



Spatial analysis of reconstructed mine soils : soil survey, statistical modeling and terrain analysis for land resource inventory
by Thomas James Keck

A dissertation submitted in partial fulfillment of the requirements for the degree of Doctor of Philosophy in Crop and Soil Science
Montana State University
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Abstract:

Mining companies and regulatory agencies need clearly defined methods by which sample data of reconstructed mine soils can be interpolated to determine soil spatial variability and suitability for reclamation. Objectives of this study were to examine the distribution of reconstructed mine soils from several perspectives: soil survey, spatial statistics, and terrain modeling. Mine soils, in this context, provided a special case for a larger discussion of soil resource inventory in general.

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Spatial statistics were used to assess the spatial distribution of mine soil attributes from data collected by Western Energy Company. Soil attributes, in all cases, were spatially independent at the 300 foot sample spacing used at the mine. Kriging was deemed unwarranted due to spatial independence of the data and more traditional statistical methods that rely on independent data assumptions were used to interpolate the data. For many soil properties, a constant surface through the overall sample mean provided the best prediction at unsampled locations.

Initial results were tested further using data collected exclusively for application of spatial statistics. Closer grid spacing resulted in semivariograms exhibiting weak to moderate spatial dependence for subsoil attributes. Despite the empirical evidence of spatial correlations, kriging estimates did not outperform use of the field mean in predicting measured values of an independent data set. Knowledge about the physical processes controlling spatial distributions of soil properties appears to be an important, yet often overlooked, consideration in decisions about the appropriateness of applying kriging techniques.

Terrain models provide a unique vantage point to study how mine soils and reconstructed landscapes will evolve in the future. A terrain model generated for the Area-E portion of the Rosebud Mine provides the basis for discussion of changes that are certain to occur in the reclamation resource.

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APPROVAL

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Thomas James Keck

This dissertation has been read by each member of the thesis committee and has been found to be satisfactory regarding content, English usage, format, citations, bibliographic style, and consistency, and is ready for submission to the College of Graduate Studies.

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Date Jan. 20, 1998

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ABSTRACT

Mining companies and regulatory agencies need clearly defined methods by which sample data of reconstructed mine soils can be interpolated to determine soil spatial variability and suitability for reclamation. Objectives of this study were to examine the distribution of reconstructed mine soils from several perspectives: soil survey, spatial statistics, and terrain modeling. Mine soils, in this context, provided a special case for a larger discussion of soil resource inventory in general.

Initially, mine soils at the Rosebud Mine in Colstrip, Montana were mapped using standard soil survey procedures. Reconstructed mine soils are uniquely different from their native counterparts. They provide a uniformly deep soil substrate for plant roots and have been largely homogenized by soil salvaging. Erratic spatial variations in soil textures are the result of mixed sedimentary parent materials and the reclamation process.

Spatial statistics were used to assess the spatial distribution of mine soil attributes from data collected by Western Energy Company. Soil attributes, in all cases, were spatially independent at the 300 foot sample spacing used at the mine. Kriging was deemed unwarranted due to spatial independence of the data and more traditional statistical methods that rely on independent data assumptions were used to interpolate the data. For many soil properties, a constant surface through the overall sample mean provided the best prediction at unsampled locations.

Initial results were tested further using data collected exclusively for application of spatial statistics. Closer grid spacing resulted in semivariograms exhibiting weak to moderate spatial dependence for subsoil attributes. Despite the empirical evidence of spatial correlations, kriging estimates did not outperform use of the field mean in predicting measured values of an independent data set. Knowledge about the physical processes controlling spatial distributions of soil properties appears to be an important, yet often overlooked, consideration in decisions about the appropriateness of applying kriging techniques.

Terrain models provide a unique vantage point to study how mine soils and reconstructed landscapes will evolve in the future. A terrain model generated for the Area-E portion of the Rosebud Mine provides the basis for discussion of changes that are certain to occur in the reclamation resource.

CHAPTER 1

INTRODUCTION

Research included in this dissertation was funded by Western Energy Company in the expectation that geostatistical analysis of their mine soil data could be used to justify a reduction in the level of soil sampling required for reclaimed soils. This expectation never materialized. There may be good reason to reduce soil sampling requirements in post-reclamation mine soils but the justification has little to do with geostatistics. Early analysis, reported in Chapter 4, showed that spatial correlations were just not present in the existing mine soil data to justify such a reduction.

The overall focus of the dissertation has been expanded well beyond initial interests of Western Energy Company to a larger perspective of soil resource inventories. This expansion was partly due to the professional interests and occupation of the author and, in part, was an attempt to connect reclamation resource issues to the larger picture. Analysis of mine soils, became a medium for the expanded discussion. They represent a special case, one that is analogous to native soils in many respects but one that has distinct differences. This presented both advantages and disadvantages in how concepts in the dissertation were developed and how specific resource inventory tools have been applied.

The entire field of soil survey and soil resource inventory has seen a huge expansion in the level of information and technology available during the past ten to twenty years. The same can be said for many other fields of study. Often, new developments and new technologies create dilemmas in how new ideas relate to the old and what is the best or most appropriate mix of procedures to obtain desired results.

USDA soil surveys have for years been the standard for soil resource inventories. They have their strengths and their weaknesses and are largely based on semi-quantitative methods of soil inventory. Geostatistical and other more quantitative techniques are more recent developments which approach the problem, of how to expand knowledge from a relatively few known sample points to the larger landscape, from an entirely different direction. Unfortunately, professionals on both sides of the isle are largely ignorant of the other's knowledge. The majority of field soil scientists are apprehensive of any quantitative methods whereas while most statisticians appear to discount professional judgements unless based on valid, statistical analysis. Newer tools such as terrain models or satellite imagery add new wrinkles to the puzzle.

The ultimate goal of this dissertation is to help bridge this gap in understanding; to introduce appropriate quantitative techniques into the world of soil survey and to bring field expertise and knowledge of soil landscapes to bear on quantitative procedures. This will be accomplished through the perspective of mine soil inventories at the Rosebud Mine in Colstrip, MT. Two of the chapters are published papers. They deal with specific issues relative to mine soils and mine land reclamation and are noticeably shorter in length. The three other main chapters read more like a dissertation, which may be the only opportunity in a professional career to expand ideas to their fullest extent; short of writing a textbook. It is anticipated that up to six professional papers will be developed from materials in these three chapters.

Chapter 2 is the only chapter that does not specifically relate to mine soils. It provides a conceptual basis for distinctions between soil survey and geostatistical approaches to soil inventories and advances ideas about future directions in both areas. From a dissertation standpoint, Chapter 2 functions as background information, literature review, and an introduction to the overall topic of soil resource inventory.

A reasonable approach to assessing mine soil resources was to start with the simplest and most straight forward methodology first. Chapter 3 looks at reconstructed mine soils at the Rosebud Mine from a standard soil survey perspective. Mine soils can be described, classified and generally mapped like any native soil resource. Soil interpretations are then generated from the information. This paper was quite important to the mining company in that it helps dispel the myth of mine soils as some exotic substance. Reconstructed mine soils are soils, much like any other soil. Differences between mine soils and their native counterparts are discussed.

Chapter 4 addresses Western Energy's questions with regard to the potential use of geostatistics. The existing Western Energy data are analyzed for spatial dependence and in the absence of spatial dependence, appropriate statistical techniques that rely on independent data are applied. A paper on this work was published in the Soil Science Society of America Journal in June of 1993.

Questions answered invariably lead to more questions. Several questions were raised in the initial application of geostatistics to Western Energy data. Was the mine soil data truly distributed in a spatially independent manner, or was the somewhat random 300 foot sample spacing used by Western Energy too coarse to identify spatial correlations present? Could a trade-off be made by incorporating field procedures for sample analysis and increasing sample density, to obtain better resource information for the same effort? To answer the above questions, a soil sampling grid was established on two reclaimed fields in the Area-E portion of the Rosebud Mine. The grid was specifically designed to study potential spatial correlations on mine soil data that could be reasonably used in an operational, post-reclamation soil sampling strategy. This sampling provided the data for all analyses in Chapter 5.

Chapter 5 presents the main data analysis portion of the dissertation. Kriging predictions generated from the experimental Area-E data set are compared against measured values from independently collected Western Energy data. Additional comparisons are made against a randomly selected test data set. In the last section, indicator kriging is introduced as a potentially more appropriate analytical tool for assessing mine soil suitability.

Chapter 6 examines the application of terrain models. Unlike native landscapes, correlations between terrain attributes of reconstructed landscapes and mine soil properties do not exist. Terrain modeling can still provide valuable insights into how mine soils and reconstructed landscapes will evolve in the future. For all our efforts to inventory the existing soil resource, soils there today will not be the same tomorrow. Processes of erosion, deposition, water movement and soil formation are all spatially variable functions modified by terrain. This chapter takes a more theoretical slant, looking towards the future and inevitable changes that will occur in the reconstructed landscapes and mine soil resources.

Chapter 7 summarizes results of previous chapters from two perspectives. First, how can existing technologies of soil survey, spatial statistics, terrain modeling, and image analysis be combined to model the distribution of soil properties on native landscapes? Secondly, what is the goal of a post-reclamation soil inventory? Several potential goals exist. Two different scenarios are discussed suggesting drastic changes in how reconstructed mine soils are inventoried. In the end, the path taken depends on the purpose for the journey. Happy reading!

CHAPTER 2

MODELING THE SPATIAL DISTRIBUTION OF SOIL PROPERTIES ON LANDSCAPES: SOIL SURVEY AND GEOSTATISTICAL APPROACHES

2.1. Introduction

Accurate information about soil resources provides an essential component to making sound land-management decisions. The value of such information will continue to increase as future pressures in the marketplace, changing land-use patterns and world population growth force us to continually search for new and better ways to produce more food and more fiber on less land. After four decades of record increases in agricultural production (Brown, 1995), the world marketplace for agricultural commodities has begun to swing from a buyer's to a seller's market. Increases in agricultural production have slowed as producers in the world's most productive agricultural countries reach limits where significant yield increases can no longer be coaxed from additional applications of chemical fertilizers (Brown, 1995). Environmental concerns related to large chemical inputs further limit these options. Thus, our standard approach to increasing agricultural productivity through increasing chemical inputs can no longer be expected to keep pace with the world's demands for food and fiber.

Increasingly, we look towards more and better information to boost agricultural production. Improved information about the soil and crop production system and how it varies across landscapes will play a vital role in this regard. Information age tools, like geographic information systems (GIS) the global positioning system (GPS), and relational computer databases

enable us to locate, store and manipulate spatial data in ways never before thought possible.

Genetically engineered plants are an important part of the information age. Agricultural scientists, armed with knowledge of genetics, search for new ways to increase yields without the undesired side-effects of excessive fertilizer or herbicide use. Management practices that take advantage of the new information and new technology available today are still largely in developmental stages. Opportunities for future advancements in these areas are substantial.

Site specific farming and intensive grazing management provide two examples of information based land management practices in use today. Site specific farming, as it is currently applied, utilizes precise spatial information about soil conditions and weed infestations to target variable rates of fertilizer and pesticide applications. Oftentimes, these systems require the use of both a GPS receiver and a GIS terminal on the tractor. A detailed soils map provides one of the primary input data layers within the GIS. In contrast, intensive grazing management applies a similar, though less technology intensive, information based approach to rangeland management. This approach attempts to improve rangelands through the management of grazing animal impacts. It was first proposed by Allan Savory as one "tool" in an overall program of Holistic Resource Management (Savory, 1988). Correct management of animal impacts is based on precise information about the development and timing of plant growth, the condition of different plant communities and, when available, precise information about soil resources. While traditional farm and ranch managers often question the need for additional information about soils or crop production in their operations, managers involved with such intensive land management systems are always searching for more information.

Similar applications of information-based technology will inevitably be developed in other land management professions; from forestry and silviculture to land use planning and urban

development. Nutrient management, waste disposal and other environmental protection programs increasingly depend on more and better soils information. The shrinking worldwide land base, relative to human populations, will ensure that trends toward more intensive land management continue. As a result, precise information about the spatial distribution of soil properties across landscapes will play an increasingly important role in the management of nearly all of our land resources.

2.1.1. Sources of Soil Resource Information

Traditionally, information about soil resources has been provided through soil surveys. USDA soil surveys have been published for most counties in the United States. Additional special use soil surveys have been conducted by both private and public concerns, including private consultants, timber and mining companies, state and federal agencies. All soil surveys provide soil maps, usually photo-based, showing the location of different soil "types" within the survey area. Accompanying the soil maps are narrative descriptions of the different "types" of soil identified within the survey area and information about the potential use and limitations of those soils for one or many different land uses. Within these confines, there can be a wide range of variation among soil surveys with respect to mapping scale, the intensity of field sampling, the intended use of the survey, the soil attributes sampled and even the level or type of classification scheme used to combine similar soil "types".

Increasingly, soil survey maps today are displayed and analyzed in geographic information systems (GIS). Within the GIS system, there may be a whole host of spatial data layers, including soils, climate, land ownership, geology and many other spatial coverages. GIS technology presents many new opportunities for environmental and other land-resource assessments through various

spatial analysis techniques and combinations of the different spatial data layers. It has also brought soil survey directly into the arena of computer modeling. While most soil mappers do not think of themselves as computer modelers, the soil maps they provide currently represent the most widely used and most widely available models of soil properties on natural landscapes. Soils data today, regardless of the source, represents one of the most sought after spatial data layers for many GIS analyses, from natural resource management to urban planning (Craig et. al., 1996).

Spatial interpolation techniques present an alternative means of modeling the distribution of soil attributes across landscapes. Many different interpolation methodologies exist, including distance weighting, spline fitting, least squares methods, Gauss-Markov techniques and geostatistics. The geostatistical interpolation method is called kriging. Kriging is often referred to as the "best linear unbiased estimator" (B.L.U.E.) because it uses a linear and unbiased weighted average to make predictions at unsampled locations and attempts to minimize the prediction variance associated with those predictions (Isaaks and Srivastava, 1989 and Clark, 1979). Geostatistical methods offer an additional advantage over most other spatial interpolation procedures by providing an estimate of interpolation error.

Soil survey techniques and geostatistical methods are similar in at least one respect. They both attempt to interpolate information from a limited number of "known" point samples to a much greater number of unsampled locations. Soils, by their very nature, are hidden from view. This makes the use of point sampling inevitable. How these different methodologies accomplish the task of interpolating limited information and the basic assumptions used by each are vastly different. This chapter explores the underlying assumptions, strengths and weaknesses of standard soil survey and geostatistical techniques for **modeling** the distribution of soils on landscapes.

2.1.2. Computer Models

Even the best computer models provide only a representation of reality. With respect to soil surveys, the only “absolute truths” about soils are found in the soils themselves. No matter how accurately we examine and measure these truths, our observations are at best “approximations” of the truth (Cline 1986). Many of the processes we attempt to model in soils are enormously complex. The above statement applies whether we are trying to model the transport of water and solutes through soils or trying to model the spatial distribution of relatively static soil properties across landscapes. As a result, computer models of all but the most simple systems are based on some set of simplifying assumptions. Assumptions vary from one model to another, but they all serve the primary purpose of making models functionally usable. How accurately underlying assumptions match real-world processes and/or properties of the phenomenon in question largely determine the accuracy limits to which a model can ascribe. The results from any modeling exercise can only be as accurate as the accuracy of underlying model assumptions, no matter how perfectly the model gets applied. A corollary to the above states that model outputs can only be as accurate as the input data on which they are based.

2.1.3. Model Classifications

Computer models can be generally split into two classes, stochastic models based on the laws of probability and deterministic models which attempt to mirror underlying physical or chemical processes. Stochastic models may also be referred to as empirical models. This type of model does not necessarily rely on any detailed understanding of the processes involved. Results depend solely on the data set at hand or some empirical evidence of what happened the last time. Regression equations are perhaps the most commonly used stochastic models. They describe the

relationships found in an existing data set irrespective of reasons why. The researcher is then left to interpret results based on his or her own hypotheses as to why they came out as they did.

In contrast, physically based deterministic models depend on some prior understanding of the process or processes involved. Richard's equation for soil-water flow is one example of a simple deterministic model. Mathematical deterministic models, like the Richard's equation, attempt to reduce physical processes to one or a series of mathematical equations. Alternately, non-quantitative, deterministic models use expert knowledge or understanding to predict results. Because deterministic models use an understanding of the processes involved, we will consider them to be "knowledge-based" models.

Differences among computer models can also be viewed in terms of the preciseness of their results. A continuum (Fig. 2.1) exists from the purely quantitative to the purely qualitative. At one end of the spectrum, a purely qualitative model might predict only that soil-A is a "good" soil with respect to clay content, a loam of some kind, while a purely quantitative model assessing clay content might predict the clay content of soil-A to be exactly 16%. Obviously, the prediction from the second model is more precise. It does not follow, however, that the second prediction is necessarily more accurate.

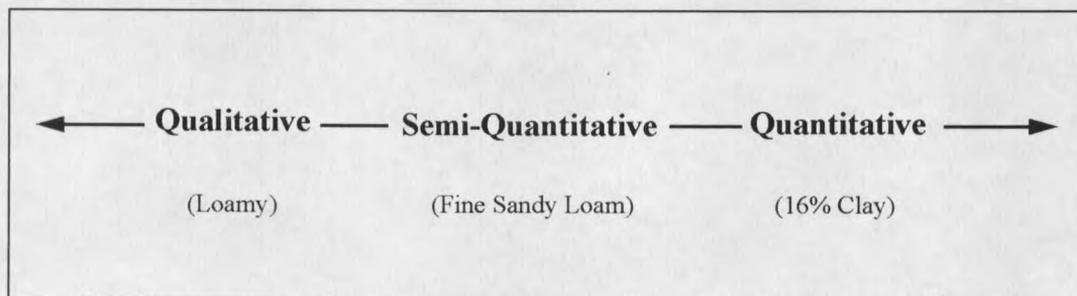


Figure 2.1. Continuum of computer models with respect to the precision of results.

Quantitative models rely on primary data for inputs. Such primary data in soils may include measurements of soil properties or estimates of those properties based on pedotransfer functions. They often require some parameter estimates which in an ideal sense are derived from an understanding of the processes and/or the model involved. Inputs for qualitative models are much more likely to be abstract class data. Twelve percent clay would be an example of primary data while a coarse sandy loam texture is an example of class data. The soil series represents a more extreme example of abstract class data.

2.2. Soil Survey

Soil survey today appears to be caught between two seemingly contradictory paradigms. The first paradigm is that of the soil-landscape continuum. Hans Jenny systematically described the influence of five soil forming factors in his book on *Factors of Soil Formation* in 1941. Since that time, it has become an accepted fact that differences in soils occur in response to differences in (1) climate, (2) parent material, (3) living organisms, both plant and animal, (4) topography and (5) time. Figure 2.2 provides a graphic representation of the factors affecting soil formation. Soils form in a continuously changing pattern across the landscape due to many different variations among the five soil forming factors. By understanding the influence of the environment, past and present, on soil formation, a soil scientist is able to predict the occurrence of different soil types. This predictability provides the scientific basis that makes soil survey possible (Hartung et al., 1991; Hudson, 1992).

The soil scientist maps soils through a continual process of predictions and verifications. In this manner, soil maps are drawn based on a very limited sample of the total ground surface.

