of the variogram. However, the focus of that investigation was on mapping soil properties using geostatistics and not necessarily to aid crop management decisions.

A review of the literature does not provide a clear indication of when the first zone-based variable-rate nutrient management was initiated. Mulla et al. (1992) reported the results of their study in the late 1980s on nutrient management based on management zones in the Pacific Northwest of the USA. In studies prior to that by Mulla et al. (1992), recommendations were made by soil scientists for variable rates of fertilizer application based on patterns in soil fertility (Dow and James 1973). However, such recommendations could not be implemented because of the limitations associated with the technology available to map patterns in soil fertility and to apply fertilizer at a variable rate (Mulla et al. 1992). With developments in agricultural equipment, new fertilizer applicators were introduced in the late 1980s that were capable of map-based fertilizer application (Fairchild and Hammond 1988). Around the same time advances were made in within-field mapping of soil properties with the aid of GPS and GIS, enabling map-based variable-rate fertilizer application to become a reality (Mulla and Hammond 1988; Hammond et al. 1988; Mulla et al. 1992). Grid sampling of the soil continued to play a major role in quantifying within-field variation and producing variable-rate fertilizer prescription maps, whereas management zones were in the early stages of development and evaluation. It took several years and many studies to indicate the success of management zones for quantifying within-field variation of soil and crop properties accurately before they were recognized as a viable tool for precision nutrient management.

8.3.1 Soil Properties, Crops and Geographic Distribution of Management Zones

Table 8.1 gives the frequency of various soil, crop and other properties that have been used, individually or in combination, to delineate site-specific management zones for crop management. The list of properties and frequency of their occurrence (a total of 162) were collated from over 100 refereed publications from around the world published between 1992 and 2008. Table 8.1 clearly reflects the diversity of properties (46 in total) that have been used by researchers and practitioners to delineate management zones. These properties can be divided into eight broad categories (Table 8.1). It is evident that, both physical and chemical soil properties are the most widely reported properties used for delineating management zones, followed closely by those from sensing technologies, crop properties and landscape attributes. Although sensing is a separate category in Table 8.1, the methods were used to measure aspects of both soil and crop properties. In addition, sensing technologies, such as the Veris soil electrical conductivity unit (Veris Tech., Salina, KS), remote-sensing for bare soil imagery, normalized difference vegetation index (NDVI), etc., are reported in more recent literature (Kitchen et al. 2005; Khosla et al. 2002; Inman et al. 2008) and are a reflection of the progress that has been made (i.e. accessibility to innovative sensors and tools) in the last decade in site-specific crop management. Table 8.1 also gives a few of the rare properties that have been used for delineating management zones, such as tillage depth, tillage force, weed populations and soya bean cyst nematode densities, for site-specific crop management.

Tables 8.2 and 8.3 give the frequency of the various crops and geographical locations, respectively, where site-specific management zones have been developed and evaluated or applied for site-specific crop management. Table 8.2 shows that the majority of management zone research has focused on ‘row-crops’ primarily maize (*Zea mays*), followed by soya beans (*Glycine max*), cotton (*Gossypium hirsutum*), wheat (*Triticum aestivum*), potatoes (*Solanum tuberosum*) and rice (*Oryza sativa*). Inclusion of other crops, fruits, vegetables and tree species illustrate unique

Table 8.1 A list of properties used in various techniques of delineating site-specific management zones

Category	Properties used to delineate management zones	Number of occurrences
I. Soil properties		[61][a]
Chemical	Soil organic matter and soil carbon	8
	Nitrogen	7
	Phosphorous	7
	Potassium(4), Magnesium(1) and Calcium(1)[b]	6
	Cation exchange capacity	2
	Grid sampling	2
	Soil pH	1
	Targeted sampling	1
	Gypsum requirement	1
Physical	Soil texture	13
	Soil type	7
	Soil colour	6
	Soil moisture content	4
	Aggregate stability in water test	1
	Hard pan	1
	Penetration resistance	1
	Water content/holding capacity	2
II. Landscape attributes		[18]
	Topography	14
	Aspect	2
	Curvature	1
	Other	1
III. Crop properties		[28]
	Yield map (Spatial)	14
	Yield map (Temporal)	9
	Shoot density	3
	Ground based leaf area index (LAI)	1
	Protein content (wheat)	1
IV. Sensing		[40]
	Soil electrical conductivity sensor	18
	Satellite imaginary and other platforms	12
	Normalized differential vegetative index (NDVI)	5
	Digital photography (crop canopy)	4
	Electromagnetic induction sensors	1
V. Management practice		[4]
	No-tillage, chisel-plow, with and without traffic	1
	Tillage depth	1
	Tillage force	1
	Weeding, mulching and traffic-aisles	1

(continued)

Table 8.1 (continued)

Category	Properties used to delineate management zones	Number of occurrences
VI. Weed and pest management		[4]
	Weed population	2
	Soya bean cyst nematode densities	1
	Silverleaf whitefly population	1
VII. Subjective approach		[4]
	Self made zones for soil management	4
VIII. Modeling		[3]
	Crop/simulation/GIS	3
Total		162

[a]Total of each category is bracketed.
[b]Number of occurrences for each nutrient is in parenthesis.

applications of management zones (Table 8.2). Proliferation in the use of management zones around the world has been fairly rapid. Table 8.3 shows that research on management zones has been reported from several countries across six continents. While it comes as no surprise that the majority of research has been reported from the USA, followed by Europe, it is still encouraging that use of management zones is proliferating in other parts of the world.

Although the original primary purpose of management zones was to replace grid sampling for site-specific nutrient management, a review of the literature (Tables 8.1–8.3) indicates that management zones have been developed for managing a wide variety of crop inputs. A partial list includes management of crop irrigation, manure, weeds and pests, tillage, in addition to crop nutrients such as N, P, K, Ca, Mg and Fe, ameliorants such as gypsum, and characteristics of crop quality such as the protein content of wheat or wine quality from grapes, etc. Tables 8.1–8.3 provide an overview and insight into the diversity as well as the similarities among the parameters used globally in developing and delineating management zones for various crops that have been reported in the literature.

8.3.2 Techniques of Delineating Management Zones

There are numerous techniques for delineating management zones across a field. Over the years, these techniques have evolved and have been transformed from being primarily soil property based to minimally intrusive (i.e. do not rely strictly on soil sampling) and, therefore, have the potential to be more economically feasible than grid sampling for variable-rate management (Hornung et al. 2006). Management zones may be delineated based on a single soil or crop property (such as soil texture or yield) or a combination of several that are known to affect crop productivity and yield (Table 8.1). Likewise, some techniques are based on a simple process

Table 8.2 Frequency distribution of crops, fruits, vegetables and trees, reported to be managed with site-specific management zones in the literature

Category	Name of crop	Botanical name	Number of occurrences
Crops			[106][a]
	Maize	*Zea mays*	34
	Wheat	*Triticum aestivum*	17
	Soya beans	*Glycine max*	15
	Cotton	*Gossypium hirsutum*	12
	Potato	*Solamum tuberosum*	6
	Barley	*Hordeum vulgare*	4
	Rice	*Oryza sativa*	4
	Sugar beet	*Beta vulgaris*	4
	Rape	*Brassica compestris*	2
	Sunflower	*Helianthus annuus*	2
	Bean	*Phaseolus vulgaris*	1
	Flax	*Linum usitatissimum*	1
	Millet	*Pennisetum americanum*	1
	Sweet potato	*Ipomea batatus*	1
	Sorghum	*Sorghum bicolor*	1
	Sugarcane	*Saccharum officinarum*	1
Vegetables			[5]
	Cassava	*Manihot esculenta*	2
	Arrow roots	*Maranta arundinacea*	1
	Cowpeas	*Vigna unguiculata*	1
	Tomato	*Lycopersicon esculentum*	1
Fruits			[3]
	Banana	*Musa paradisiacal*	1
	Grapes	*Vitis vinifera*	1
	Pineapples	*Ananas comosus*	1
Trees			[2]
	Oil palm	*Elaeis guineensis*	2
Others			[2]
	Pasture		2
Total			[118]

[a]Total of each category is shown in brackets.

that involves only a clustering algorithm with one property, such as soil electrical conductivity, to classify the field into zones (Fleming et al. 2004). Conversely, there are other complex techniques that may involve a variety of GIS data layers (i.e. remotely sensed red, green and near infra-red bands; soil organic matter; soil cation exchange capacity; soil sand, silt and clay content; and the previous year's digital yield data) to create the final management zone surface (Hornung et al. 2006).

Digital soil survey maps are becoming increasingly available in the USA and have been investigated as a means of generating site-specific management zones (Franzen et al. 2002; Kitchen et al. 1998; Anderson-Cook et al. (2002). Franzen et al. (2002) found that although order 2 digital soil survey maps (i.e. map scales

Table 8.3 Frequency distribution of countries where the site-specific management zone approach has been reported in the literature

Continent	Country name	Number of occurrences
North America		[59][a]
	USA	56
	Canada	3
Europe		[16]
	England	5
	Belgium	2
	Italy	2
	Austria	1
	Czech Republic	1
	Finland	1
	France	1
	Hungary	1
	Germany	1
	Spain	1
South America		[2]
	Argentina	1
	Chile	1
Africa		[2]
	Kenya	1
	South Africa	1
Australia		[7]
	Australia	6
	New Zealand	1
Asia		[11]
	Bangladesh	2
	China	2
	Pakistan	2
	Iran	1
	Japan	1
	Malaysia	1
	Thailand	1
	Papua New Guinea	1
Total		[97]

[a]Total of each category is shown in brackets.

of 1:15 840 to 1:30 000) are readily available to farmers, they were inadequate for developing N management zones. However, Franzen et al. (2002) further reported that order 1 soil survey maps (i.e. map scales of 1:5000 to 1:10 000) were useful for developing N management zones. In a similar study, Kitchen et al. (1998) compared soil survey maps of order 2, order 1 and enhanced order 1 with a scale of 1:5000. They found that while order 1 soil survey maps (both, enhanced and standard) were

Don't understand map scale in context of sampling - sample sites are essentially infintessimal

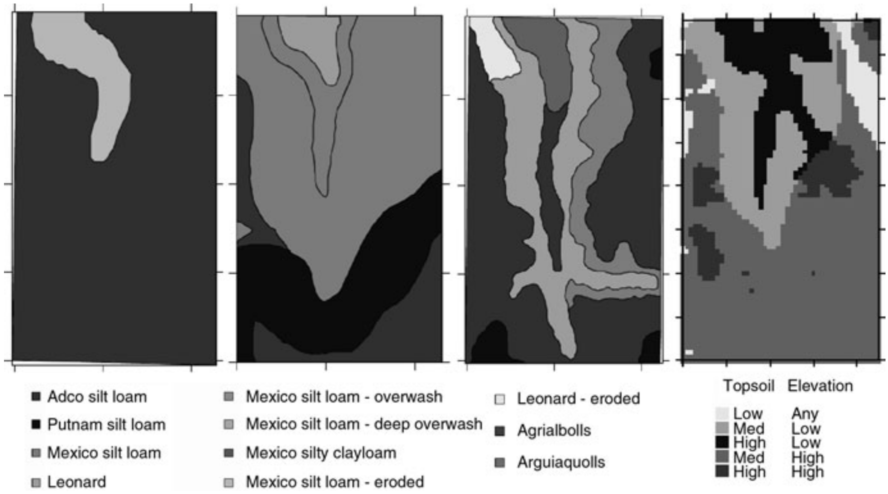

Fig. 8.1 Soil surveys conducted on the research field. From *left to right*: order 2 soil survey (1989–91), order 1 soil survey (1993), 'enhanced' order 1 soil survey (1997) and management zones created by topsoil depth and elevation (modified and adapted from Kitchen et al. 1998)

unquestionably better (Fig. 8.1) than order 2 maps, they concluded that order 2 maps were better than having no subfield delineation at all (Kitchen et al. 1998). It is important to note that order 1 soil surveys are generally not available free of charge to the public, whereas order 2 soil surveys are. Therefore, a soil consultant would have to generate a custom soil survey order 1 map of the area, which could be expensive depending on the size of the area (Hornung et al. 2006). Although order 2 soil survey maps may be a starting point for sub-field management, order 1 or enhanced order 1 soil survey maps would be needed for site-specific crop management.

As order 1 soil survey maps are expensive to generate, Anderson-Cook et al. (2002) investigated an alternative technique for soil mapping. They compared order 1 soil type maps with apparent soil electrical conductivity (EC_a) measurements and found that it was possible to classify the soil type correctly 62–81% of the time from EC_a values alone. When EC_a was used with crop yield data, the accuracy increased to between 80% and 91% (Table 8.4). This is a major contribution because soil EC_a measurements are relatively inexpensive to record compared to obtaining order 1 soil survey maps.

Previous studies with soil EC_a have shown that in addition to identifying variation in soil texture, it relates closely to other properties that often determine a field's productivity (Lund et al. 1999). Heermann et al. (1999) found that soil EC_a was the best predictor of crop yield when compared with many other common soil and crop properties. Fleming et al. (2004) used only soil EC_a to delineate management zones and found that it consistently identified areas of different productivity potential across a field. Johnson et al. (2003), however, indicated that the soil properties that control soil EC_a do not necessarily correspond to yield limiting factors. They

Table 8.4 Percentage of correct classification of order 1 soil type maps versus apparent electromagnetic conductivity (EC_a) and combined EC_a and crop yield for four soil types

Number of observations	EC_a alone	EC_a and crop yield
	% Correctly classified	
129	85.3	91.5
197	91.4	96.4
67	95.5	95.5
211	87.2	93.4
259	86.6	90.3

Modified and adapted from Anderson-Cook et al. (2002).

found that patterns on soil EC_a maps were correlated weakly with variation in corn yield and that there was no consistent relationship between EC_a-based management zones and corn grain yield (Johnson et al. 2003). It is evident that EC_a alone may not be appropriate under all crop production systems. However, there is a potential for using soil EC_a when it is combined with other soil and crop properties.

Variation in landscape attributes (topography, aspect, slope, curvature, etc.) have also been a focus of investigation for the delineation of management zones. Even before the advent of management zones, field topography was used to generate variable-rate nutrient application maps. Previous studies have described the link between field topography and soil nitrogen content (Bruulsema et al. 1996; Cassel et al. 1996) as well as topography and yield variation (Ciha 1984; Verity and Anderson 1990). Kravenchenko and Bullock (2000) found that topography together with other data such as organic matter, cation exchange capacity, phosphorus and potassium accounted for 40% of the variation in grain yield. Nolan et al. (2000) found that management zones based on elevation, curvature and slope could account for as much as 51% of the variation in crop yield. These are important findings because topography is a stable property and relatively easy and inexpensive to measure with current high resolution GPS technology.

Crop yield can be mapped easily by yield monitoring devices and the result is a reflection of within-field variation at a fine resolution. Hence, many have tried to use this valuable information to classify fields into areas of different productivity to aid management decisions. Most researchers who have used yield maps as a data layer for management zone delineation have concluded that yield maps alone are not a suitable basis for delineating zones, primarily because yield patterns are inconsistent between growing seasons (Welsh et al. 2003a,b; Godwin et al. 2003). Nevertheless, they provide valuable ancillary data (Stafford et al. 1998). For example, combining grain yield data with other soil variables could potentially explain variation associated with both crop and soil properties. This hypothesis was tested by Hornung et al. (2006) with the previous year's yield data and eight other data layers (red, green and near infra-red bands; soil organic matter; cation exchange capacity; sand, silt and clay content). They reported only marginal success with the management zone technique, primarily because of the temporally unstable nature of the yield data. They concluded that perhaps a weighting system is needed in the delineation process of management zones that would allocate different weights to different data layers on the basis of their importance to the variation in crop production. Nanna and Franzen (2003), in a separate study, considered a weighted classification method for nitrogen zone delineation. Recently, studies have focused on several years of yield data to generate management zones and have reported significant success (Lauzon et al. 2005; Jaynes et al. 2003; Bakhsh et al. 2005). In a previous study, Moore and Wolcott (2000) correctly suggested that management zones based on several years of yield maps should be generated only after the stability of yield zones within a specific field has been tested.

Remote sensing platforms (aerial and or satellite-based passive remote sensing or ground based active remote sensing) are promising alternatives to intensive grid sampling and analysis for characterizing the spatial variation of soil and crop properties for management zone delineation and variable-rate nutrient application. Bare soil imagery, together with topography and the farmer's experience of the farm were used to delineate management zones by Khosla et al. (2002). This technique characterized grain yields accurately (Fig. 8.2) into high, medium and low productivity potential management zones in 9 out of 10 site years (Inman et al. 2005; Khosla et al. 2008). The management zones also characterized the economic returns accurately that followed the productivity potential of each zone closely (Fig. 8.3). Mzuku et al. (2005) evaluated several soil physical and chemical properties across management zones that were delineated using bare soil imagery. They found that soil properties had a significant ($p < 0.05$) correlation with low, medium and high management zones where bulk density decreased, organic carbon increased, sand content decreased and silt content increased significantly from low to high productivity potential zones (Fig. 8.4). More recent studies have focused on using remote sensing for in-season crop management. Inman et al. (2005) compared NDVI and relative maize grain yield with management zones and found similar spatial patterns among the, low, medium and high potential yield zones. They concluded that

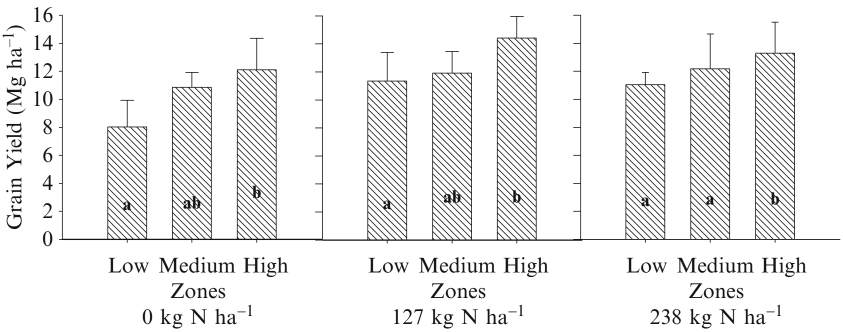

Fig. 8.2 Mean grain yield for each N application rate across site-specific management zones. *Bars with a different letter* are significantly different at $p \leq 0.05$, *bars with similar letters* are not significantly different at $p \leq 0.05$ (adapted from Inman et al., 2005)

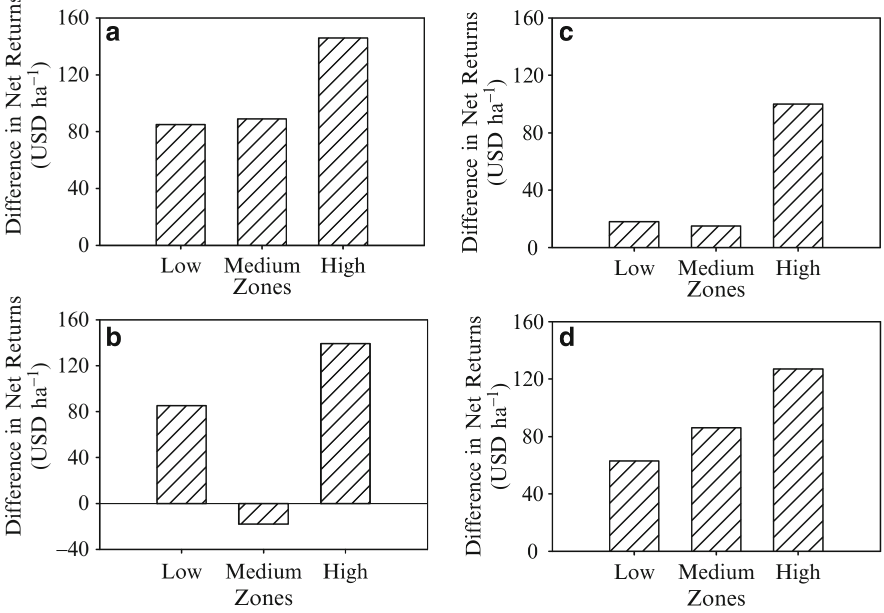

Fig. 8.3 Average differences in net returns (USD ha^{-1}) between the uniform and variable-rate nitrogen management that closely followed the productivity potential of management zones across site years: (**a**) I, (**b**) II, (**c**) III and (**d**) all years. A positive difference in net returns indicates that the variable-rate strategy performed better than the uniform rate. (Adapted from Inman et al. 2008)

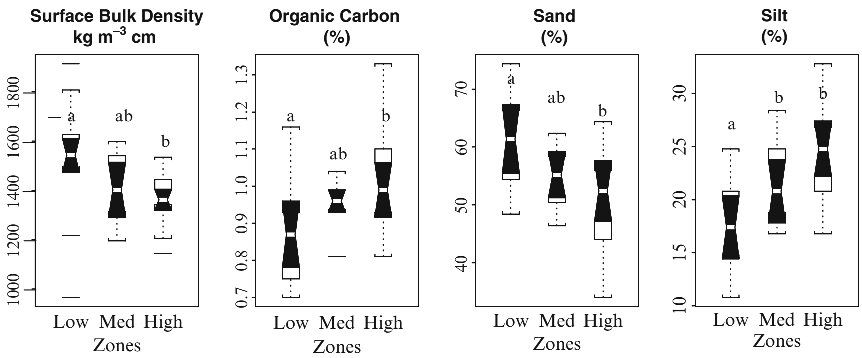

Fig. 8.4 *Box plots* of soil physical properties across site-specific management zones. Within a plot, *boxes with different letters* are statistically different at $p \leq 0.05$ (modified and adapted from Mzuku et al. 2005)

NDVI can potentially be used to model grain yield as early as the six- to eight-leaf crop growth stage in irrigated maize. Remote sensing applications in precision nutrient management with or without management zones continue to be important. Ground based active remote sensing devices hold even further potential to optimize crop nutrient management.

Techniques of management zone delineation proposed in the literature are numerous. However, to date there are few studies that have compared management zone delineation techniques on the basis of their relative performance to characterize areas of different crop productivity. A case study comparing four different management zone delineation techniques that uses a diversity of properties and complex geostatistical approaches is presented below.

8.4 Statistical Evaluation of Management Zone Delineation Techniques: A Case Study

Irrespective of the technique used to create management zones, it must be possible to characterize within-field spatial variation and classify crop yields correctly into separate productivity classes, such as low, medium and high potential production management zones. The best way to select the most appropriate management zone delineation technique would be to compare several techniques on the same field, replicated over time and space, yet few studies have done this (Fleming et al. 2004; Hornung et al. 2006; Derby et al. 2007). Gangloff (2004) did a comprehensive study on a maize field of 58 ha with centre pivot irrigation that compared four techniques for delineating management zones.

Four techniques for delineating management zones were applied to create three zones of low, medium and high productivity potential for each field. Management zone techniques ranged from simple (technique 1) to complex (technique 4). Technique 1, referred to as the soil colour management zone technique (SCMZ), uses bare soil imagery, field topography and the farmer's past management experience as three GIS data layers to delineate zones (see Khosla et al. 2002 for the detail). Technique 2, uses apparent soil electrical conductivity generated by Veris® (model 3100 EC) as a single GIS data layer to delineate management zones (ECMZ) (see Fleming et al. 2004 for the detail). Technique 3, referred to as yield based management zones (YBMZ), uses several GIS data layers, which included: multi-spectral bare soil imagery, OM, CEC, soil texture (sand, silt and clay content) and previous years' yield monitor data (see Hornung et al. 2006). Technique 4 is new and is referred to as the remotely sensed data and cluster sampling management zone technique (RCMZ). Geostatistics is used to analyse bare soil imagery and soil sample data, which are combined to delineate management zones (see Gangloff 2004 for more detail).

The RCMZ was the most complex technique among the four techniques that were compared because it uses remote sensing, soil sampling and geostatistical procedures to create the final zone map. Bare soil imagery was used to develop a directed soil sampling procedure to characterize small scale variation associated with selected soil properties (i.e. organic matter, nitrate-N (NO_3-N), zinc, electric conductivity and ammonium –N (NO_4-N)). Soil reflectance for each bare soil image was quantified into three distinct bands: blue (0.48–0.50 μm), green (0.55–0.60 μm) and red (0.62–0.68 μm) with Imagine software (Leica Geosystems® 2003). Bare soil imagery was used to identify regions or strata with similar spectral properties. The number of strata delineated in a field was determined through a subjective iteration procedure.

HAH

1. Ten strata were initially delineated over each field using an unsupervised classification algorithm.
2. If the image appeared too pixilated and lacked visually obvious and distinctly contiguous regions, the clustering algorithm was run again after reducing the number of strata by one.
3. This procedure was repeated until visually obvious and distinctly contiguous regions were apparent.

After stratification, three sets of soil samples were obtained by sampling randomly within each stratum. At each sample location, three soil samples were taken at the vertices of an equilateral triangle and were about 5 m apart. The variation identified by these small clusters of sampling points is the small-scale spatial variation in soil properties, whereas the variation between clusters is the large-scale spatial variation.

A stepwise Akaike information criterion (AIC) was used to identify the combination of satellite bands (red, green and blue) and x,y-coordinates to include in the regression model to describe soil properties in the field. Regression and variance model parameters were estimated simultaneously by maximum likelihood (O'Connell and Wolfinger 1997). The variogram model that minimized the AIC was selected to krige the residuals from the regression model of a given soil property (fit.geospatial; S-PLUS©, Reich and Davis 1998). A spherical function provided the best fit to the experimental variograms of the regression residuals (Table 8.5 and Fig. 8.5). The variogram ranges of the soil properties have a similar magnitude, with an average range of 131 m. Figure 8.6 shows the grey scale maps from regression kriging of the five soil properties for one field. The spatial variation in these properties illustrates the difficulty of delineating management zones from several properties at the same time.

Table 8.5 Model parameters of spherical variograms for regression residuals of soil properties used as input to the RCMZ management zone delineation technique

		Model parameters			
Soil property	Regression variables[a]	Model	Nugget	Spatially correlated component	Range (m)
Organic matter	Red, green X^2	Spherical	0.0	0.034	141.0
Nitrate-N (NO_3-N)	X,Y	Spherical	0.0	7.615	137.7
Zinc	Green, blue, Y,Y^2	Spherical	0.005	0.239	101.1
Electrical conductivity	X,Y^2	Spherical	0.0	0.003	150.0
Ammonium-N (NH_4-N)	Green, X,Y,X^2	Spherical	0.243	1.694	126.9

[a]Red, green, blue – spectral bands of bare soil imagery; X,Y – geographical coordinates of soil sample.

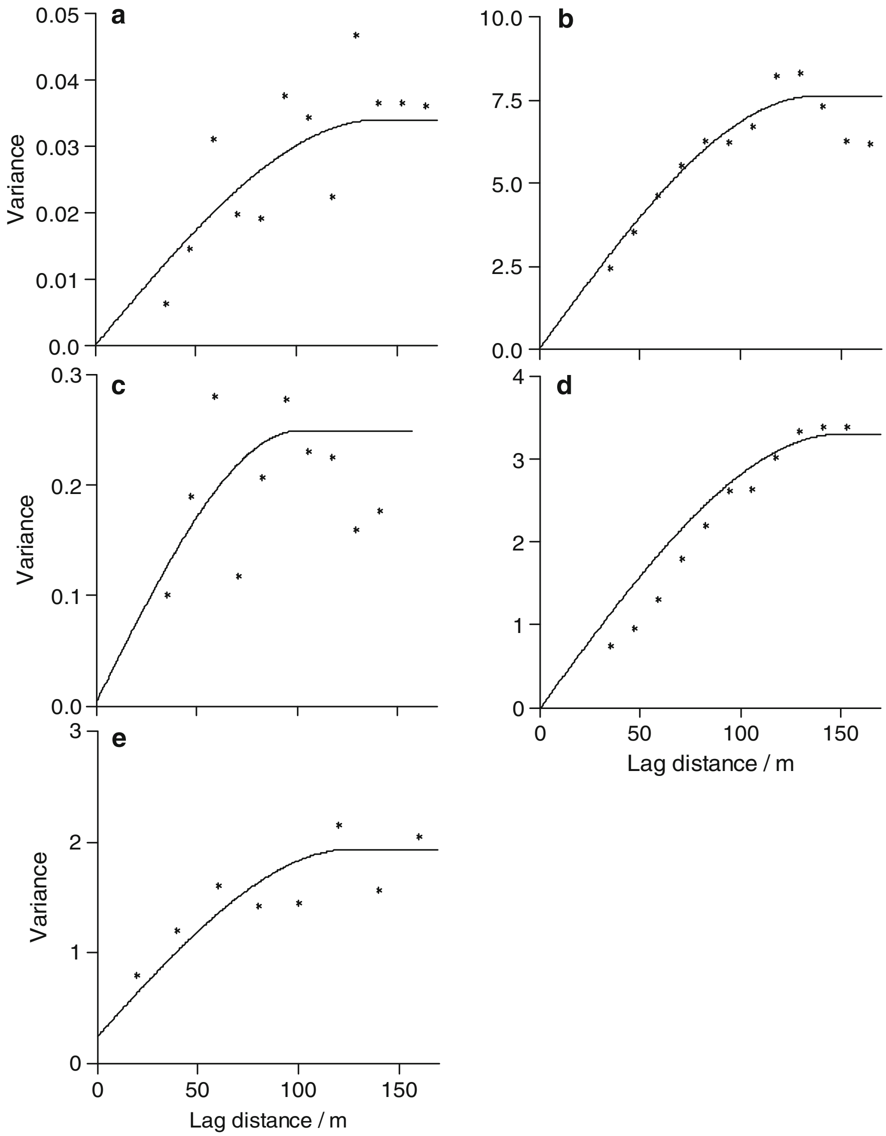

Fig. 8.5 Experimental variograms (*symbols*) and fitted spherical model (*solid line*) for regression residuals of: (**a**) organic matter, (**b**) nitrate-N (NO_3-N), (**c**) zinc, (**d**) electric conductivity and (**e**) ammonium –N (NH_4-N)

The predictions for the five soil properties were then analysed with a nonhierarchical k-means clustering algorithm for spatial data to create three management regions for each field (MSCA; S-PLUS©, Reich and Davis 1998). The algorithm groups the sites in the field into management zones using spatial attributes. In k-means clustering the grouping aims to minimize or maximize some criterion, in this

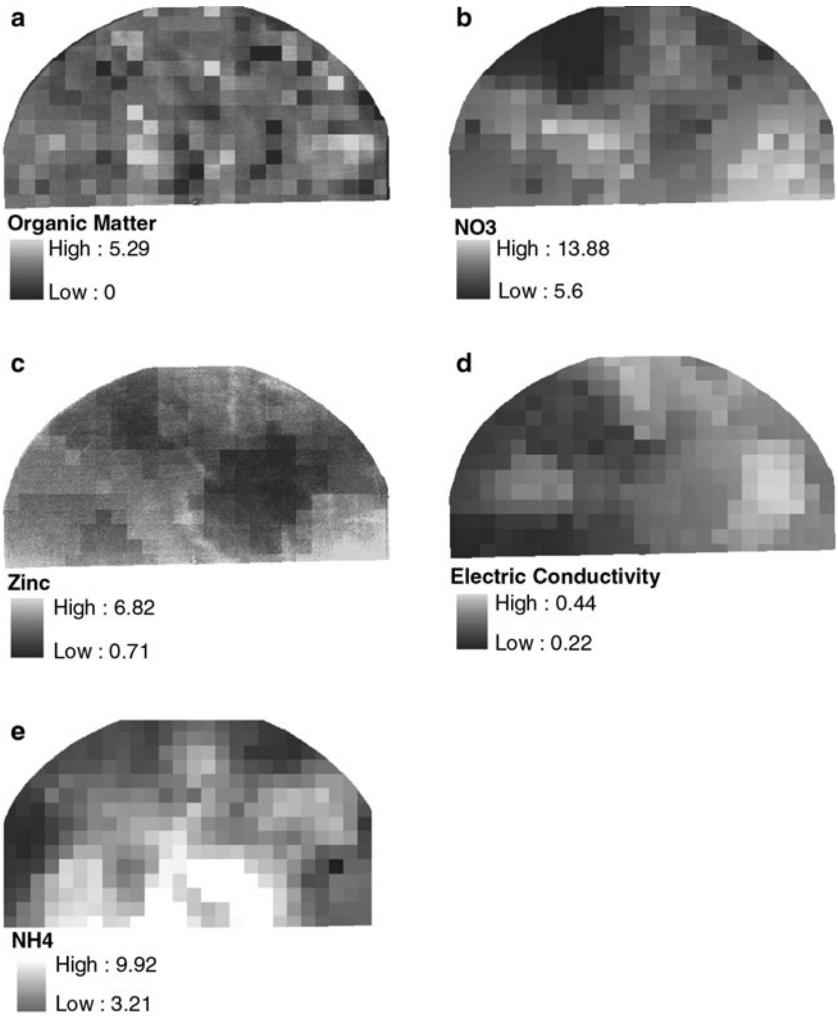

Fig. 8.6 Pixel maps of predictions from regression kriging for: (**a**) organic matter, (**b**) nitrate-N (NO_3-N), (**c**) zinc, (**d**) electric conductivity and (**e**) ammonium –N (NH_4-N)

case minimizing the sum of squares of distances between data and corresponding cluster centroid. Regions of high productivity potential were identified as regions with higher soil OM and NO_3-N levels, and the converse was the case for low productivity management zones. The resulting management zone surface map is a noisy representation of the zones, which would be difficult for a farmer to work with practically. The minimum size and shape of a zone for management is limited by the ability of the farmer and available implements to apply nutrients variably across a field. Therefore, some form of spatial filtering or contiguity constraint is necessary to reduce the fragmentation of the original classes to create smoother management

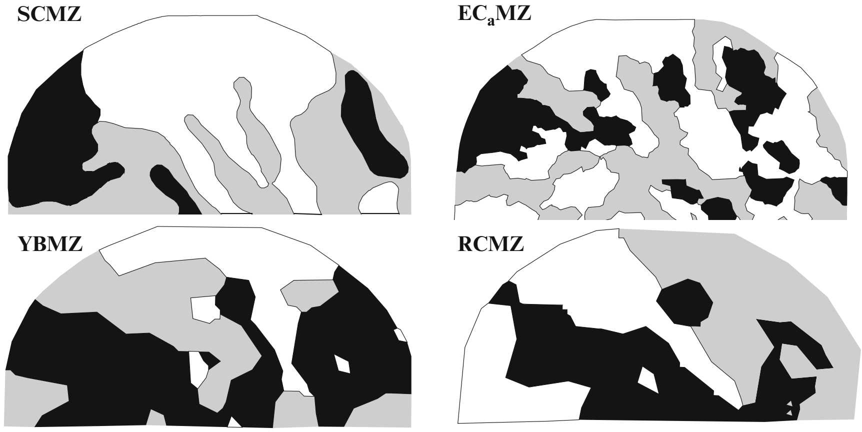

Fig. 8.7 Four techniques of management zone delineated on one centre pivot irrigated field. SCMZ, soil colour management zone technique; EC$_a$MZ, apparent soil electrical conductivity technique; YBMZ, yield based management zone technique; RCMZ, remotely sensed data and cluster sampling technique. Low productivity zone is *white*, medium productivity zone is *grey*, and high productivity zone is *black* (adapted from Gangloff 2004)

zones (Zhang et al. 2002; Kvien and Pocknee 2000). In this example, smoothing was accomplished by applying a focal majority function to the three initial k-means classes. The function finds the majority class value (the value that appears most often) for each location within a specified neighborhood and this become the class value at the corresponding location for the smoothed management zone map. An alternative method is to apply a contiguity constraint to the classification and this can be done using the variogram as described by Frogbrook and Oliver (2007).

Figure 8.7 shows the management zones delineated by the four techniques for one field. A visual comparison shows that there are similarities and differences in identifying areas of different productivity potential in the same field (Fig. 8.7). All four techniques delineated the north-west section of the field as a low productivity zone; similarly, high productivity zones were delineated in the south-central and western section of the field. These correspond to some extent with the areas of large and small values on the plots for the five soil variables (Fig. 8.6). Overall, the medium productivity zones show the least correspondence from a visual comparison. Quantitative assessments are needed, however, to identify the best technique for delineating management zones.

To evaluate how accurately the four management zone techniques delineate zones, a variety of statistical procedures were used (Gangloff 2004). First, an S-statistic was used to test the null hypothesis that management zones consist of a random collection of yields. The S-statistic is a median-based non-parametric, absolute deviation statistic designed to evaluate whether the within-management zone variability in yields is minimized over the field. If the zones differentiate yields into low, medium and high productivity regions, one would expect the variation in yield within management zones to be at a minimum and that the S-statistic would be small. By contrast, if yields were assigned randomly to management zones, one would expect the variation in yield within management zones to be large, resulting in a large S-statistic. The results of the analysis showed a significant organization ($p < 0.05$) in grain yields in 30 out of 36 comparisons for the full analysis (three fields, three zones, four techniques) indicating that the yield patterns under analysis did not occur by chance and are worth classifying into low, medium and high classes.

The delineation techniques were analysed further using areal association statistics (Rees 2008), which determine how well the management zone delineation techniques worked. Each delineated management zone (potentially low, medium and high yield) was evaluated against spatially referenced yield data, which were classified into three classes (i.e. low, medium and high) by the following three approaches. The first used an objective, k-means clustering algorithm to classify each yield value as high, medium or low. The second approach used an objective, non-parametric classification procedure. Yield values were sorted and classified as 'high' if they were greater than the 3rd quartile yield value; 'medium' if they were within the 1st and 3rd quartiles; and 'low' if they were below the 1st quartile value. The third yield classification approach was subjective and based on knowledge of maize yields in the region; this was accomplished with the help of cooperating farmers. Yield values were classified as high ($>11.9\,\mathrm{Mg\ ha^{-1}}$), medium ($8.8$–$11.9\,\mathrm{Mg\ ha^{-1}}$) or low ($<8.8\,\mathrm{Mg\ ha^{-1}}$) based on farmers' knowledge.

The classified yield value at each location was compared with the associated management zone classification, and summarized in square error matrices with classified yield in the columns and management zone in the rows, where the columns and rows are the categories in the classification. The diagonal elements of the matrix are the number of times the two data sets agree. Non-diagonal elements give the number of misclassified times by category. The sum of the diagonal cells on the matrix represents the total number of correctly classified yield observations The proportion of the total number of correctly classified yield observations in the matrix gives the overall aerial agreement for a given delineation technique. A chi-square goodness-of-fit test and Kappa statistic were used to compare the areal agreement against that which might be expected by chance. The Kappa statistic can be thought of as a chance-corrected proportional agreement that ranges from $+1$ for perfect agreement, to 0 for no agreement above that expected by chance and to -1 for complete disagreement. The areal agreement analysis was done for all approaches to yield classification, but only the results for the clustering approach that proved superior to the traditional grid-sampling approach are discussed. Cluster sampling accounted for, on the average, 34% (minimum = 1% and maximum = 74%) more of the variability in soil properties compared to grid sampling. Estimates of bias were small and estimates of the root mean squared error suggested that cluster sampling captured more of the small-scale variation in soil properties than the traditional grid sampling approach. Overall percentage agreement for the cluster sampling approach ranged from 12% to 49% (Table 8.6). All comparisons were significant based on the chi-squared goodness-of-fit test. Overall, the RCMZ technique has the greatest

Table 8.6 Areal agreement (in percent) between yield classes (high, medium or low) using a clustering approach to classify yield and four management zone delineation techniques as evaluated with the chi-square goodness-of-fit test

Management zone techniques	Low yield vs low MZ	Medium yield vs medium MZ	High yield vs high MZ	Weighted mean
	Percentage			
[a]SCMZ	36	46	32	42
[b]ECMZ	33	40	39	36
[c]YBMZ	23	40	12	22
[d]SSMZ	49	49	45	49

[a]SCMZ refers to soil colour based management zone technique.
[b]ECMZ refers to soil electrical conductivity based management zone technique.
[c]YBMZ refers to yield based management zone technique.
[d]RCMZ refers to remote sensing and soil sampling based management zone technique.

overall percentage agreement when compared with the other delineation techniques. The SCMZ technique has the second highest percentage agreements. The RCMZ was the only technique that used soil samples in the delineation process. The bare-soil imagery was used to develop a directed soil sampling procedure to capture the small-scale variation associated with soil properties. This information was used to interpolate soil properties. The ability to interpolate soil properties was the main reason the RCMZ technique was superior to other delineations techniques.

It is interesting to observe in the Gangloff (2004) study, that although the areal associations between the grain yield classes are significant (Table 8.6), the agreements in general may appear quite small (12–49%). This may be attributed to the intentional smoothing or spatial filtering that is part of the process of management zone delineation (Zhang et al. 2002). Smoothing removes the isolated islands of low, medium and high zones distributed throughout the field, thereby decreasing the areal association between management zones and yield classes.

When multi-sectional fertilizer sprayer booms with individual nozzle control become economically feasible, perhaps there will be little to no need for spatial filtering of management zones to create a smooth surface. Also, with the availability of a suite of active remote sensors that can be mounted on tractors to assess the health and vigour of the plant while 'in-motion' there is potential for further improvements in the optimization of input applications for site-specific crop management. "*Farming by the foot*" as perceived from the early precision agriculture concept may perhaps then become a reality.

8.5 Conclusions

Spatial variation in agricultural fields has been recognized worldwide. However, there have been limitations associated with quantifying within-field spatial variation in an easy, inexpensive and accurate way. Site-specific management zones have been developed and evaluated as a successful tool that characterizes within-field spatial variation, and groups homogeneous areas of a field into small regions (called zones) so that each zone can be managed differently based upon the limiting factor of that zone. Some may argue that the concept of management zones may be perceived as a setback from the original concept of precision agriculture, i.e. "*farming by the foot*" or micro-management (Zhang et al. 2002). However, site-specific crop management across management zones has been shown to maintain or enhance crop yields, nutrient use efficiency, to be environmentally suitable and economically feasible. With the advent of new technologies and a suite of active sensors, when coupled with management zones, there is a tremendous potential to improve further the efficiency, economics and overall crop production systems. Nevertheless, management zones are probably an interim measure to fully variable-rate management. The latter will be become more economically feasible when spatially intensive soil and crop information become available cheaply from on-the-go measurement devices for geostatistical analysis and mapping.

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