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ANALYZING FIELD-MEASURED SOIL-WATER PROPERTIES

D.R. NIELSEN

Department of Land, Air and Water Resources
University of California, Davis
Davis, California 95616
U.S.A.

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D.R. Nielsen, Patricia M. Tillotson and S.R. Vieira

1. INTRODUCTION

It is a challenge to the world community of earth and geophysical scientists to develop a better technology for sampling the earth's crust. That thin mantle of soil has been managed for countless human generations with the primary objective being the production of food and fiber to meet the needs of the earth's inhabitants. In the past, that management has been judged on annual measurements of crop productivity, and not on measurements taken below the soil surface that could be used to signal the long term consequences of present-day management of soil and water resources. We are indebted to the pioneering works of R. A. Fisher and subsequent efforts of others that have and continue to afford conceptual frameworks to statistically judge and compare the merits of different management schemes or treatments, particularly those used for enhancing agricultural production. The selection of a preferred cultivar, an optimal fertilizer application, the best timing of an irrigation or the most effective soil fumigant has been accomplished in the agricultural sciences by analysis of variance procedures advocated by Fisher. Such "aggie" statistical procedures are invaluable, and it is not our intent to de-emphasize their importance now or in the future. Our intent here is to expand that conceptual framework to include a consideration of statistical analyses normally not included in the agricultural sciences. Such an expansion is fully justified when we wish to examine the changing quality of soils as well as that of water moving over and through them as a result of different management schemes. We believe more attention should be given to developing techniques to better monitor the soil environment, and at the same time we recognize that such development should, concomitantly, potentially enhance the efficiency of crop production.

Our objective of this presentation is to provide a qualitative review of statistical concepts not usually covered in "aggie" statistics, and to provide an opinion of the questions we believe future research shall answer in light of the kinds of efforts reported at the 1982 meeting of the European Geophysical Society. Our intentions preclude the identification of analytical prescriptions or algorithms to carry out various statistical procedures. We also shall not attempt to be rigorous in the identification of the fundamental underlying assumptions of each concept. The concepts have been known and used in other scientific disciplines for a relatively long time. If our presentation is successful, we would urge the reader to refer to the list of references to learn and fully appreciate the fundamentals

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of each concept, and not to rely on our qualitative descriptions and examples.

2. SPATIAL AND TEMPORAL DEPENDENCE

Our reference to "aggie" statistics highlights the fact that most statistical analyses advocated in the agricultural sciences implicitly disregard the spatial coordinate at which an observation is made. For the most part, emphasis is given to the identification of an average value and its potential dispersion for a soil attribute within a given parcel of land, a regression of one attribute versus one or more other attributes relative to their magnitudes (not their coordinate positions on the landscape), and a difference between two mean values of a soil attribute that may exist for two parcels of land chosen more or less arbitrarily without regard to their spatial coordinate system. In fact, it is generally considered necessary or advantageous in "aggie" statistics to assume that observations are spatially independent of each other, and hence, a set of observations are reduced to their mean value and a measure of its uncertainty expressed in terms of an assumed probability density distribution estimated by a set of observations without regard to their spatial positions. We refer the reader to standard texts for such analyses.

Intuitively, we do not expect field observations of soil properties to be necessarily spatially independent. We would expect measurements made close together to yield nearly equal values, and measurements made some distance apart to yield values more correlated to each other. We would also expect a spatially repetitious behavior of soil observations as a result of cyclic tillage traffic and cropping patterns in cultivated fields, sequences of low and high topographical positions giving rise to cyclic locations of greater and lesser degrees of leaching, and sequences of soil mapping units not randomly located within a landscape owing to soil formation processes that are linked spatially to the coordinates of the soil surface. Because of the above expectations, it would appear advantageous to sample a field in a manner that would allow the detection of cyclic irregularities in relation to the size of the parcel of land being measured. Such expectations raise questions regarding the "proper" size of an observation, the "proper" distance between observations, the "proper" location of each observation and the "proper" number of observations. These questions are all relevant to the geostatistical concept which defines the size of the domain characterized by a single observation within a field soil. This differs markedly from the "aggie" statistical concept that defines for a given level of probability the accuracy and precision of an estimate of an average value within a field soil from a set of observations.

2.1 Spatial autocorrelation

A measure of the strength of the linear association between pairs of observations is useful in defining the separation distance between observations beyond which there is no correlation between pairs of

values. The autocorrelation coefficient, r_a, a function of the separation distance h, is a measure of that strength and is defined as

$$r_a(h) = \frac{\text{autocovar}[G(x),G(x+h)]}{\sqrt{\text{var}[G(x)]}\sqrt{\text{var}[G(x+h)]}} \quad (1)$$

for a set of soil water content observations G taken along a transect in the x-direction*. For example, when observations are taken 1 unit apart, $r_a(1)$ is the value of the linear regression coefficient for h = 1 (lag 1) when values of G(x+1) are plotted against values of G(x). In other words, nearest neighbors are plotted against each other. Similarly, when h = 2, $r_a(2)$ is the value of the coefficient when values of G are plotted against other values observed a distance of 2 units away. Fig. 1 shows two examples. For example A, the autocorrelation coefficient decreases abruptly from 1 to zero within a lag of 1 (the smallest distance between observations). The value

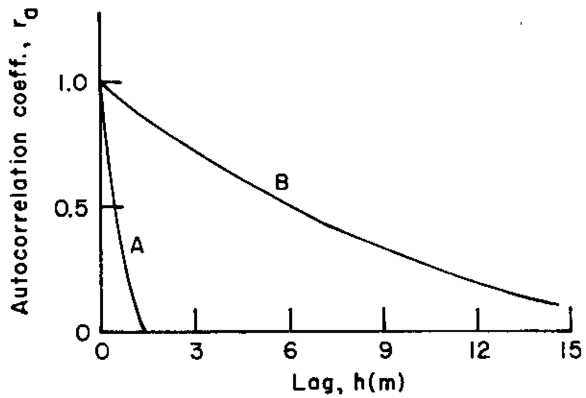

Fig. 1. Idealized autocorrelograms for average soil water content G observed at 1-m intervals along transects within fields A and B.

of r_a for example B approaches zero for lags in excess of 10. For example A, one concludes that the observations are spatially independent - that is, one cannot estimate the value of an observation from that of its nearest neighbor. Interpreting the results for example B where r_a decreases rather gradually as h increases, one concludes that

* Throughout this presentation, concepts expressed in one direction can be generalized to n directions.

the observations are spatially dependent. In other words, within a distance of about 10, it is possible to estimate from one neighbor the expected values of other neighbors. Soil scientists are beginning to use this concept to express the spatial dependence of field-measured soil properties and crop yields.

The functional relation $r_a(h)$ has been expressed with several empirical formulae. One of the most commonly used expressions is

$$r_a(h) = \exp(-h/\lambda) \tag{2}$$

where λ is selected in order that the sum of the measured deviations of r from the above expression is zero. Notice that the value of λ is equal to that distance h between measured values for which their correlation coefficient is 1/e. λ is called the autocorrelation length or the scale of observation. A rather liberal interpretation of the significance of λ is that it represents the distance across the landscape characterized by a single observation within the field. In general, there are several ways of defining autocorrelation lengths. Important to our discussion here is that when sampling the field from which curve B (Fig. 1) was obtained, observations made at sampling intervals less than 10 units are somewhat unnecessary because they are related to each other. On the other hand, sampling the field from which curve A was obtained at sampling intervals greater than 1 unit does not allow meaningful interpolation between neighboring observations. It should be obvious that the functional relation between r_a and h depends upon the size of the sample, and that in general, the greater the sample size, the greater the value of the autocorrelation length λ. For any particular study, the investigator should consider the minimum distance between sampling locations (h = 1) in relation to the objectives of the experiment and the potential utility of the values of λ for each kind of observation.

2.2 Spatial cross-correlation

Instead of measuring only one kind of observation across a field, let us assume that two kinds are made: soil water content, G, as described above as well as the temperature, F, of a grain crop uniformly covering the field. The spatial cross-correlation coefficient r_c is defined by

$$r_c(h) = \frac{\mathrm{covar}[F(x),\ G(x + h)]}{\sqrt{\mathrm{var}F(x)}\sqrt{\mathrm{var}G(x + h)}} \tag{3}$$

where, in this case, F, the crop temperature and G, the soil water content, are each measured along a transect at positions x. Let us assume that as available soil water is depleted, evapotranspiration decreases and crop temperature, consequently, increases. For such a condition, crop temperature is inversely related to available soil water with the value of $r_c(0) < 0$. Equation (3) reduces to the linear

regression coefficient normally calculated using "aggie" statistics when h = 0 (a value of -0.8 for our example). Fig. 2 illustrates the use of equation (3) for other values of $h \geq 0$. In Fig. 2a, with the two distributions F(x) and G(x) overlapped a distance h, a linear regression analysis is calculated for the pairs [F(x), G(x + h)]. The results of such calculations of r_c are plotted in Fig. 2b for two hypothetical transects (one in field A and one in field B) having identical values of $r_c(0) = -0.8$. For field A, if the value of h is increased only slightly from 0, r_c rapidly approaches zero. On the

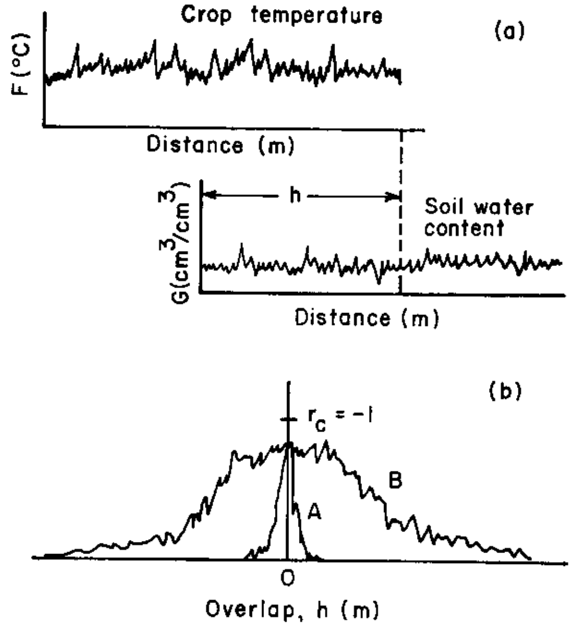

Fig. 2. Idealized cross-correlogram for crop temperature F(x) and soil water content G(x) along transects within fields A and B.

other hand, the results from field B show that crop temperatures measured at much greater distances from where the average soil water content observations were made remain significantly correlated. The general utility of such cross-correlation should be obvious. The area under each curve in Fig. 2b or the range of h over which the value of r_c remains near unity is an indication of the spatial distance over which a linear relation exists between F and G. It allows the investigator to consider the spacing and size of one set of observation (F) with those of another (G), particularly when one set is difficult to obtain or relatively expensive. A related example would be the optimum choice of the size and spacing of observation pixels from overflight or satellite vehicles compared with size and spacing of those of ground observations.

2.3 Spectral analysis

In the paragraphs above, the interpretation of the correlation coefficients r_a and r_c of equations (1) and (3) were restricted to values of h for observations compared more or less in near vicinity to each other (i. e., for h much, much less than the width of the field being sampled). An opportunity to discern repetitious irregularities or cyclic patterns in soil or plant communities across a field exists with a spectral analysis that utilizes the function $r_a(h)$. We illustrate by assuming our measured distribution of average soil water content across a field G(x) was taken where a crop had previously been grown along furrows 1 m apart. As a result of both plant extraction of soil water and infiltration occurring in 1-m cyclic patterns across the field, measured values of G will reflect local variations as well as a tendency toward a sinusoidal behavior having a 1-m period. A spectral analysis identifies this periodicity and can be calculated by

$$S(f) = 2\int_0^{\infty} r_a(h)\cos(2\pi fh)\, dh \qquad (4)$$

where f is the frequency equal to 1/p where p is the period. Fig. 3

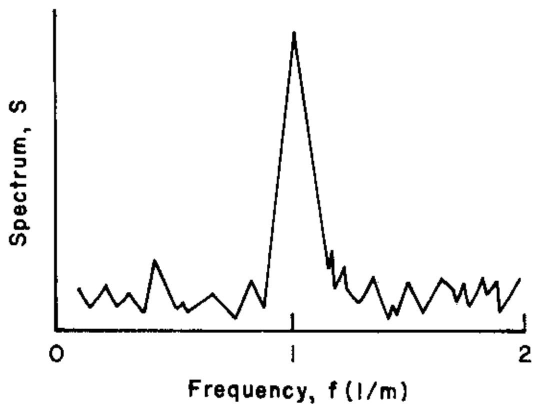

Fig. 3. Spectrogram S(f) for a transect of soil water content observations taken normal to the direction of furrows.

illustrates the shape of the function S(f) where it can be seen that most of the variance about the mean value of G(x) is accounted for by observations of soil water content that reflect oscillations of wet and dry soil occurring, on the average, every 1 meter. Depending upon the kinds of repetitious features and processes that may be operating in a field, S(f) may have a number of relative maxima that identifies their specific spatial occurrences. In other words, a spectral analysis is useful in partitioning the total variance of a set of observations among different frequencies and then assessing which of those frequencies has any significance for the field problem being studied. If we extend the above example to conditions illustrated in Fig. 4, we see two additional periodicities - those greater water contents occurring every 2 meters owing to tractor tire compaction, and those occurring approximately every 10 meters associated with pre-plant border irrigation or some other kinds of previous traffic pattern. In this example, most of the total variance is accounted for by variations from the mean value occurring at periods of 1, 2 and 10 m. Had

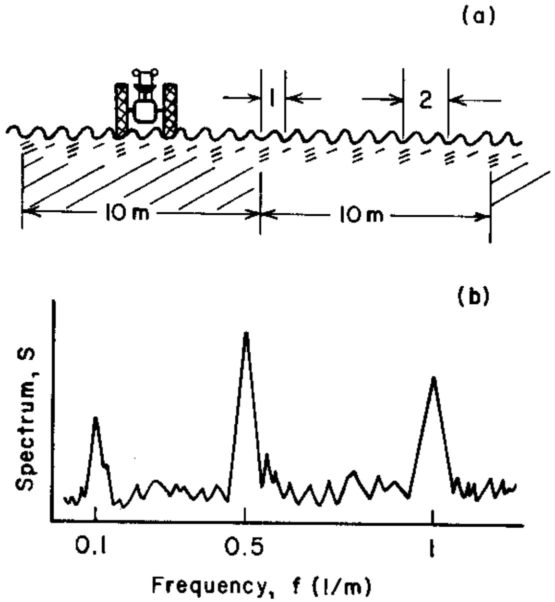

Fig. 4. Schematic diagram of furrows, tractor compaction and pre-plant irrigation causing cyclic variations of soil water content, and idealized spectrogram.

plant extraction, infiltration, compaction and pre-plant border irrigation had no influence on the spatial variations of average soil water content, S(f) would have manifested no relative maxima.

2.4 Cospectral analysis

In a manner similar to the usage of $r_a(h)$ in spectral analysis, $r_c(h)$ is used to partition the total covariance for two sets of observations across a field. A cospectral analysis is made by

$$Co(f) = 2 \int_0^{\infty} \bar{r}_c(h)\cos(2\pi fh)dh \qquad (5)$$

where $\bar{r}_c(h) = [r_c(h < 0) + r_c(h > 0)]/2$. Let us extend further our illustration given in Fig. 4 by assuming that a grain crop is growing in the field whose soil water content has cyclic distributions of soil water owing to furrows, compaction and pre-plant border irrigation. We have the distribution of crop temperatures F(x) and the distribution of soil water contents G(x) from which we calculate the cross-correlation coefficient $r_c(h)$ from equation (3). Having calculated the average value $\bar{r}_c$ and integrating equation (5), we obtain Co(f) depicted in Fig. 5. It is not surprising that three relative minima occur at periods of 1, 2 and 10 m. The area beneath the abscissa has a negative value and represents the total covariance between crop temperature and soil water content. A linear regression between F(x) and G(x) using "aggie" statistics would be negative indicating statistically that crop temperature is inversely related to

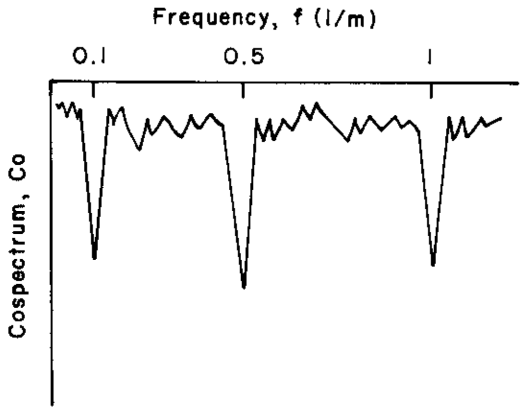

Fig. 5. Cospectrogram of crop temperatures F(x) and soil water content G(x) along a transect normal to the furrows shown schematically in Fig. 4a.

average soil water content. In this example, had pairs of observations of F and G been made in a spatially random manner across the field, the "aggie" linear regression correlation coefficient would have been approximately equal to $r_c(0)$ but such random samplings would not have identified the periodicity within both sets of observations.

For the above example it is advantageous for our discussion to recognize an alternative situation where soil compaction occurs with relatively higher soil water contents. For this situation, it is possible that root growth is impeded, or because of ever-present root-rot microorganisms thriving in a wet, compacted soil environment, the crop roots are diseased. In either case, the crop temperature would be directly related to soil water content in zones of compacted soil, and inversely related in other locations in the field. For such a situation, equation (5) would give rise to a cospectral analysis illustrated in Fig. 6. Even though the total area is zero, the relative minima and a maximum show inverse correlations between F and G at spatial periods of 1 and 10 m, and a direct correlation at a period of 2 m. Had pairs of F and G been taken randomly across the field, a routine linear regression would have provided no enlightenment of the processes occurring inasmuch as its value would have been near zero.

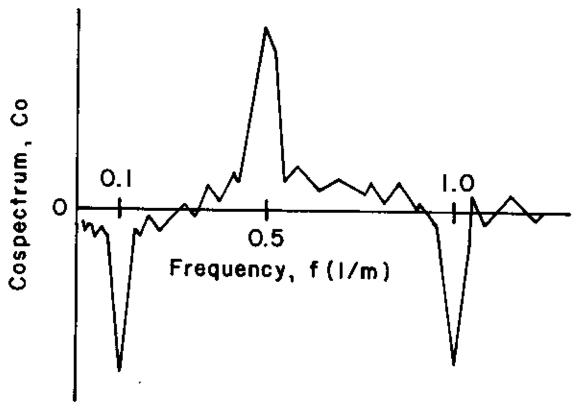

Fig. 6. Cospectrogram of crop temperatures F(x) and soil water content G(x) along transect normal to the furrows shown in Fig. 4a when compaction decreases evapotranspiration.

2.5 Cospectral phase angles and coherence

The above examples of cospectral analysis compared two sets of observations whose periodicities were spatially equal for the same locations across the field. Soil attributes or processes that are correlated for a particular spatial frequency may manifest this correlation at any phase angle of not necessarily zero. We illustrate this possibility in Fig. 7 where observations of crop temperature, T(x), and soil salinity, SS(x), have a periodicity of 1 m. We assume that crop temperatures are directly related to soil salinity and that soil salinity levels are smaller in the bottom of the furrows 1 m apart. For such conditions, each set of observations yields a relative maximum in its spectral analysis at a frequency of 1 as shown in the figure. However, because the sun's radiation is not received from a vertical direction, the maximum temperature of the crop will occur at a distance ϕ from where the highest soil salinity is observed. The phase angle ϕ illustrated in Fig. 7 is given by

$$\phi = \frac{1}{2\pi f}\tan^{-1}[Q(f)/Co(f)] \qquad (6)$$

where Q(f) is the quadrature spectrum calculated in an equation similar to that of equation (5) where the cosine term has been replaced by

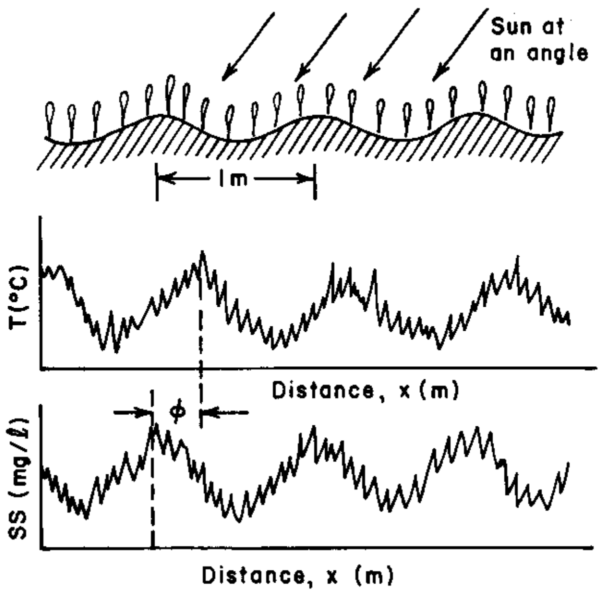

Fig. 7. Schematic diagram of observations of crop temperature T(x) and soil salinity SS(x) along a transect normal to furrows with the sun radiation being received from one side.

a sine term. Having calculated $r_c(h)$ for the two distributions T(x) and SS(x), Q(f) can also be calculated from equation (5) if $r_c(h)$ is replaced by $\underline{r}_c(h)$ where $\underline{r}_c(h) = [r_c(h > 0) - r_c(h < 0)]/2$. The coherence of the cospectral analysis is given by

$$Ch(f) = \frac{Q^2(f) + Co^2(f)}{S_T(f)S_{SS}(f)} \qquad (7)$$

where S_T and S_{SS} are calculated from equation (4) for T and SS, respectively. The coherence, whose values range between 0 and 1, is analogous to the r^2-value in ordinary regression analysis of "aggie" statistics. It provides a measure of the certainty at which the phase angle is identified.

Spectral and cospectral analyses are potentially powerful tools for managing and increasing our knowledge of land resources. With them, we can spatially link observations of different physical, chemical, and biological phenomena. We can identify the existence and persistence of cyclic patterns across the landscape. In some cases, the cyclic behavior of soil attributes may be of more or equal importance than the average behavior. From a spectral analysis, some insights may be gained relative to the distances over which a meaningful average should be calculated. It should also be recognized that the selection of a particular size of a sensor should be based upon a knowledge of the potential periodicities to be manifested by such observations. And, with spectral analyses, it is possible to filter out trends across a field to examine more closely local variations, or vice versa. It should also be recognized that all of the above discussion from the beginning of this presentation could have had the time variable substituted for that of the distance variable.

2.6 Semivariograms and kriging

The spatial dependence of neighboring observations may also be expressed by the semivariogram $\gamma(h)$ estimated by

$$\gamma(h) = \frac{1}{2N(h)} \sum_{i=1}^{N(h)} [G(x_i) - G(x_i + h)]^2 \qquad (8)$$

where N(h) is the number of experimental pairs of observations $[G(x_i), G(x_i + h)]$ separated by a vector distance h. The shape of the semivariogram gives an indication of the spatial dependence of the soil physical properties. If for all values of h greater than zero γ remains essentially constant, it indicates that the observations are spatially independent. If for all values of h greater than zero, γ increases and approaches a constant value, it indicates that the observations are spatially dependent within a spatial area that can be characterized as a single domain. On the other hand, if as h increases, γ continues to increase, it indicates the area being sampled continually changes and is not comprised of a single domain. The semivariogram describes the "variance structure" of a field, and is to geostatistics as the probability density distribution is to "aggie" statistics. Analytical interpretations of the shapes of variograms have proven especially helpful in the definition of soil mapping units as used in the context of soil morphology and classification.

Semivariograms, when the spatial dependence of observations exists, are useful to make interpretations between observed values and to identify improved future sampling schemes. Owing to the fact that the semivariogram gives the expected relation between pairs of observed neighbors, it is obvious for interpolation that different weights should be given to neighbor values depending upon their distance from the one to be interpolated. Hence,

$$G(x_o) = \sum_{i=1}^{n} \beta_i G(x_i) \qquad (9)$$

where $G(x_o)$ is the estimated value at location x_o, β_i are the weights associated with each of the values G measured at locations x_i, and n is the number of locations. This interpolation method developed by G. Matheron, which he called kriging in honor of D. G. Krige is an optimum interpolator because it interpolates without bias and with minimum variance. And, because it allows the variance of the estimates to be estimated, it is extremely helpful for identifying improved sampling schemes. Kriging is becoming more common in geophysical studies, and in light of the presentation of Webster and Burgess, we shall not illustrate its usage. We point out, however, that through its usage for soil observations taken within and between furrows, or within and between rows of crop plants it is possible to construct contours of isovalues that are more meaningful than simplistic values of means calculated for the two positions - within the row and between the row, frequently repeated in agronomic journals.

2.7 Cross-semivariograms and cokriging

In many field situations, one set of observations $G(x_i)$ may not be sampled sufficiently to yield interpolated values at other locations of acceptable accuracy. By considering the spatial correlation that may exist between that variable and another more frequently observed variable $H(x_i)$, cokriging may improve the precision of estimating the former. Cokriging relies not only upon the semivariogram but also on the cross-semivariogram estimated by

$$\gamma_c(h) = \frac{1}{2N(h)} \sum_{i=1}^{N(h)} [G(x_i) - G(x_i + h)][H(x_i) - H(x_i + h)] \qquad (10)$$

where the pairs of values $[G(x_i), G(x_{i+h})]$, $[H(x_i), H(x_{i+h})]$ are separated by the vector h. An interpolated value of G at location x_o is cokriged using

$$G(x_o) = \sum_{i=1}^{n} \beta_i^H H(x_i) + \sum_{j=1}^{m} \beta_j^G G(x_j) \qquad (11)$$

where β_i^H and β_i^G are the weights associated with observations H and G, and n and m are the number of H and G used in the estimation of G at location x_o. Values of H and G are measured while values of β_i^H and β_i^G are calculated from values of the semivariogram and cross semivariogram given in equations (10) and (8), respectively. Cokriging is attractive when one of the two sets of observations correlated with each other is relatively inexpensive and abundant. We believe it has the potential of more precisely delineating boundaries between soil mapping units, especially when either or both G and H above are each functions of several soil properties. Present-day and future soil mapping units should be judged, in some degree, on the behavior of their semivariograms and cross-semivariograms.

3. DETERMINISTIC VERSUS STOCHASTIC EQUATIONS

Differential equations derived and solved for the description of soil processes have most often been based upon deterministic concepts regarding both their variables and parameters. Their derivations explicitly demanded that sufficient observations were available to identify the expected value of each term with more than sufficient precision deemed necessary for their accurate solution. Such equations, often used under strict laboratory conditions where observations of each term were reasonably precise and accurate, are now being questioned when their solutions are extended to natural field conditions. That questioning initially embraced both measurement error and sampling error. But with the continual development of instruments and methodology to assess soil properties in situ with greater accuracy, it is now recognized that the sampling error associated with spatial and temporal variations of those properties must be considered separately. That is, with any reasonably affordable present day sampling scheme, the spatial and temporal variance of field soil properties are sufficient to render estimates of their means highly unreliable. Hence, deterministic equations are giving way to mixed deterministic - stochastic and stochastic equations with levels of probability of their solution defined.

3.1 Scaling

Scaling is part of a more general methodology known as fractional analysis which seeks to find partial solutions to physical problems which cannot be solved explicitly. Their complete solutions are unattainable owing to either some lack of understanding or the mathematical analysis is intractable. An example of such a problem is the simultaneous transport of water, solutes, heat and gases within an unsaturated field soil subjected to diurnal conditions. From a theoretical viewpoint, scaling is a process which reduces through dimensional or inspectional analysis the number of variables important in a given problem to the smallest number of variables which completely describe the system. This reduction greatly simplifies the description of the system as well as provides descriptions of a great number of other systems having different values for common parameters. More than 25 years ago, E. E. Miller and R. D. Miller introduced scaling and the concept of similar media using inspectional analysis for describing the retention and transport of water through unsaturated soils. They and others have derived scale factors for soil water flow properties that have shown utility for structureless soils comprised of particles of different sizes having similar geometric shapes. Soil scientists have yet to address the scaling of solute, gas or heat movement through soils by dimensional or inspectionl analysis, and further consideration of that for water movement appears justified.

3.2 Stochastic equations

More recently different kinds of scale factors, not necessarily related to those mentioned above, have been identified through regression analysis to aid in the quantitative description of field-measured soil-water functions or parameters required for the solution of deterministic equations. Such identification simplifies the description of the functions for a spatially variable field soil into one or more stochastic scale factors. Hence, the precision for which soil-water functions are known for a field can be ascertained from the probability density function and the spatial variance of these scale factors. Incorporating such scale factors with mathematical expressions of their statistical and geostatistical variances into the usual deterministic equations for soil water allows solutions and simulations of soil water and related processes to be calculated within prescribed levels of probability. The practicality of routinely using stochastic scale factors would be enhanced considerably if they could be adequately estimated through correlations of easily measured soil properties such as soil texture, porosity, bulk density, etc. potentially available for each soil mapping unit.

It is becoming clear that there is a need to analyze and simulate the behavior of field soils and agronomic regimes using equations in probabilistic viewpoints. It is also becoming obvious that a knowledge of the mean behavior of a field may be of less importance in some cases than that of its statistical or spatial variance. In this respect, solutions of deterministic equations calculated repeatedly using Monte Carlo procedures to identify realizations of their soil parameters are beneficial. Such repeated calculations theoretically correspond to a series of repeated field-measured values. Analytic solutions of deterministic equations containing random or regionalized variables are also gaining recognition. Stochastic differential equations beginning to be used in hydrology relating variations in the saturated hydraulic conductivity to the dispersion of solutes need to be explored for unsaturated soils. There also is the possibility of using transfer function models that treat the transformation of a soil profile input into an output without a knowledge or modelling of the mechanisms inside the profile. Such models have been used recently to investigate the transfer of solutes added to the soil surface to

greater depths in the soil profile. Physical, chemical and biological reactions of the solutes within the profile were explicitly ignored but implicitly included through estimated probabilities of the amount and rate at which the solutes arrived at a greater soil depth.

4. FUTURE RESEARCH

A dearth of properly designed field-measured observations of soil water properties precludes an adequate assessment of their spatial variance structure and the development of an efficient field technology to optimize the size and spacing of their measurement. Sampling schemes based upon "aggie" statistics are relatively inexpensive owing to fewer observations required compared with those based upon geostatistical concepts. Each statistical analysis has advantages and disadvantages. A particular sampling scheme should embrace the attributes of both "aggie" statistics and geostatistics. Unfortunately, present-day soil mapping units have been developed without sufficient regard to quantitative evaluations of the spatial variances of soil parameters. Future research needs to answer the question if present-day mapping units manifest commensurate spatial variance structures for each of their soil properties. Within each mapping unit, when should sampling schemes be 1-, 2-, or 3-dimensional? Should observations be equally spaced or should they be clustered in some manner? For 2-dimensional sampling schemes, are othogonal configurations more, or less informative than triangular, pentagonal, and other configurations? Is there a future for the turning bands concept in soil water studies? Do spectral and cospectral analyses of soil water properties offer opportunities for improved soil water management? Are there particular frequencies associated with cultivation or with pedologic processes that should be more amenable to cospectral analysis? What is the future of kriging and cokriging in soil water studies? Does cokriging offer any substantive advantage over simply taking more observations of that parameter of primary interest? How much better an understanding of transport of solutes, heat and gases through field soils can be gained through dimensional and inspectional analysis? Are scaling factors correlated with soil properties and are they linked within or between soil mapping units?

Of paramount importance is to identify criteria for choosing deterministic rather than stochastic algorithms for ascertaining the behavior of water in field soils. The presentations that follow as well as those we envision during the next decade will make substantive contributions toward that identification.

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