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COLLEGE ON SOIL PHYSICS
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"Analyzing Field-Measured Soil Properties"

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Please note: These are preliminary notes intended for internal distribution only.

PUBLICATIONS

Nielsen, D. R. and J. W. Biggar. 1961. Miscible displacement in soils: I. Experimental information. Soil Science Society of America Proceedings 25(1):1-5. January-February.

Biggar, J. W. and D. R. Nielsen. 1962. Miscible displacement: II. Behavior of tracers. Soil Science Society of America Proceedings 26(2): 125-128. March-April.

Nielsen, D. R. and J. W. Biggar. 1962. Miscible displacement: III. Theoretical considerations. Soil Science Society of America Proceedings 26(3):216-221.

Biggar, J. W. and D. R. Nielsen. 1962. Some comments on molecular diffusion and hydrodynamic dispersion in porous media. Journal of Geophysical Research 67(9):3636-3637. August.

Nielsen, D. R. and J. W. Biggar. 1963. Miscible displacement: IV. Mixing in glass beads. Soil Science Society of America Proceedings 27(1):10-13. January-February.

Corey, J. C., D. R. Nielsen and J. W. Biggar. 1963. Miscible displacement in saturated and unsaturated sandstone. Soil Science Society of America Proceedings 27(3):258-262. May-June.

Nielsen, D. R. and J. W. Biggar. 1963. Hydrodynamic dispersion in porous media. Transactions of the American Geophysical Union 44(2): 574-575.

Biggar, J. W. and D. R. Nielsen. 1963. Miscible displacement: V. Exchange processes. Soil Science Society of America Proceedings 27(6): 623-627.

Nielsen, D. R., J. M. Davidson, J. W. Biggar and R. J. Miller. 1964. Water movement through Panoche clay loam soil. Hilgardia 35(17):491-506. July.

Biggar, J. W. and D. R. Nielsen. 1964. Chloride-36 diffusion during stable and unstable flow through glass beads. Soil Science Society of America Proceedings 28(5):591-595. September-October.

Miller, R. J., J. W. Biggar and D. R. Nielsen. 1965. Chloride displacement in Panoche clay loam in relation to water movement and distribution. Water Resources Research 1(1):63-73. First Quarter.

Biggar, J. W., D. R. Nielsen and K. K. Tanji. 1966. Comparison of computed and experimentally measured ion concentrations in soil column effluents. Transactions of the American Society of Agricultural Engineers 9(6):784-787.

Corey, J. C., D. R. Nielsen, J. C. Picken, Jr., and Don Kirkham. 1967. Miscible displacement through gamma radiation-sterilized soil columns. Environmental Science and Technology 1:144-147. February.

Corey, J. C., D. Kirkham and D. R. Nielsen. 1967. The movement of chloride and nitrate through certain Iowa soils. Journal Paper No. J-5381 of the Iowa Agriculture and Home Economics Experiment Station, Ames. pages 130-141.

Biggar, J. W. and D. R. Nielsen. 1967. Miscible displacement and leaching phenomenon. Irrigation of Agricultural Lands, Agronomy Monograph No. 11, American Society of Agronomy, Madison, Wisconsin. pages 254-274.

Nielsen, D. R., J. W. Biggar and R. J. Miller. 1967. Field observations of infiltration and soil-water redistribution. Transactions of American Society of Agricultural Engineers 10(3):382-387, 410.

Corey, John C., Donald R. Nielsen, and Don Kirkham. 1967. Miscible displacement of nitrate through soil columns. Soil Science Society of America Proceedings 31(4):497-501. July-August.

Rolston, D. E., D. Kirkham and D. R. Nielsen. 1969. Miscible displacement of gases through soil columns. Soil Science Society of America Proceedings 33(4):488-492. July-August.

Mansell, R. S., Don Kirkham and D. R. Nielsen. 1970. Nitrate and detergent recovery in aerated soil columns. Soil Science Society of America Proceedings 34(5):883-889. November-December.

Warrick, A. W., J. W. Biggar and D. R. Nielsen. 1971. Simultaneous solute and water transfer for an unsaturated soil. Water Resources Research 7(5):1216-1225. October.

Rolston, D. E., D. R. Nielsen and J. W. Biggar. 1971. Miscible displacement of ammonia in soil: Determining sorption isotherms. Soil Science Society of America Proceedings 35:899-905. November-December.

Krupp, H. K., J. W. Biggar and D. R. Nielsen. 1972. Relative flow rates of salt and water in soil. Soil Science Society of America Proceedings 36(3):412-417. May-June.

Rolston, D. E., D. R. Nielsen and J. W. Biggar. 1972. Desorption of ammonia from soil during displacement. Soil Science Society of America Proceedings 36(6):905-911. November-December.

Nielsen, D. R. and J. W. Biggar. 1973. Analysing soil water solute movement under field conditions. pages 111-127. In Soil-Moisture and Irrigation Studies II. International Atomic Energy Agency, Vienna.

Nielsen, D. R. (one of 18 authors). 1973. Nitrates in the Upper Santa Ana River Basin in relation to groundwater pollution. In R. S. Ayers and R. L. Branson (Eds.). University of California, Division of Agricultural Sciences, California Agricultural Experiment Station Bulletin 861:1-60. May.

Kirda, C., D. R. Nielsen and J. W. Biggar. 1973. Simultaneous transport of chloride and water during infiltration. Soil Science Society of America Proceedings 37(3):339-345. May-June.

Corey, J. C. and D. R. Nielsen. 1973. Some factors influencing the interpretation of soil-solute-water interactions. pages 87-110. In Soil-Moisture and Irrigation Studies II. International Atomic Energy Agency, Vienna.

Nielsen, D. R., J. W. Biggar and K. T. Erh. 1973. Spatial variability of field-measured soil-water properties. Hilgardia 42(7): 215-259. November.

Starr, J. L., F. E. Broadbent and D. R. Nielsen. 1974. Nitrogen transformations during continuous leaching. Soil Science Society of America Proceedings 38:283-289. March-April.

Misra, C., D. R. Nielsen and J. W. Biggar. 1974a. Nitrogen transformations in soil during leaching: I. Theoretical considerations. Soil Science Society of America Proceedings 38:289-293. March-April.

Misra, C., D. R. Nielsen and J. W. Biggar. 1974b. Nitrogen transformations in soil during leaching: II. Steady state nitrification and nitrate reduction. Soil Science Society of America Proceedings 38: 294-299. March-April.

Nielsen, D. R., C. Misra, J. L. Starr and C. Kirda. 1974. Movement and fate of nitrogen fertilizers and other agrochemicals applied to soils. pages 7-18. In Effects of Agricultural Production on Nitrates in Food and Water with Particular Reference to Isotope Studies. International Atomic Energy Agency, Vienna.

Kirda, C., J. L. Starr, C. Misra, J. W. Biggar and D. R. Nielsen. 1974. Nitrification and denitrification during miscible displacement in unsaturated soil. Soil Science Society of America Proceedings 38(5):772-776. September-October.

Biggar, J. W., D. R. Nielsen and J. L. MacIntyre. 1975. Measurement of water and nitrogen fluxes in soil profiles planted to maize. pages 417-428. In Isotope Ratios as Pollutant Source and Behaviour Indicators. International Atomic Energy Agency, Vienna.

Misra, C., D. R. Nielsen and J. W. Biggar. 1974c. Nitrogen transformations in soil during leaching: III. Nitrate reduction in soil columns. Soil Science Society of America Proceedings 38:300-304. March-April.

Nielsen, D. R., J. L. Starr, C. Kirda and C. Misra. 1974. Soil-water and solute movement studies. pages 117-133. In Isotope and Radiation Techniques in Soil Physics and Irrigation Studies, 1973. Proceedings, Symposium of the International Atomic Energy Agency, Vienna.

Kirda, C., D. R. Nielsen and J. W. Biggar. 1974. The combined effects of infiltration and redistribution on leaching. Soil Science 117(6): 323-330. June.

Canarache, A., D. R. Nielsen and J. W. Biggar. 1974. Cercetari privind dispersia hidrodinamica in sol si aplicarea acestei tehnici la studiul respingerii anionice. Analele Institutului De Studii Si Cercetari Pedologice XL:45-72.

Biggar, J. W. and D. R. Nielsen. 1976. Spatial variability of the leaching characteristics of a field soil. Water Resources Research 12(1):78-84. February.

Kirda, C., J. L. Starr and D. R. Nielsen. 1976. Azotlu gübrflerin topraktaki yikanmalâri ve ugradiklari mikrobiyel degişimler. Topraksu 42:96-105.

Van De Pol, R. M., P. J. Wierenga and D. R. Nielsen. 1977. Solute movement in a field soil. Soil Science Society of America Journal 41(1):10-13. January-February.

Warrick, A. W., G. J. Mullen and D. R. Nielsen. 1977. Predictions of the soil water flux based upon field-measured soil-water properties. Soil Science Society of America Journal 41(1):14-19. January-February.

Warrick, A. W., G. J. Mullen and D. R. Nielsen. 1977. Scaling field-measured soil hydraulic properties using a similar media concept. Water Resources Research 13(2):355-362. April.

Biggar, J. W., K. K. Tanji, C. S. Simmons, S. K. Gupta, J. L. MacIntyre and D. R. Nielsen. 1977. Theoretical and experimental observations of water and nitrate movement below a crop root zone. pages 71-77. In J. P. Law, Jr. and G. V. Skogerboe (Eds). Proceedings, National Conference on Irrigation Return Flow Quality Management, Fort Collins, Colorado, May 16-19. Sponsored by U. S. Environmental Protection Agency and Colorado State University.

Wagenet, R. J., J. W. Biggar and D. R. Nielsen. 1977. Tracing the transformation of urea fertilizer during leaching. Soil Science Society of America Journal 41(5):896-902. September-October.

Nielsen, Donald R. and J. G. MacDonald (Eds.). 1978. Nitrogen in the Environment. Volume I, Nitrogen Behavior in Field Soil. Academic Press. 526 pages plus Appendix.

Nielsen, Donald R. and J. G. MacDonald (Eds.). 1978. Nitrogen in the Environment. Volume II, Soil-Plant-Nitrogen Relationships. Academic Press. 528 pages plus Appendix.

Rose, C. W., P. W. A. Dayananda, D. R. Nielsen and J. W. Biggar. 1979. Long-term solute dynamics and hydrology in irrigated slowly permeable soils. Irrigation Science 1(2):77-87. August.

Simmons, C. S., D. R. Nielsen and J. W. Biggar. 1979. Scaling of field-measured soil-water properties. Hilgardia 47(4):77-174. September.

Nielsen, D. R., J. W. Biggar and Y. Barrada. 1979. Water and solute movement in field soils. pages 165-183. In Isotopes and Radiation in Research on Soil-Plant Relationships. International Atomic Energy Agency, Vienna.

Biggar, J. W. and D. R. Nielsen. 1978. Field monitoring of soil water constituents in the unsaturated zone. pages 106-121. In Lorne G. Everett and Kenneth D. Schmidt (Eds.). Establishment of Water Quality Monitoring Programs. American Water Resources Association Symposium Proceedings, San Francisco, California, June 12-14.

Starr, J. L., J. Y. Parlange and D. R. Nielsen. 1979. The use of open soil systems and mathematical models to study N reactions and movement of soils. pages 1-34. In J. K. R. Gasser (Eds.). Modelling Nitrogen from Farm Wastes, Applied Science Publishers Ltd., London.

Libardi, P. L., K. Reichardt, D. R. Nielsen and J. W. Biggar. 1980. Simple field methods for estimating soil hydraulic conductivity. Soil Science Society of America Journal 44(1):3-7. January-February.

Hajrasuliha, S., N. Baniabbassi, J. Metthey and D. R. Nielsen. 1980. Spatial variability of soil sampling for salinity studies in southwest Iran. Irrigation Science 1:197-208.

Nielsen, D. R., J. W. Biggar, J. MacIntyre and K. K. Tanji. 1980. Field investigation of water and nitrate-nitrogen movement in Yolo soil. pages 145-168. In Soil Nitrogen as Fertilizer or Pollutant, International Atomic Energy Agency, Vienna.

Warrick, A. W. and D. R. Nielsen. 1980. Spatial variability of soil physical properties in the field. Chapter 13. pages 319-344. In D. Hillel (Ed.). Applications of Soil Physics, Academic Press, New York.

Biggar, J. W. and D. R. Nielsen. 1980. Mechanisms of chemical movement in soils. pages 213-227. In A. Banin and U. Kafkafi (eds.), Agrochemicals in Soils. Pergamon Press.

Ahuja, L. R., R. E. Green, S. K. Chong, and D. R. Nielsen. 1980. A simplified functions approach for determining soil hydraulic conductivities and water characteristics in situ. Water Resources Research 16(5):947-953. October.

Nielsen, D. R., and P. J. Wierenga. 1980. Movement of water and solutes in field soils. pages 5-6. In Proceedings of the Third Colloquium on Planetary Water. Niagra Fall, New York, October 27-29.

Nielsen, D. R., J. Metthey and J. W. Biggar. 1981. Soil hydraulic properties, spatial variability, and soil-water movement. pages 47-68, Section Two. In I. K. Iskandar (Ed.), Modeling Wastewater Renovation: Land Treatment. J. Wiley & Sons.

Nielsen, D. R., J. W. Biggar and C. S. Simmons. 1981. Mechanisms of solute transport in soils. pages 115-135, Section Two. In I. K. Iskandar (Ed.), Modeling Wastewater Renovation: Land Treatment. J. Wiley & Sons.

Nielsen, Donald R. 1982. Soil physics research: a leap into the future without the academia of the past. pages 59-64. In Whither Soil Research. Panel Discussion Papers of the 12th International Congress of Soil Science, New Delhi, India, February 8-16.

Vieira, S. R., D. R. Nielsen and J. W. Biggar. 1981. Spatial variability of field-measured infiltration rate. Soil Science Society of America Journal 45(6):1040-1048. November-December.

Amoozegar-Fard, A., D. R. Nielsen, and A. W. Warrick. 1982. Soil solute concentration distributions for spatially varying pore water velocities and apparent diffusion coefficients. Soil Science Society of America Journal 46(1):3-9. January-February.

Nielsen, D. R., J. W. Biggar and P. J. Wierenga. 1982. Nitrogen transport processes in soil. pages 423-448, Chapter 11. In F. J. Stevenson (Ed.), Nitrogen in Agricultural Soils. Agronomy Monograph No. 22. 940 pages.

PUBLICATIONS

Donald R. Nielsen

Land, Air and Water Resources

86. Reichardt, K., D. R. Nielsen and J. W. Biggar. 1972. Scaling of horizontal infiltration into homogeneous soils. Soil Science Society of America Proceedings 36(2):241-245. March-April.

99. Nielsen, D. R., J. W. Biggar and K. T. Erh. 1973. Spatial variability of field-measured soil-water properties. Hilgardia 42(7): 215-259. November.

113. Reichardt, Klaus, Paulo L. Libardi and Donald R. Nielsen. 1975. Unsaturated hydraulic conductivity determination by a scaling technique. Soil Science 120(3):165-168. September.

115. Biggar, J. W. and D. R. Nielsen. 1976. Spatial variability of the leaching characteristics of a field soil. Water Resources Research 12(1):78-84. February.

121. Warrick, A. W., G. J. Mullen and D. R. Nielsen. 1977. Predictions of the soil water flux based upon field-measured soil-water properties. Soil Science Society of America Journal 41(1):14-19. January-February.

122. Warrick, A. W., G. J. Mullen and D. R. Nielsen. 1977. Scaling field-measured soil hydraulic properties using a similar media concept. Water Resources Research 13(2):355-362. April

131. Simmons, C. S., D. R. Nielsen and J. W. Biggar. 1979. Scaling of field-measured soil-water properties. Hilgardia 47(4):77-174. September.

137. Hajrasuliha, S., N. Baniabbassi, J. Metthey and D. R. Nielsen. 1980. Spatial variability of soil sampling for salinity studies in southwest Iran. Irrigation Science 1:197-208.

139. Warrick, A. W. and D. R. Nielsen. 1980. Spatial variability of soil physical properties in the field. Chapter 13. pages 319-344. In D. Hillel (Ed.). Applications of Soil Physics, Academic Press, New York.

151. Vieira, S. R., D. R. Nielsen and J. W. Biggar. 1981. Spatial variability of field-measured infiltration rate. Soil Science Society of America Journal 45(6):1040-1048. November-December.

152. AmoozegarFard, A., D. R. Nielsen, and A. W. Warrick. 1982. Soil solute concentration distributions for spatially varying pore water velocities and apparent diffusion coefficients. Soil Science Society of America Journal 46(1):39. January-February.

161. Vauclin, M., S. R. Vieira, G. Vachaud, and D. R. Nielsen. 1983. The use of cokriging with limited field soil observations. Soil Science Society of America 47(2):175-184. March-April.

162. Nielsen, D. R., Patricia M. Tillotson, and S. R. Vieira. 1983. Analyzing field-measured soil-water properties. Agricultural Water Management 6:93-109.

163. Vieira, S. R., J. L. Hatfield, D. R. Nielsen, and J. W. Biggar. 1983. Geostatistical theory and applications to variability of some agronomic properties. Hilgardia 51(3):1-75.

170. Ahuja, L. R., J. W. Naney, R. E. Green, and D. R. Nielsen. 1984. Macroporosity to characterize spatial variability of hydraulic conductivity and effects of land management. Soil Science Society of America Journal 48(4):699-702. July-August.

171. Ahuja, L. R., J. W. Naney, and D. R. Nielsen. 1984. Scaling soil water properties and infiltration modeling. Soil Science Society of America Journal 48(5):970-973. September-October.

172. Tillotson, Patricia M. and Donald R. Nielsen. 1984. Scale factors in soil science. Soil Science Society of America Journal 48(5):953-959. September-October.

175. Nielsen, D. R. and J. Bouma. 1985. Soil Spatial Variability. Proceedings of a Workshop of the International Soil Science Society and the Soil Science Society of America, Las Vegas, Nevada, 30 November-1 December, 1984, Pudoc. Wageningen, The Netherlands. 243 pages.

177. Tillotson, Patricia M. and Donald R. Nielsen. 1985. Reply to "Comments on Scale Factors in Soil Science." Soil Science Society of America Journal 49(3):790. May-June.

178. Morkoc, F., J. W. Biggar, D. R. Nielsen, and D. E. Rolston. 1985. Analysis of soil water content and temperature using state-space approach. Soil Science Society of America Journal 49(4):798-803. July-August.

180. Morkoc, F., J. W. Biggar, R. J. Miller and D. R. Nielsen. 1985. Statistical analysis of sorghum yield: A stochastic approach. Soil Science Society of America Journal 49:1342-1348.

184. Kutilek, M., T. Vogel, and D. R. Nielsen. 1985. Note on the physical characteristics of linear soils. Soil Science 139(6):497-499. June.

186. Greminger, P. J., Y. K. Sud, and D. R. Nielsen. 1985. Spatial variability of field-measured soil-water characteristics. Soil Science Society of America Journal 49(5):1075-1082.

187. Nielsen, D. R., M. Th. van Genuchten, and J. W. Biggar. 1986. Water flow and solute transport processes in the unsaturated zone. Water Resources Research 22(9):89S-108S. August.

188. Warrick, A. W., D. E. Myers and D. R. Nielsen. 1986. Geostatistical methods applied to soil science. Chapter 3, pages 53-82. In Methods of Soil Analysis, Part 1. Physical and Mineralogical Methods-Agronomy Monograph no 9 (2nd Edition). American Society of Agronomy-Soil Science Society of America.

190. Hendrickx, J. M., P. J. Wierenga, M. S. Nash and D. R. Nielsen. 1986. Boundary location from texture, soil moisture, and infiltration data. Soil Science Society of America Journal 50(6):1515-1520. November-December.

191. Nielsen, D. R., M. Th. van Genuchten and W. A. Jury. 1987. Monitoring and analyzing water and solute transport in the vadose zone. Proceedings Complex IV, Rational Use of Groundwater Resources and Their Protection Against Pollution in Areas of Intensive Groundwater Exploitation. International Symposium on Groundwater Monitoring and Management, 23-28 March 1987, Dresden, German Democratic Republic.

192. Nielsen, Donald R. 1987. Emerging frontiers in soil science. Geoderma 40:267-273.

193. Sully, M. J., R. G. Flocchini, and D. R. Nielsen. 1987. Linear distribution of naturally occurring radionuclides in a Mollic Xerofluvent. Soil Science Society of America Journal 51:276-281.

194. Morkoc, F., J. W. Biggar, D. R. Nielsen, and D. E. Myers. 1987. Kriging with generalized covariances. Soil Science Society of America Journal 51:1126-1131.

195. Bazza, M., R. H. Shumway, and D. R. Nielsen. 1988. Two-dimensional spectral analysis of soil surface temperature. Hilgardia 56:1-28.

196. Alemi, M. H., M. R. Shahriari, and D. R. Nielsen. 1988. Kriging and cokriging of soil water properties. Soil Technology 1:117-132.

197. Alemi, M. H., A. S. Azari, and D. R. Nielsen. 1988. Kriging and univariate modeling of a spatially correlated data. Soil Technology 1:133-147.

198. Miller, M. P., M. J. Singer, and D. R. Nielsen. 1988. Spatial variability of wheat yield and soil properties on complex hills. Soil Science Society of America Journal 52:1133-1141.

199. Tillotson, W. R., J. W. Biggar, R. H. Shumway, and D. R. Nielsen. 1988. Multivariate statistical analysis of potassium and chloride redistribution from a line-source sprinkler experiment. Soil Science Society of America Journal 52:909-915.

203. Morkoc, F., R. H. Shumway, J. W. Biggar, and D. R. Nielsen. 1989. River qualtiy modeling: Time domain approach. ASCE, Journal of Irrigation and Drainage Engineering 115(4):663-673. August.

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ANALYZING FIELD-MEASURED SOIL-WATER PROPERTIES

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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 deemphasize 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

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

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

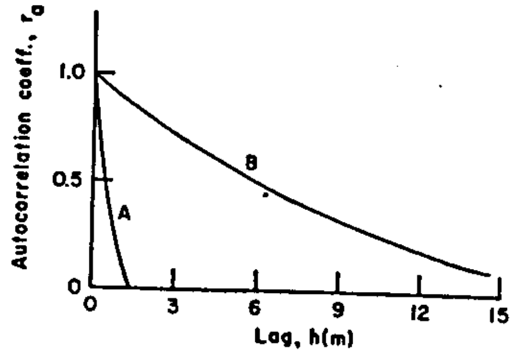

Fig. 1. Idealized autocorrelograms for average soil water content G observed at 1-m intervals along transects within fields A and B.

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

$$r_a(h) = \exp(-h/\lambda) \qquad (2)$$

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

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

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

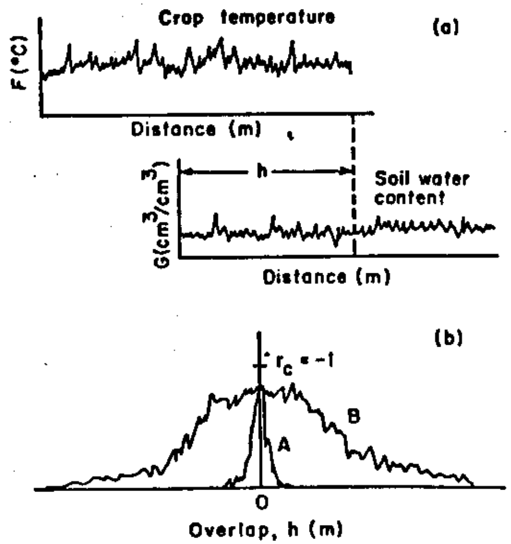

Fig. 2. Idealized cross-correlogram for crop temperature F(x) and soil water content G(x) along transects within fields A and B.

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

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

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

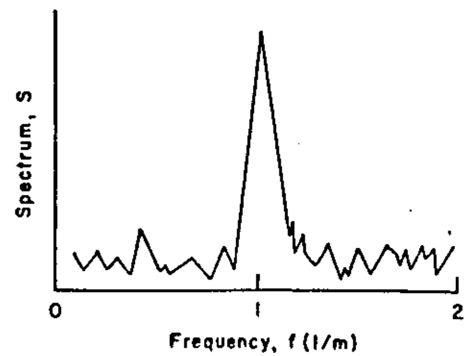

Fig. 3. Spectrogram S(f) for a transect of soil water content observations taken normal to the direction of furrows.

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

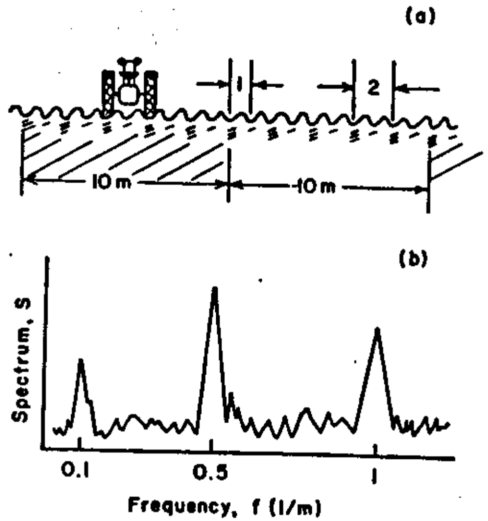

Fig. 4. Schematic diagram of furrows, tractor compaction and pre-plant irrigation causing cyclic variations of soil water content, and idealized spectrogram.

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 $r_s(h)$ 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

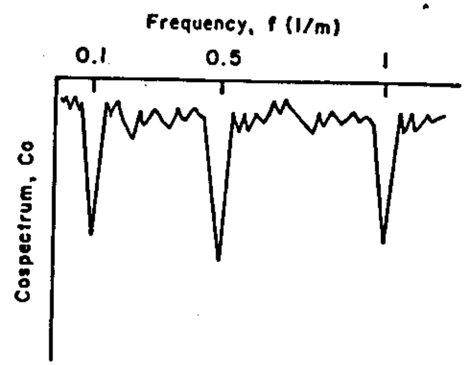

Fig. 5. Cospectrogram of crop temperatures $F(x)$ and soil water content $G(x)$ along a transect normal to the furrows shown schematically in Fig. 4a.

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.

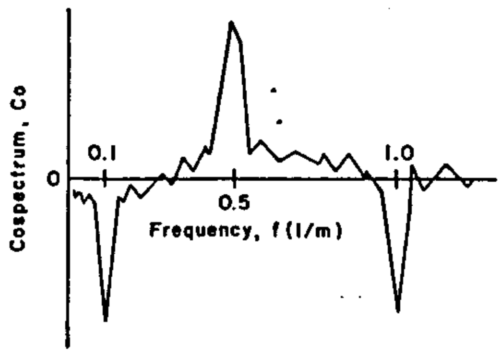

Fig. 6. Cospectrogram of crop temperatures F(x) and soil water content G(x) along transect normal to the furrows shown in Fig. 4a when compaction decreases evapotranspiration.

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

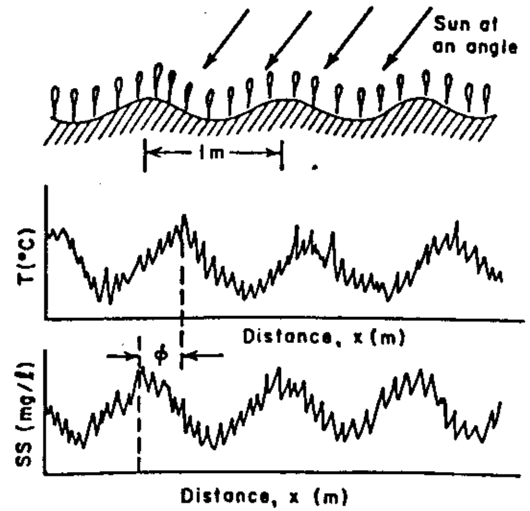

Fig. 7. Schematic diagram of observations of crop temperature T(x) and soil salinity SS(x) along a transect normal to furrows with the sun radiation being received from one side.

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

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

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

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

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,

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

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

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

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_j^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 correllated 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.

REFERENCES

1 A. Amoozegar-Fard, D. R. Nielsen and A. W. Warrick, Soil Sci. Soc. Am. J., 46(1982)3-9.
2 J. W. Biggar and D. R. Nielsen, Water Resour. Res., 12(1976)78-84.
3 G. E. P. Box and G. M. Jenkins, Time Series Analysis, Holden-Day, Inc., San Francisco. 1976. 575 pp.
4 E. Bresler and G. Dagan, Soil Sci. Soc. Am. J., 43(1979)467-472.
5 E. Bresler and G. Dagan, Water Resour. Res., 17(1981)1683-1693.
6 T. M. Burgess and R. Webster, J. Soil Sci., 31(1980)315-331.
7 T. M. Burgess and R. Webster, J. Soil Sci., 31(1980)333-341.
8 J. B. Campbell, Soil Sci. Soc. Am. J., 42(1978)460-464.
9 I. Clark, Practical Geostatistics, Applied Sci. Publ., Ltd., London, 1979, 129 pp.
10 J. C. Davis, Statistics and Data Analysis in Geology, John Wiley & Sons, Inc., New York, 1973, 550 pp.
11 J. P. Delhomme, Water Resour. Res., 15(1979)269-280.
12 R. A. Fisher, Statistical Methods and Scientific Influence, Oliver & Boyd, Edinburgh, 1956, 175 pp.
13 R. A. Freeze, Water Resour. Res., 11(1975)725-741.
14 Y. M. Gajem, A. W. Warrick and D. E. Meyers, Soil Sci. Soc. Am. J., 45(1981)709-715.
15 L. W. Gelhar, Water Resour. Res., 10(1974)539-545.
16 C. T. Haan, Statistical Methods in Hydrology, Iowa State Univ. Press, Ames, 1977, 378 pp.
17 A. G. Journel and Ch. J. Huijbregts, Mining Statistics, Academic Press, Inc., New York, 1978, 600 pp.
18 W. A. Jury, Water Resour. Res., 18(1982)363-368.
19 S. J. Kline, Similitude and Approximation Theory, McGraw-Hill, New York, 1965, 229 pp.
20 J. L. Lumley and H. A. Panofsky, The Structure of Atmospheric Turbulence, John Wiley, New York, 1964, 239 pp.
21 G. Matheron, Econ. Geol., 58(1963)1246-1266.
22 E. E. Miller and R. D. Miller, J. Appl. Phys., 27(1956)324-332.
23 D. R. Nielsen, J. W. Biggar and K. T. Erh, Hilgardia, 42(1973) 215-259.
24 B. Ostle and R. W. Mensing, Statistics in Research, Iowa State Univ. Press, Ames, 1979, 596 pp.
25 H. A. Panofsky and G. W. Brier, Some Applications of Statistics to Meterology, Penn. State University, University Park, 1958, 224 pp.
26 A. J. Peck, R. J. Luxmoore and J. L. Stolzy, Water Resour. Res., (1977)348-354.
27 M. V. Petrova, Pochvovedeniye, 7(1978)144-150.
28 K. Reichardt, D. R. Nielsen and J. W. Biggar, Soil Sci. Soc. Am. Proc., 36(1972)241-245.
29 A. S. Rogowski, Water Resour. Res., 8(1972)1015-1023.
30 D. Russo and E. Bresler, Soil Sci. Soc. Am. J., 45(1981)675-681.
31 D. Russo and E. Bresler, Soil Sci. Soc. Am. J., 46(1982)20-26.
32 M. L. Sharma and R. J. Luxmoore, Water Resour. Res., 15(1979) 1567-1573.
33 C. S. Simmons, D. R. Nielsen and J. W. Biggar, Hilgardia, 47(1979) 44-174.
34 J. B. Sisson and P. J. Wierenga, Soil Sci. Soc. Am. J., 45(1981) 699-709.
35 L. Smith and R. A. Freeze, Water Resour. Res., 15(1979)521-528.
36 R. E. Smith and R. H. B. Hebbert, Water Resour. Res., 15(1979) 419-429.
37 R. G. D. Steel and J. H. Torrie, Principles and Procedures of Statistics: a Biometrical Approach, McGraw Hill, New York, 1980, 633 pp.
38 S. R. Vieira, D. R. Nielsen and J. W. Biggar, Soil Sci. Soc. Am. J., 45(1981)1040-1048.
39 A. W. Warrick, G. J. Mullen and D. R. Nielsen, Soil Sci. Soc. Am. J., 41(1977)14-19.
40 A. W. Warrick, G. J. Mullen and D. R. Nielsen, Water Resour. Res., 13(1977)355-362.
41 A. W. Warrick and A. Amoozegar-Fard, Water Resour. Res., 15(1979) 116-1120.
42 R. Webster, Math. Geol., 5(1973)27-37.
43 R. Webster, J. Soil Sci., 29(1978)388-402.
44 R. Webster and T. M. Burgess, J. Soil Sci., 31(1980)505-524.
45 R. Webster and H. E. de la C. Cuanalo, J. Soil Sci., 26(1975) 176-194.
46 P. Whittle, Biometrika, 41(1954)434-449.

M. Clarholm and L. Bergström (Eds.), Ecology of arable land, 261–272.

* Chapters indicated with an asterisk were first published in *Plant and Soil*, Volume 115 (1989).

Statistical opportunities for analyzing spatial and temporal heterogeneity of field soils

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Key words: coherency, geostatistics, kriging, state-space, stochastic, time-series analysis

Abstract
Statistical techniques for analyzing data in the agricultural sciences have traditionally followed the pioneering efforts of R.A. Fisher who assumed that observations in the field were independent and identically distributed. Such techniques, proven useful in the past and still being used today for comparing the merits of different management practices or different treatments, are presently giving way to additional methods that are based upon observations being spatially or temporally correlated. It is physically more sensible to expect soil attributes to be correlated when they are measured at adjacent points in space or time. Spatially repetitious patterns of soil attributes for physical and biological processes occurring at distances of a few molecules to those of kilometers are also expected. Opportunities to use geostatistics, time series analyses, state-space models, spectral analyses of variance, lagged regression models and other alternative techniques for analyzing multidimensional random fields are available to enhance the understanding of agro-ecosystems. Approaches to modeling and fitting data using stochastic partial differential equations and scaling techniques also help reveal the underlying processes occurring in field soils. Inclusion of these alternatives in the development of an agro-ecological technology leads to improved sampling designs to better entire management units, rather than ascertaining the impact of particular, sometimes arbitrary treatments applied to a set of small plots using analysis of variance methods.

Introduction

Although agricultural scientists have conducted experiments throughout the world at an accelerated pace during the last half century, they have been less than successful explaining and managing biological processes that occur at different scales of space and time. The soil chemist, for example understands the kinetics of chemical reactions within a homogeneous soil sample but cannot usually extend the results to a larger, more heterogeneous rhizosphere. Likewise, the microbiologist cannot easily account for shifts in microbial populations within the rhizosphere when the crop canopy experiences nonuniform, larger scale microclimate perturbations. And many agronomists or plant scientists never "trust their luck" with only one year's data, but rely on fertilizer trials made repetitiously during a period of several years. Too often they have found that the results from one year are not "typical" or that the response of the crop to the treatments was biased owing to a variety of local conditions not included in the experimental plan.

Because of the educational opportunities and research techniques usually made available to agricultural or biological scientists, most field experiments conducted by them consist of relatively small plots receiving replicated treatments arranged in a randomized block or similarly related statistical design. The size of the plot is usually selected on the basis of the area needed for a "good" measurement of crop yield, the area perceived to effectively establish a treatment, and the area considered adequate for obtaining samples or that area required for various cultural practices. The total collage of plots is usually squeezed into a sufficiently small area to hopefully guarantee the entire experiment is performed on a uniform site representative of a larger

management unit. The investigators have the belief that an analysis of variance of the result stemming from their semi-empirical treatments will allow the development of superior management alternatives for agricultural production for sites of similar characteristics. Such alternatives are indeed developed with whole fields being treated or managed the same, but seldom are quantitative observations made without resorting to the use of additional treated plots to assess the appropriateness or impact of the management alternative.

The above experimental scenarios stem from the pioneering work of R.A. Fisher. Recognizing that the properties and attributes of our natural resources are heterogeneous and vary from one location to another, he developed, in the absence of computers, the concept of analysis of variance which quantified the impacts of treatments within prescribed limits of probability. In a sence, he was able to ignore where soils vary from location to location. The benefits of his pioneering statistical efforts have been enormous, but today's complex environmental problems need to be alternatively approached using different, more global methods. We must be able to monitor fields or regions at particular locations and times to ascertain the behavior of our natural resources integrated over different scales of space and time and to be able to ascertain the value of a plant or soil attribute at unsampled locations within prescribed limits of accuracy and precision.

The objective here is to briefly introduce statistical concepts that require and take advantage of experimental observations manifesting spatial and/or temporal dependence and to provide a few examples of the many available methods having potential relevance to microbial ecology of arable lands. We give here a perhaps overly simplistic presentation of the theory and its potential practice. A secondary objective is to suggest the advantages of stochastic equations and models over the more common deterministic formulations normally used in agricultural and environmental sciences.

Because of the spatially continuous nature of the landscape, soil formation processes and climatic zones, it is not unreasonable to expect that soil measurements taken in close proximity to each other would be correlated. It is also reasonable to expect spatial or temporal variations in one or more ecological attributes to be related to variations of other parameters or properties indigenous to the landscape. Using statistical techniques that rely on observations made at different scales being spatially or temporally dependent allows greater opportunity to explore and understand biological and physical processes occurring in arable lands.

An approach for examining spatial structure is time series analysis, a methodology used to study temporally and spatially correlated data. Both time domain and frequency domain analysis are treated in time series methodologies (Shumway, 1988). Time domain analysis expresses the observation variable in terms of a linear function of its past values and a random error, and is used for estimating equally spaced univariate and multivariate processes. This analysis, known as autoregressive modeling (Box and Jenkins, 1970), may not easily be used to estimate missing observations. Another analysis, known as state-space modeling introduced by Kalman (1960) and Kalman and Bucy (1961), yields two linear equations called observation and state equations which describe the observed series. Two different kinds of errors are recognized. The first is the observation error which might be due to measurement error or disturbances observed in the data not related to the variable under study. The second is the state error caused by the noise inherent in the variable under study. Frequency domain analysis assigns the variations of the observation variable to combinations of sine and cosine waves. Spectral analysis examines the series to find those frequencies that contribute the most to the total variance assuming an expected value or mean for the observation variable.

An approach utilizing the spatial structure of a data set is kriging which is an estimation technique for regionalized variables that exhibit significant spatial autocorrelation (see, for example Ripley, 1981). The theory of regionalized variables was developed by Matheron (1963) and has been applied in the field of mining in estimation of ore reserves and more recently has been applied to agronomic and soil water properties (Vieira *et al.*, 1983). Applications of this theory are now popularly known as geostatistics. The kriging estimate is a weighted sum of the observed data in which the weights are determined by using the spatial distribution of the observations. In addition to kriging Journl and Huijbregts (1978) developed the geostatistical cokriging technique of estimating a variable that is undersampled by considering its spatial correlation with other variables that are more densely sampled (David, 1977). Cokriging was used by Vieira *et al.* (1983) to estimate agronomic properties. Many other applications of regionalized variable analyses or geostatistics are available and continue to be developed. We only introduce them here and begin with the definition of spatial dependence.

Quantification of spatial dependence

Consider a set of observations $Z(x_1)$, $Z(x_2)$, . . . , $Z(x_n)$ at locations $x_1, x_2, \ldots x_n$ where each location defines a point in 1-, 2-, or 3-dimensional space. The correlogram r(h) of the observations is estimated by

$$r(h) = \left[\frac{\sigma^{-2}}{n(h)-1}\right]\sum_{i=1}^{n(h)}\left[Z(x_i)-\bar{Z}\right] \times \left[Z(x_i+h)-\bar{Z}\right] \quad [1]$$

where n(h) is the number of pairs of observation points a distance h apart, $\bar{Z}$ the mean and σ^2 the variance. The correlogram has possible values from −1 to 1. Some idealized correlograms are given in Figure 1. In Figure 1A the value of r(0) is unity while r(h) gradually decreases to zero as h increases. Figure 2A shows autocorrelation of a nematode population calculated from 625 data points separated by a distance of 6.5 m (Alemi *et al.*, in manuscript). For large separation distances no correlation or spatial dependence exists. For a set of observations in 1 dimension the integral scale I defined by

$$I = \int_0^\infty r(h)\,dh \quad [2]$$

gives a measure of the distance h beyond which the pairs of observations are considered independent. The correlation length λ defined by

$$r = \exp(-h/\lambda) \quad [3]$$

gives still another measure beyond which the observations are considered independent. Numerically, the value of λ is that of h when r equals 1/e.

Figure 1B is a correlogram manifesting a set of observations that are not correlated. In other words, for all separation distances, the observations are independent or may be said to be purely random. Figure 1C illustrates a set of observations whose values vary somewhat sinusoidally in space. The correlogram of an ideally sinusoidal set of observations would be a cosine curve having the same period as the observations and an amplitude of unity. In general, the correlogram shows fluctuations with the same kinds of periods as the original observations, except that all the fluctuations have been put in phase so that they reach a maximum value at h = 0. Figure 2B shows correlograms of water flow and its salt concentration measured monthly in a stream during a 6-year period. The autocorrelation functions indicate that both variables have strong cyclic behavior with a period of 12 lags (a yearly cycle).

Another measure of spatial dependence is given by the variogram γ(h) estimated by

$$\gamma(h) = \frac{1}{2n(h)}\sum_{i=1}^{n(h)}[Z(x_i+h)-Z(x_i)]^2. \quad [4]$$

Figure 3 provides an illustrative example of the several potential features of a variogram. Although γ(0) = 0, γ(h) will appear to remain nonzero in many cases as h approaches zero as shown by the value C_0 commonly called the nugget. The value h = a, called the range, is the maximum separation distance for which pairs of observations remain

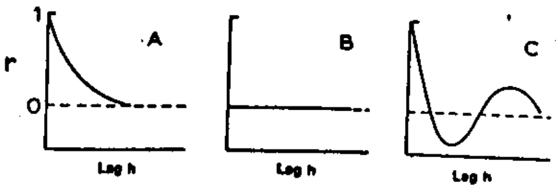

Fig. 1. Idealized correlograms. A is well-behaved and decreases monotonically to zero, B is for spatially independent or random observations. C is for observations that manifest repetitious, cyclic variations.

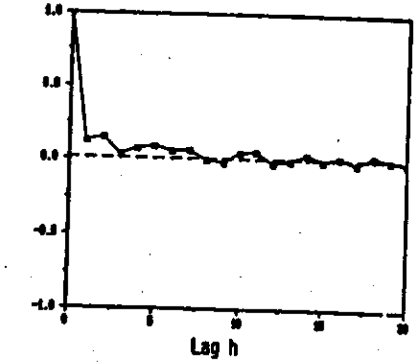

Fig. 2A. Autocorrelation function for observations of *Paratrichodorus* populations.

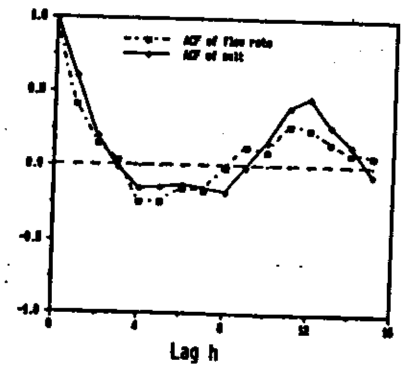

Fig. 2B. Autocorrelation functions of water flow and salt concentration.

correlated. For greater separation distances γ remains equal to C + C_0 and is called, the sill. Some variograms do not manifest one or more of the features C_0, C or a. The use of the variogram provides an opportunity for interpolation and mapping schemes, for identifying new observation locations to improve estimates for a total region or subregion, and to ascertain the impact of the size of observation on the scale of the field problem being studied as well as to develop efficient sampling strategies.

We assume that the reader is relatively unfamiliar with the concepts of time series and geostatistical analysis of data. Hence in the following section these methods are described briefly with real world examples.

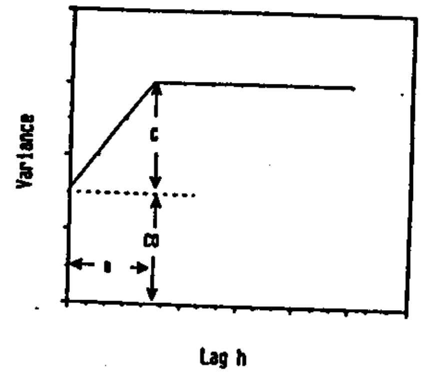

Fig. 3. Idealized variogram with range a, sill (C + C_0) and nuggest C_0.

Autoregressive integrated moving average (ARIMA) models

A stationary process Z_t is said to be autoregressive of order p, AR(p) if

$$Z_t = \sum_{k=1}^{p}\Phi_k Z_{t-k} + \omega_t \qquad s = 1,2,\ldots \quad [5]$$

where ω_t is a white noise (independent and identically distributed normal variable) and Φ_k are coefficients to be estimated. The moving average of order q is defined as

$$Z_t = \omega_t - \sum_{k=1}^{q}\theta_k\,\omega_{t-k} \qquad s = 1,2,\ldots \quad [6]$$

where ω_t is again white noise and θ_k are coefficients to be estimated. The mixed autoregressive process of order p and moving average of order q, ARMA (p, q) is defined as

$$Z_t = \sum_{k=1}^{p}\Phi_k Z_{t-k} - \sum_{k=1}^{q}\theta_k\,\omega_{t-k} + \omega_t. \quad [7]$$

ARMA modeling can be applied to a nonstationary series, if the nonstationarity is removed for

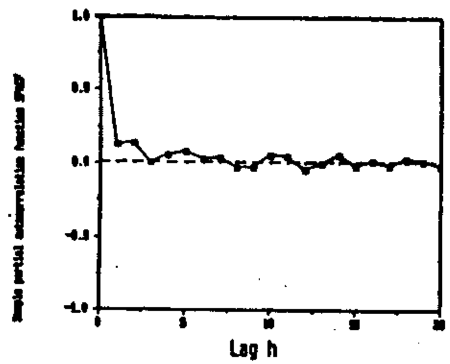

Fig. 4. Sample partial autocorrelation of *Paratrichodorus* series.

example by differencing the original series. If a difference of order d is applied, and an autoregressive model of order p and moving average of order q is used, the model is called autoregressive integrated moving average of orders p, d, and q or ARIMA (p, d, q)

The first step in ARIMA modeling is model identification. Autocorrelation and partial autocorrelation functions are the main tools in detection of the nonstationarity and model identification. For a complete description of the procedures for model identification and testing the adequacy of the model see Shumway (1988). The sample partial autocorrelation (SPAC) of a series of nematode

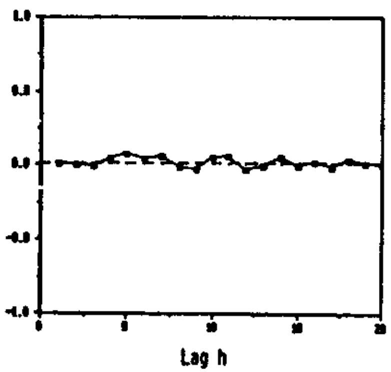

Fig. 5. Autocorrelation function of residuals of the autoregressive model.

(*Paratrichodorus*) populations given in Figure 4 indicates that the SPAC is significant at lags one and two. Thus an AR(2) seems to be the appropriate model. The ACF of residuals (differences between the observed and estimated values in the series) is given in Figure 5 with no significant peak (ACF less than $1.96\,(S)^{-.5}$ where S is the length of the series). Hence, the AR(2) is an adequate model to describe the nematode series and can be written as

$$Z_s = 0.1068\, Z_{s-1} + 0.1324\, Z_{s-2} + \omega_s. \quad [8]$$

We note that the nematode population at location s can be described in terms of its magnitude at the two previous locations (s−1) and (s−2).

State-space models

State-space models have been used to describe data in many different scientific endeavors. The multivariate version of the model is defined by the observation equation

$$Z_s = A_s \xi_s + \nu_s \qquad s = 1,2,3,\ldots,S \quad [9]$$

where the p-dimensional vector $Z_s = (Z_{s1},\ldots,Z_{sp})$ is represented as a linear combination of unobserved q-dimensional vector $\xi_s = (\xi_{s1},\ldots,\xi_{sq})$, using a pxq design matrix A_s. The additive noise vector ν_s is a px1 vector of measurement error related to the observation vector Z_s. It is assumed that ν_s are zero mean independent random vectors with covariance matrix R. The unobserved or so called state vector ξ_s satisifies the state equation

$$\xi_s = B\,\xi'_{s-1} + \omega_s, \qquad s = 1,2,\ldots,S \quad [10]$$

where B is a q × q transition matrix and ω_s is the state noise vector independent of ν_s with mean zero and covariance matrix Q. The initial value of ξ_s is assumed to be ξ_0 with mean vector μ and covariance matrix Σ.

In state-space modeling μ, Σ, B, Q, and R are estimated from the observed series Z_s, s = 1,2,…,S by an iterative procedure using Kalman filtering and expectation maximization (EM) algorithm given in Shumway and Stoffer (1982) and Shumway (1988). An example of application of a state-space model is given in Figure 6 where a series of cotton yield observations and that of a nematode population were used to estimate the cotton yield

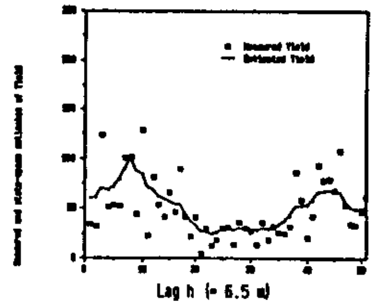

Fig. 6. Measured and state-space estimates of cotton yield.

series. The observation equation is

$$Z_s = A_s \xi_s + \nu_s. \quad [11]$$

The state equation for the bivariate process using *Paratrichodorus* (P) and cotton yield (Y) series is

$$\begin{Bmatrix} P \\ Y \end{Bmatrix}_s = \begin{bmatrix} 0.92 & 0.23 \\ 0.01 & 0.94 \end{bmatrix} \begin{Bmatrix} P \\ Y \end{Bmatrix}_{s-1} + \begin{Bmatrix} \omega_P \\ \omega_Y \end{Bmatrix} \quad [12]$$

with variance ν equal to 683 and 165, and those of ω equal to 4277 and 944, respectively. Using the standard deviation of variances, the magnitude of measurement and process errors can be calculated. The solid line given in the figure stems from equation [12] and tends to "smooth" the cotton yield data on the basis that there is a spatial correlation between cotton yield and nematode infestation. Our example has involved only two observation variables — cotton yield and number of nematodes. State-space modeling easily handles several variables, does not require long series of observations, and is an excellent method to identify which local field properties or attributes tend to be related to the behavior of an observation variable of primary interest. Noting that the solid line in Figure 6 does not indicate a constant yield of cotton across the field implies that additional properties or attributes affecting crop yield are not accounted for in the bivariate state space model. The use of a multivariate model would potentially allow the identification of other properties or attributes that are responsible for the manner in which the cotton yield varies across the field.

Spectral analysis

Arable land is often cultivated with animals or machines in repeatable, cyclic patterns during one or more growing seasons. In addition, irrigations, fertilizers, agrochemicals, and crop residues are usually applied on or into the soil in cyclic patterns having various periodicities or frequencies depending upon the spacing between plant rows or the method of cultivation or irrigation. Under such conditions observations $Z(x_s)$ made in the field will yield a correlogram r(h) that can be used to identify those portions of the spatial variance structure that are associated with sinusoidal patterns of specific periods or frequencies. The identification is made from a spectral analysis by calculating the power spectra from the correlogram in one or more directions. For one direction, the power spectra f(v) is

$$f(v) = 2\int_0^\infty r(h)\cos(2\pi v h)\,dh \quad [13]$$

where v is the frequency of the periodic observations. A graph of f(v) reveals relative maxima at those values of v for which the observations manifest a sinusoidal behavior.

Soil surface temperature observations of a fallow, 6-ha field measured with an infrared thermometer on a 36 by 64 regular grid 2 days after a 2 cm rain are examined here to illustrate the use of spectral analysis (Bazza, 1985). Figures 7 and 8 show 3-dimensional plots of all 2304 observations viewed from the east and north, respectively. The most striking feature of the data is that variability is not the same across the field. An obvious feature is that variability in the E-W direction is completely stationary as compared with that in the other direction. The correlogram of the observations for the E-W direction indicated spatial independence while that for the N-S direction revealed a periodic behavior. The graph of f(v) for the N-S direction (Fig. 9) shows a relative maximum of a frequency of about 0.06 corresponding to a period of about 18 lags. Figure 10 of average values of temperature of all 36 columns shows this periodic behavior about a mean of 6.6°C along the N-S direction. Also given in the figure is a graph of the salinity of the water used to irrigate the field for cotton production during the previous summer. Notice that there appears to be an inverse relation between the soil tem-

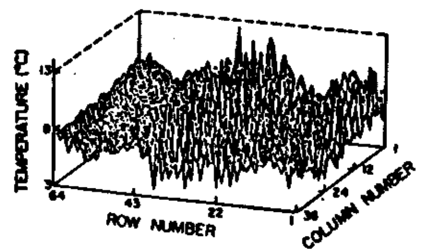

Fig. 7. Soil surface temperature observations viewed from the east.

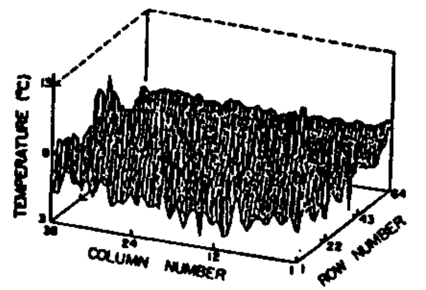

Fig. 8. Soil surface temperature observations viewed from the north.

perature and the salinity level of the irrigation water. The cross spectrum for two series Y_t and X_t can be written as

$$f_{xy}(v) = C_{xy}(v) - i\, q_{xy}(v) \quad [14]$$

where $f_{xy}(v)$ is cross spectrum between two series, $C_{xy}(v)$ and $q_{xy}(v)$ are called cospectrum and quadspectrum, respectively and i is the imaginary number. The cross-spectrum is the frequency dependent measure of the covariance between two series Y_t and X_t. The dependence between the two series Y_t and X_t with frequency can be explained by the coherence function between the two series. The coherence, defined by

$$\gamma^2_{yx}(v) = |f_{xy}(v)|^2 / f_x(v)\, f_y(v) \quad [15]$$

is the frequency dependent correlation between two series. If Y_t is an exact linear version of X_t then coherence becomes equal to unity at all frequencies.

After first calculating the cross-correlogram between the temperature versus salinity data already given as average values in Figure 10 in a manner analogous to equation [1] only for two variables. The cross-spectrum $f_{xy}(v)$ comes from equation [14]. The strong negative peak shown in Figure 11 indicates that the erratic small differences in temperature values across the field and salinity are spatially related at a frequency of about 0.06. At that frequency, the magnitude of the coherence was nearly unity and indicates that the two series, temperature and salinity, were almost perfectly related. The reason behind the cyclic temperature behavior is probably due to the salinity causing lower soil water potential, lower evaporation and reduced hydraulic conductivity tending to prevent redistribution of soil water.

The concept of time stability of a spatially measured series as defined by Vachaud *et al.* (1985) has recently been expanded to include general linear transformations in time and to account for the occurrence of spatial scale dependency (Kachanoski and de Jong, 1988). Vachaud defined time dependency as the time invariant association between spatial location and classical statistical parametric

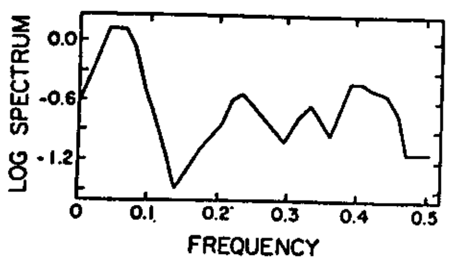

Fig. 9. Spectrum of surface soil temperature.

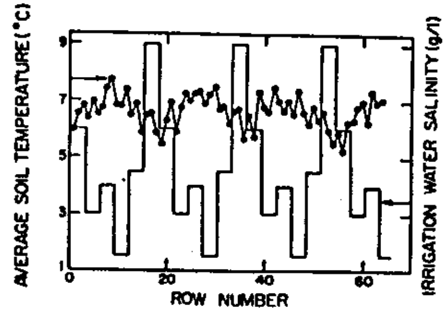

Fig. 10. Row averages of surface soil temperature and salt content of irrigation water.

values. For example, a given location in a field will tend to have a soil water content that remains in the same ranked order with those of other locations. In other words, a location that is relatively dry at one time compared to others will remain relatively dry at other times while a wet location will remain wet.

Let D represent the spatial domain of interest, j represent a horizontal spatial location vector in D, and $S_t(j)$ represent the cumulative soil water storage to depth L at location j and time t. If $s_t(j)$ is the realization of the variable $S_t(j)$ at location j and time t, the relative deviation from the expected or mean soil water storage $E[S_t(j)]$ at the same time across the spatial domain D is given by (Vachaud *et al.*, 1985):

$$\delta_t(j) = \frac{S_t(j) - E[S_t(j)]}{E[S_t(j)]}. \quad [16]$$

According to Vachaud *et al.*, a small temporal variation in $\delta_t(j)$ (*i.e.* time independence) is an indication of time stability, thus

$$\delta_{t_1}(j) \simeq \delta_{t_2}(j) \quad [17]$$

where t_1 and t_2 represent two different measurement times. Substitution of equation [16] into equation [17] and taking the variables $S_{t_1}(j)$ and $S_{t_2}(j)$ in lieu of the observations $s_{t_1}(j)$ and $s_{t_2}(j)$ respectively, gives:

$$S_{t_2}(j) \simeq \frac{E[S_{t_2}(j)]}{E[S_{t_1}(j)]} S_{t_1}(j). \quad [18]$$

Thus time stability as defined in equation [18] implies a linear relationship between soil water storage at time t_1 and t_2 across all spatial locations.

Since spatial variation is often scale dependent, it follows that time stability may also be scale dependent. For example, localized surface runoff may significantly alter the spatial variation of soil water storage on a small scale, but the changes may be insignificant compared to large scale variations. Other factors, such as climatic variations may affect time stability at large scales.

The persistence of a spatial pattern at different spatial scales was examined by Kachanoski and de Jong (1988) by expanding on the concept that time stability requires a linear relationship between successive time samplings. The presence of a significant linear relationship at different spatial scales is tested using spatial coherency analysis introduced by equation [15]. In this case, the coherency function estimates the proportion of the spatial variance of $S_{t_2}(j)$ which can be explained by the

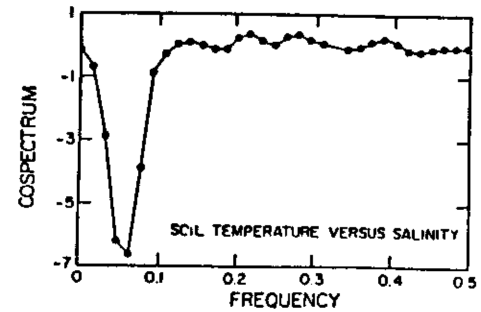

Fig. 11. Cross spectrum of surface soil temperature and salt content of irrigation water.

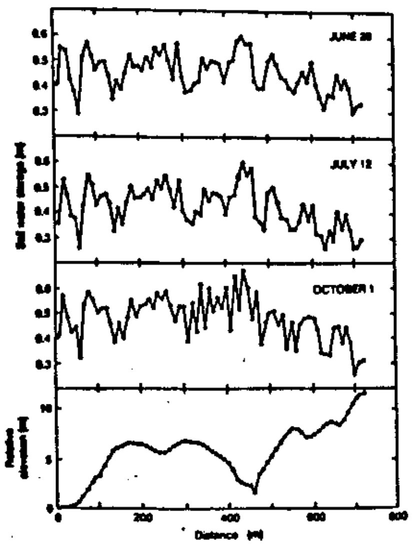

Fig. 12. Measured salt water storage and relative elevation for the study site.

spatial variance of $S_{ij}(j)$, as a function of spatial scale. Thus, the coherency function is a direct measurement of time stability as a function of spatial scale. A more detailed discussion has been given by Kachanoski *et al.* (1985a) which in turn is a summary of the direct Fourier method of spectrum estimation (Brillinger, 1981).

The soil of the study area of Kachanoski and de Jong was a moderately fine textured, moderately calcareous Typic Haploboroll resting on a gently rolling to undulating topography. Neutron probe access tubes were installed in a fallow field every 10 m in a 720 m long transect in a north-south direction. Soil water measurements were taken at all locations with depth on June 28, July 12 and October 1. Elevation measurements were taken at each location and 10 m east and west of each location using a rod and surveying level. The grid of elevation readings around each soil water sampling location was used to estimate local surface curvature by a least squares surface analysis. No significant precipitation was recorded during the first two sampling dates, (June 28-July 12), thus this period is characterized by drying. The next sampling period (July 12-October 1) had significant rainfall and represents a time of net soil water recharge. Power spectra of cumulative soil water storage observations were calculated for each of the three measurement dates. Coherency spectra were estimated for the June 28 and July 12, and July 12 and October 1 paired sampling dates.

Measurements of surface elevation and cumulative soil water storage are illustrated in Figure 12. As can be observed in the figure, the variations in soil water storage appear to persist between sampling data. In fact, a statistical analysis indicates that 94% of the observed spatial variability after the drying period measured July 12 was explained by the variability present on June 28.

The coherency spectra for the drying and recharge periods are shown in Figure 13. The coherency spectrum for the drying period, June 28-July 12, is greater than 0.90 for almost all spatial scales and indicates the presence of a higher linear correlation and thus temporal stability across all spatial scales. The coherency spectrum for the recharge period shows a high coherency for spatial scales greater than 50 m. For spatial scales less than approximately 40 m the coherency drops below the 95% confidence level for a significant linear relationship. The coherency is especially low for scales less than 30 m. The coherency clearly indicates that recharge has significantly altered the spatial pattern of soil water storage on a scale of less than 40 m, but has not affected the pattern at larger scales. Thus, time stability was present for spatial scales greater than 40 m but not for smaller scales. Large scale variations of soil water storage are no doubt related to elevation, especially in the prairie regions. However, smaller scale variations may be more affected by local conditions (curvature, gradient, *etc.*). The local variability of surface curvature resulted in variations of runoff and subsequent recharge which significantly altered the spatial pattern of soil water storage at a small scale while not affecting the large scale pattern.

Kachanoski *et al.* (1985b) have used coherency analysis to examine the effects of cultivation on the persistence of the spatial patterns of a number of soil properties. The change in spatial variance patterns as a function of scale were used to infer the scale of processes such as horizontal soil movement and mixing by tillage. In a similar manner, scale dependent time stability studies of soil water, available carbon and nutrient sources, using coherency analyses should be able to infer spatial scales of hydrologic microbial and crop community processes.

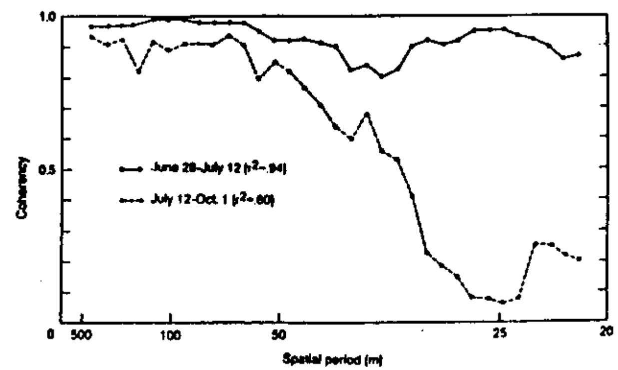

Fig. 13. Coherency spectra for the drying (June 28-July 12) and recharge (July 12-Oct. 1) periods.

Geostatistics

An example of the variogram given in Figure 3 for the nematode populations measured by Alemi *et al.* (1988) on a 6.5 m grid across an agricultural field is given in Figure 14. The values of the range, sill and nugget are 32.5 m (5 lags), 8500 and 7000, respectively. We may use this variogram to krige or estimate the nematode population at all locations across the agricultural field. The variogram can be used for estimating nematode values Z^* at locations x_0 where measurements have not been made. The procedures lead not only to the estimated values Z^*, but also an estimate of $\mathrm{var}(Z - Z^*)$ which indicates the reliability of the estimate. "Error maps" can be prepared to reveal areas within the field where the variance is highest and presumably where additional sampling should be made.

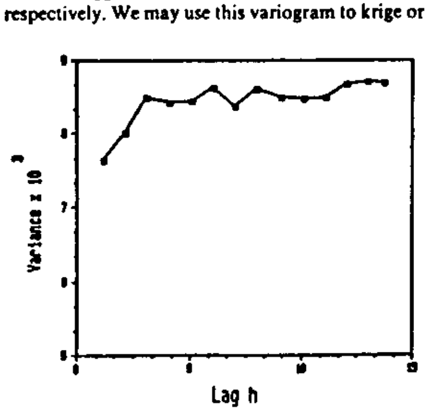

Fig. 14. Average semivariogram of *Paratrichodorus*.

In the kriging procedure, an estimate Z^* is assumed to be a linear function of the known values Z already measured at N other locations

$$Z^*(x_0) = \sum_{i=1}^{N} \lambda_i Z(x_i) \qquad [19]$$

by choosing the weight factors λ_i such that the expected value and variance of $[Z^*(x_0) - Z(x_0)]$ are zero and a minimum, respectively. The variogram showing the spatial variance structure of Z is used to estimate the values of λ_i. Cokriging is a similar procedure that takes advantage of the spatial structure of the covariance between two variables such as cotton yield and nematode. Still another procedure, block kriging, allows interpolation between averages of values centered at locations instead of individual observations for each location. Universal kriging provides for combination of a deterministic trend across the field to coexist with random variations while disjunctive kriging can be used to identify areas within a field having values expected to be above or below a threshold magnitude. Hence, there are many attractive kriging and cokriging analyses that can be used to develop and evaluate alternative sampling grids or locations relative to a specific management system.

The excellent comprehensive reference of Journel and Huijbregts (1978) on geostatistics and that of Warrick *et al.* (1986) applied to soil science provide essential details and conditions omitted from the above introductory presentation. Many additional statistical opportunities exist when one recognizes that spatial dependence also depends upon direction and that more than one variable can be treated simultaneously.

Stochastic equations

It is not possible to model a system relative to what is "a typical response to management practices" or what is "a typical pattern in ecology" without understanding the spatial and temporal variations for both small and large scales. "Models are being constructed, refined, elaborated, tinkered with and displayed with little or no effort to link them to the real world," Pielou (1981). The standard approach to field scale or plot scale problems has been to construct analytical or numerical solutions of the classical differential equations, assuming that the parameters take on known values which can be easily evaluated by a few observations. Although there have been major advances in numerical modeling techniques, standard modeling approaches are giving way to stochastic methods which incorporate the effects of natural or anthropogenically-induced variability. Stochastic models are more realistic representations of field situations than deterministic models and they provide better predictions owing to the probabilistic nature of the data incorporated. Because stochastic models can be examined in terms of the variability of the model parameters, data collection can be improved to emphasize those parameters having the greatest effects on the results.

During the past decade, stochastic analyses of groundwater (Bakr *et al.*, 1978) and unsaturated flow (*e.g.*, Yeh *et al.*, 1985) have been accelerating in number and kind of applications. Nielsen *et al.* (1987) recently reviewed conceptual alternatives for modeling water and solute transport in the vadose zone. Promising areas for further research in microbial ecology of arable lands await similar development.

References

Alemi M H, Ferris H and Nielsen D R 1989 Geostatistical analyses of the spatial and temporal variability of nematode populations (in manuscript).

Bakr A A, Gelkhar, L W, Gutjahr A L and MacMillan J R 1978 Stochastic analysis of spatial variability in subsurface flows. Water Resour. Research 14, 263–271.

Bazza M 1985 Modeling of Soil Surface Temperature by the Method of two-dimensional Spectral Analysis. Ph.D. Thesis, UC Davis.

Box G E P and Jenkins G M 1970 Time series analysis, forecasting, and control. Holden Day, Inc. San Francisco. CA.

Brillinger D R 1981 Time Series. Data Analysis and Theory. Holden Day Inc. San Fransisco, CA.

David M 1977 Geostatistical Ore Reserve Estimation. Centre D'Informatique Geologique, Fountainbleau, France.

Journel A G and Huijbregts Ch 1978 Mining Geostatistics. Academic Press, London.

Kachanoski R G and de Jong E 1988 Scale dependence and the temporal persistence of spatial patterns of soil water storage. Water Resour. Research 24, 85–91.

Kachanoski R G, Rolston D E and de Jong E 1985a Spatial and spectral relationships of soil properties and microtopography. I. Density and thickness of A horizon. Soil Sci. Soc. Am. J. 49, 804–812.

Kachanoski R G, Rolston D E and de Jong E 1985b Spatial variabilty of a cultivated soil as affected by past and present microtopography. Soil Sci. Soc. Am. J. 49, 1082–1089.

Kalman R E 1960 A new approach to linear filtering and prediction theory. Trans. ASME J. Basic Eng. 82, 35–45.

Kalman R E and Bucy R S 1961 New results in linear filtering and prediction theory. Trans. ASME J. Basic Eng. 83, 95–108.

Matheron G 1963 Principles of geostatistics. Econ. Geology 58, 1246–1266.

Nielsen D R, van Genuchten M Th and Jury W A 1987 Monitoring and analyzing water and solute transport in the vadose zone. Proceedings of International symposium on groundwater monitoring and management, 23–28 March 1987. Dresden, GDR.

Pielou E C 1981 The usefulness of ecological models: A stocktaking. Quarterly Review of Biology 56, 17–31.

Ripley B B 1981 Spatial Statistics. Wiley, New York.

Shumway R H 1988 Applied Statistical Time Series Analysis. Prentice-Hall, Englewood Cliffs, NJ.

Shumway R H and Stoffer D S 1982 An approach to time series smoothing and forecasting using EM algorithm. J. Time Series Analysis. 3, 253–264.

Vachaud G, Passerat De Silane A, Balabanis P and Vauclin M 1985 Temporal stabilty of spatially measured soil water probability density function. Soil Sci. Soc. Am. J. 49, 822–827.