

T*he Impact of Soil and Crop Management Practices on Soil Spatial Heterogeneity*

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Summary

Little is known about the potential impact of crop and soil management practices on the spatial variability of soil organisms and the processes they mediate. In fact, little is known about patterns of within-field variability even in the absence of management impact assessments. For the few systems where information is available, however, we know that within-field variability is often as high as between-field variability, that populations and processes tend to be patchily distributed, and that most populations and processes are autocorrelated at scales of <100 m. New geostatistical approaches for quantifying variability provide promise for better understanding variability and its underlying causes in a variety of cropping systems, and this information will be a prerequisite for understanding the relationship between variability and agronomic management. The need for this understanding will become more pressing as variable-input farm equipment becomes commercially available and producers move to soil-specific farming strategies.

Introduction

That soils are spatially variable is axiomatic: farmers, agronomists, and soil scientists have long recognized that heterogeneity is an inherent part of agronomic landscapes, and that it is expressed at scales of both the land form and within the individual field. Typically this recognition is used for management purposes at only a coarse level of resolution, usually at scales no finer than that of an individual field, whose size and shape is likely based less upon aggregate soil properties than upon local landform and socioeconomic factors that affect its successful cultivation. Nevertheless, although largely ignored by land managers, the heterogeneity of biologically important soil properties within a field may equal or exceed heterogeneity within the larger landscape.

Inattention to field-scale variability has probably been due to its perceived unimportance: with sufficient inputs producers can successfully manage for a whole-field average without regard to finer-scale patterning, and agronomists and other field scientists can actively avoid the confounding effects of within-field

heterogeneity by conducting experiments on the most homogeneous fields available. Inattention to this variability has also been due, however, to the historical absence of the appropriate tools for addressing it. Producers have not had available a practical means for varying management practices across individual fields, and scientists have not had available an appropriate statistical means for quantifying spatial variability.

But this situation is rapidly changing. The application of geostatistics to problems in soil science is now allowing field-level variability to be assessed free of the confounding assumptions of classical statistics, and the commercial introduction of variable-input farm machinery is now allowing producers to adjust inputs across a field based on these assessments. Driving both developments is the economic and environmental mandate to manage agronomic landscapes in as sustainable a manner as possible, a mandate that is often interpreted as a need to manage cropping systems with as few external

inputs as possible. If, because of differences in native soil fertility, part of a field requires fewer kilograms of nitrogen than another to produce the same yield, then reducing inputs on the more fertile portions of the field will save the farmer the direct costs of nitrogen fertilizer and will save the larger community the indirect costs associated with nitrate runoff and groundwater percolation. The use efficiency of other subsidies, including herbicides and pesticides, can be similarly improved.

The successful application of variable input techniques, however, depends on an appropriate knowledge of soil variability, and we have as yet a very poor understanding of field-scale variability of soil biological resources in most habitats, whether managed for pasture, managed for crops, or in native vegetation. The following pages present a brief description of the geostatistical tools that are now at the soil biologist's disposal, a review of what is known about patterns of field-scale variability with respect to soil organisms, and a discussion of the likely impact of management on variability and prospects for managing this variability to enhance sustainable land management.

Quantifying Spatial Heterogeneity: The Statistical Challenge

The development of geostatistics (Kriging, 1981; Matheron, 1971) and its application to soil science and ecology (Robertson, 1987; Robertson and Gross, 1994; Rossi *et al.*, 1992; Trangmar *et al.*, 1985; Webster, 1985) has opened new doors for the description and understanding of spatial variability in natural and managed environments. Classical parametric statistics provide no adequate means for evaluating or describing autocorrelated data without violating a central assumption of sample independence. Yet at some scale all environmental samples are autocorrelated: samples taken from locations close to each other will almost always be more similar to each other than will be samples taken from locations more distant. Usually one must assume that separation distances are sufficiently great to provide the necessary sample independence, and this assumption is often adequate for factorial experiments designed to test hypotheses about the behaviour of soil biota in response to agronomic treatment or disturbance. For quantifying spatial variability *per se*, however, such an assumption is inadequate because for a quantitative description of variability one needs to quantify this autocorrelation and, if possible, to use it to help interpolate isopleths or maps of an entire area from a limited number of sampled locations within the area.

Geostatistics provides a means both for defining spatial autocorrelation and for using the degree and scale of autocorrelation to interpolate distributions across an area. Unlike other interpolation techniques such as weighted nearest neighbour or cubic spline approaches, the geostatistical approach provides both optimal and unbiased estimates of a property at unsampled locations, and — perhaps most

significantly from an experimental perspective — provides an error term for each interpolated point. One thus can map variability across a field with known confidence.

At the heart of geostatistics is autocorrelation analysis, based on the semivariance statistic

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

where $\gamma(h)$ is the semivariance for all locations in an area separated by the distance interval h , $z(x_i)$ represents the value of the property at location x_i , and $z(x_{i+h})$ represents the value at distance h from x_i . N is the total number of pairs in the domain that are separated by distance h , usually defined as a distance class. Calculating $\gamma(h)$ for all possible distance classes within a region yields a series of semivariance values for a range of separation distances across the region, with each semivariance value based on the number of paired locations within the domain separated by a given distance class interval. In a regular 10×10 m grid covering a 1 ha area, for example, there would be 11 \times 11 or 121 pairs of locations separated by as little as 10 m, and 2 pairs (at diagonal corners) separated by as much as 141 m.

Graphing semivariance values across all separation distance classes yields the variogram (Fig. 1a), which summarizes both the degree of autocorrelation present and the geographic range (a_0) over which it is significant. The degree of autocorrelation present can be represented as the proportion of sample variance that is spatially structured, i.e. the value $C/(C_0+C)$ in Fig. 1, which is the inverse of the relative nugget effect *sensu* Isaacs and Srivastava (1989). Where no autocorrelation occurs at the scales measured, the variogram exhibits a pure nugget effect, with no portion of the sample variance spatially dependent (Fig. 1b). Usually a significant nugget term (C_0) results from a minimum sampling interval that is too large to

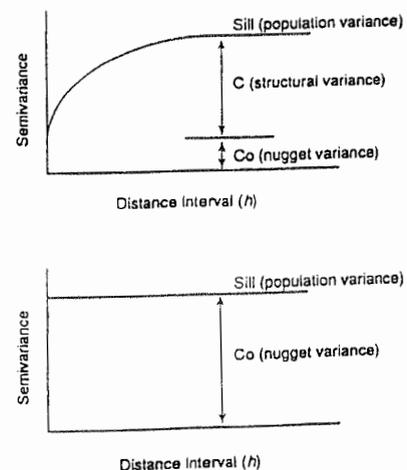


Figure 1 Generalized variograms. (a) Structural or spatially dependent variance makes up a large proportion of total sample variance. (b) Pure nugget effect — there is no spatial dependence at the scales examined. From Robertson and Gross (1994).

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capture autocorrelation at the small scale at which it is occurring: at a separation distance of 0 m, 100% of the sample variance should be spatially dependent since a sample should be perfectly autocorrelated with itself, and thus the variogram model should go through the origin. In practice, a significant C_0 term can also result from measurement error.

Where spatial dependence is present, the variogram can be used in kriging algorithms to weight the neighbours used in interpolation estimates. Neighbours within the range of spatial dependence are assigned weights based on their distance from the interpolation point and the degree of autocorrelation present at that distance interval. All neighbours outside the range of spatial dependence are given equal weight regardless of distance from the interpolation point. Estimation error is based solely on the number of points within the autocorrelation neighbourhood and their weights as assigned by the variogram model.

The Spatial Variability of Soil Biota

In most ecosystems relatively little is known about the spatial variability of soil organisms. Most existing work directed towards describing variability — whether using geostatistical or more classical approaches — has focused on soil chemical or physical properties (e.g. Burgess and Webster 1980, Downes and Beckwith 1951, Jackson and Caldwell 1993, Snaydon 1962, Trangmar *et al.* 1985). Existing soil biota studies fall into two categories: those that have quantified specific taxa or functional groups (primarily nematodes, to date) and those that have quantified rates of organism-mediated processes (primarily soil respiration and nitrogen turnover, to date).

Common to almost all studies of the variability of soil biological properties is the finding that probability distributions of both organisms and process rates tend to be highly skewed. In a comprehensive 2000-sample study of 5 species of plant parasitic nematode populations across a 7 ha alfalfa (*Medicago sativa* L.) field in California USA, e.g., Goodell and Ferris (1981) found that population counts were highly skewed towards the lognormal (Fig. 2), with a disproportionate number of locations in the field having very high populations. Robertson and Freckman (unpublished) found distributions skewed for other nematode groups

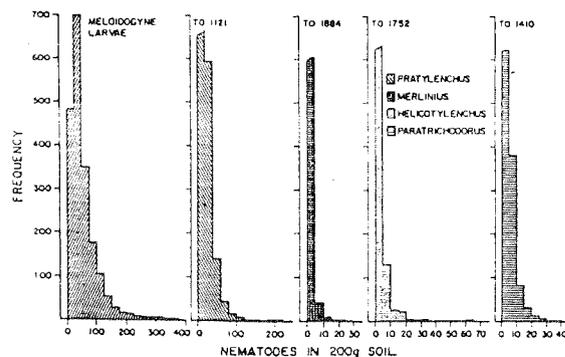


Figure 2 Frequency distributions of five species of plant parasitic nematodes across an alfalfa field in California, USA. Redrawn from Goodell and Ferris (1981).

across a 48 ha field in Michigan, and others have used measures such as variance to mean ratios to describe similarly skewed or patchy distributions (e.g. Alby *et al.*, 1983; Ferris *et al.*, 1990; McSorley and Dickson, 1991; McSorley and Parrado, 1982).

Process rates tend also to be highly skewed towards the longnormal distribution, including soil respiration (e.g. Aiken *et al.*, 1991), nitrogen mineralization (e.g. Robertson *et al.*, 1988; 1993), and denitrification (e.g. Foloronso and Rolston, 1985; Parkin, 1987; Robertson *et*

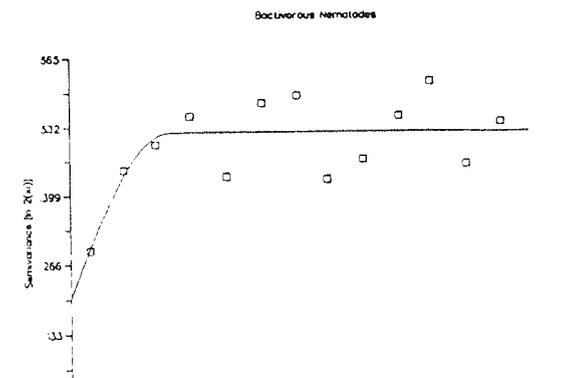
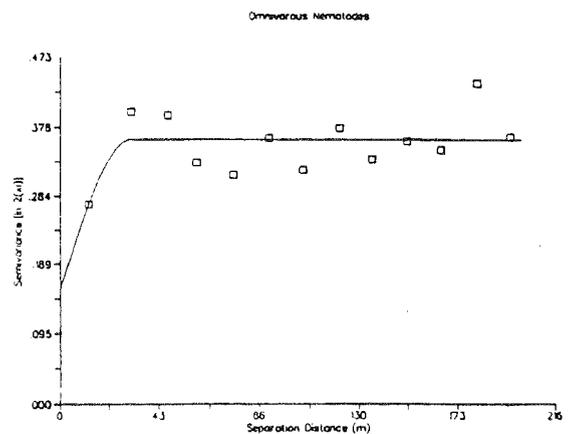
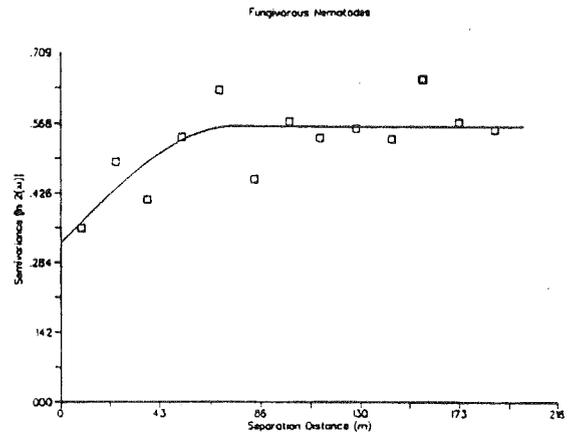


Figure 3 Variograms for soil nematode groups across a 48 ha field in southwest Michigan USA; model parameters appear in Table 1. From Robertson and Freckman (unpublished).

Table 1. Variogram model parameters for the nematode feeding group variograms in Fig. 3. C_0 = nugget variance, $C/(C_0 + C)$ = structural variance as a proportion of sample variance; range = distance (m) over which structural variance is expressed. In all cases models describe a spherical function^a. From Robertson and Freckman (unpublished).

Nematode Feeding Group	C_0 (nugget)	$C/(C + C_0)$ (relative structural)	a_0 (range)	r^2
Bacterivores	0.202	0.611	44.0	0.533
Fungivores	0.323	0.425	75.4	0.565
Omnivores	0.156	0.569	31.4	0.336

^a for $h > a_0$, $g(h) = C_0 + (C - C_0) \cdot (1.5 \cdot h/range) - 0.5 \cdot (h/range)^3$; for $h < a_0$, $g(h) = C$.

al., 1988) in a variety of different ecosystems. Such distributions greatly complicate sampling schemes intended to define population sizes or to quantify biogeochemical fluxes for a specific field because of the importance of dispersed "hot spots" to overall field values.

Although few studies to date have employed geostatistical approaches to quantify the spatial variability of soil organisms within individual fields, it seems clear from the studies available that populations and processes are rarely spatially independent at field scales of <100 m. Variograms of nematode distributions across a 48 ha soybean field in Michigan (Robertson and Freckman; unpublished), e.g., showed that 40–60% of the population variance for bacterivorous, fungivorous, and omnivorous nematodes were spatially dependent at scales of 2–75 m (Fig. 3, Table 1). Distributions of total microbial populations were also spatially dependent at these scales, as were a variety of other soil chemical and physical properties (Robertson and others, unpublished). Process rates were equally autocorrelated, although at least for soil respiration autocorrelation occurred almost exclusively at a submeter scale (Fig. 4), implying that controls on at least this process are expressed primarily at a rhizosphere or soil aggregate scale.

That soil organism distributions — and by inference, process rates — are patchily distributed within individual fields is implied by skewed frequency distributions and confirmed by indices such as Taylor's power series (Taylor, 1961; Taylor *et al.*, 1979). Such distributions cannot be visualized without mapping, however, and it has not been until recently

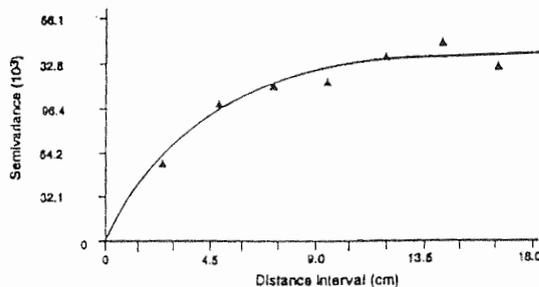


Figure 4 Variogram for soil respiration along a 1 m transect in an early-season corn field, showing strong spatial structuring at a very small field scale; variogram based on data from 40 soil cores (2.5 cm diameter) taken immediately adjacent to one another along the transect. From Merrill *et al.* (unpublished) in Robertson and Gross

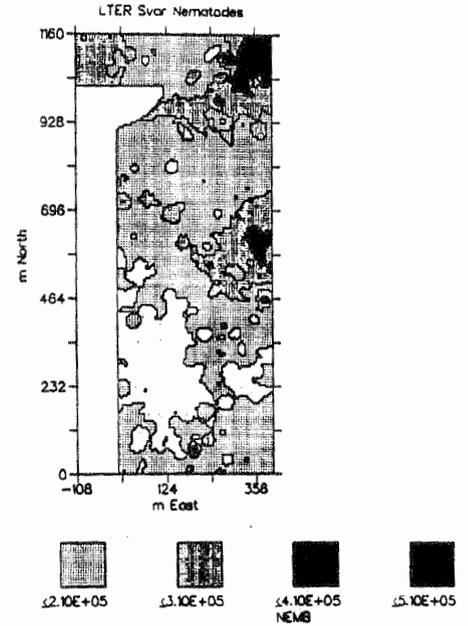


Figure 5 The spatial distribution of bacterial-feeding nematodes across a 48 ha soybean field in Michigan USA. Values were interpolated by kriging, based on 144 actual sample locations and the variogram in Fig. 2. From Robertson and Freckman (unpublished).

that optimal, unbiased maps of organisms have been generated using kriging. Such maps are available for only a handful of sites today, probably owing to a lack of available software and the intensity of sampling needed to portray a reasonably accurate picture of actual distributions. Nevertheless, with new software to aid in optimal sample design, distribution maps are becoming more available and are providing useful insight into causes of patchiness.

Perhaps the most thoroughly mapped site today with respect to soil biota is that at the 48 ha KBS Long-term Ecological Research Site in Michigan, where a variety of soil biological, chemical, and physical properties have been described, including nematode feeding groups, microbial biomass, and microbial numbers (Robertson and others, unpublished). Typical for these populations, counts of bacterivorous nematodes across the field spanned over two orders of magnitude, with large areas of the field relatively depauperate and other areas with very high population counts (Fig. 5). Similar patchiness was observed for rates of nitrogen turnover and other soil microbial processes, both in this field and others (e.g. Fig. 6).

The Impact of Management on Soil Variability and its Implications

One might expect management practices to affect the variability of soil organism populations primarily where management tends to restrict populations or to disperse limiting resources. Populations might be restricted directly by pesticide application, in which case populations might either disappear entirely or become restricted to highly dispersed refugia that may

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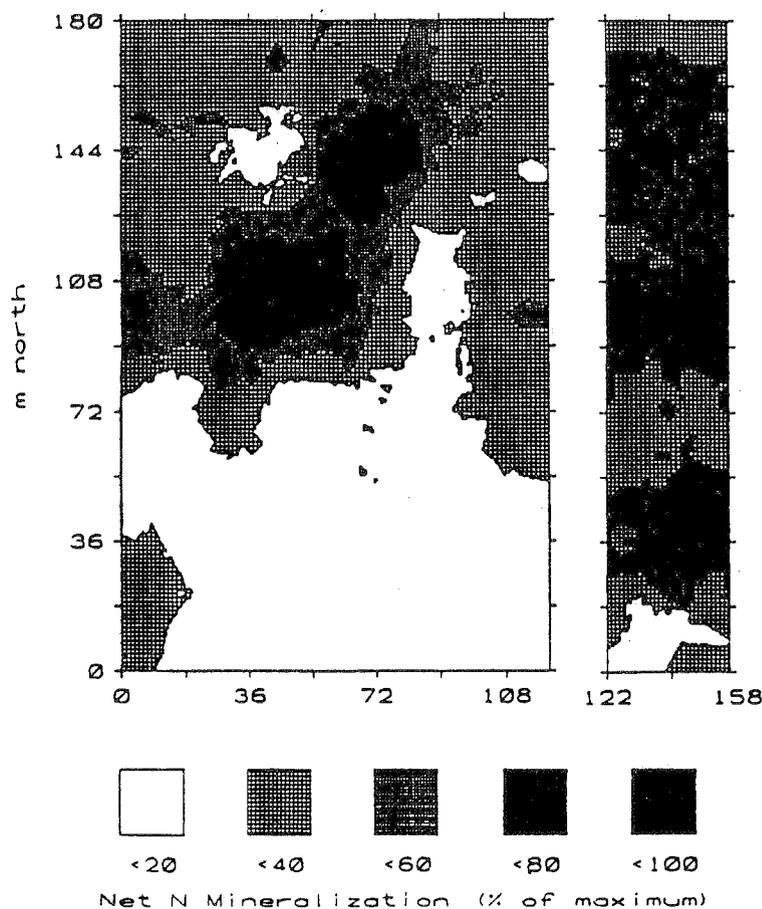


Figure 6 Soil net N-mineralization across an historically tilled (left) and adjacent never-tilled site in Michigan USA. Mean rates of production in both sites were identical (0.87 vs. $0.89 \text{ mg g}^{-1} \text{ d}^{-1}$, respectively). From Robertson *et al.* (1993).

have escaped application. Resource dispersal is a more generalized feature of cultivation, and stems from monoculture cropping practices that distribute identical plants — with similar carbon and nitrogen contents, rhizosphere characteristics, and pest resistances — across a landscape. Resource dispersal will also stem from tillage and post-harvest activities that act to homogenize the distribution of carbon and soil aggregates across small areas.

Very little work has been directed towards understanding the effects of either managed or natural disturbance on soil variability, although such efforts are now underway in a variety of ecosystems. In one of the few studies now available, Robertson *et al.* (1993) compared soil chemical properties and N mineralization distributions in a row-crop field plowed annually for decades against distributions in an adjacent field that had never been cultivated. As predicted from prior studies, the tilled site soil had less than 50% of the carbon present in soils of the uncultivated site, and had higher levels of inorganic phosphorus, moisture, and higher soil pH, with no difference between sites in potential net nitrogen mineralization and nitrification rates.

Not predictable from prior studies, however, was the effect of tillage on the spatial distribution of these

properties. Geostatistical analysis showed that almost all properties examined were strongly autocorrelated within each site, with structural variance as a proportion of sample variance ranging from 30–95% for all soil properties, and with virtually no difference for any given property on account of tillage practice. Nevertheless, while the degree of spatial dependence did not differ on account of tillage, the distance over which this spatial dependence occurred was generally much less for properties in the uncultivated site (7–26 m) than for properties in the tilled site (48–108 m), especially for total C and N turnover (Fig. 6). Such results suggest that the spatial pattern and scale of soil variability can differ markedly among edaphically identical sites and that these differences can indeed be related to disturbance history. They also suggest that a chronic disturbance such as long-term tillage can affect the distances over which spatial dependence is expressed (e.g. patch size) independently from effects on the degree of spatial dependence present — spatial dependence was not affected by tillage.

As the results of additional studies become available, we are likely to see that soil disturbance associated with crop management practices can strongly affect the spatial patterning of soil populations and resources within specific fields. The

implications for this patterning are significant, especially as soil-specific farming practices become economically feasible. To the extent that management practices reduce variability, soil-specific farming will become more simplified as the within-field patch sizes of resources and populations increase in magnitude. To the extent that patches become or remain more discrete, however, soil-specific farming will become more complex as the application of tailored inputs will require even finer resolution. It is currently premature to speculate further; knowledge of existing patch sizes is largely unavailable for most cropping systems and soil types, and this information is prerequisite for understanding the further impact of management on variability.

With software now available to soil biologists, an emerging recognition of the scientific importance of soil spatial variability, and the producer's need for further optimizing crop inputs, one might expect — and hope for — rapid progress in our attempts to address this long-recalcitrant problem.

Acknowledgements

This work was supported by funding from the NSF LTER Program (DEB 91-07481) and the Michigan Agricultural Experiment Station. Special thanks to Peter Grace, Albert Rovira, and others at the Australian Cooperative Center for Soil and Land Management for stimulating discussions and helpful comments during the preparation of this contribution.

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