



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 coaxied 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 qualitative to the purely quantitative. 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.

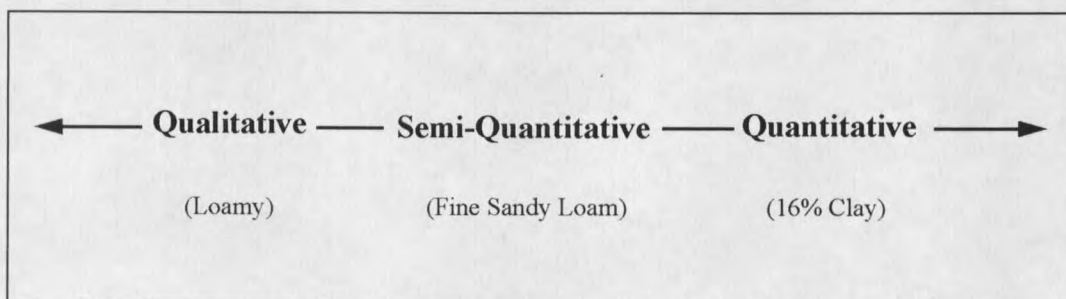


Figure 2.1. Continuum of computer models with respect to the precision of results.

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.

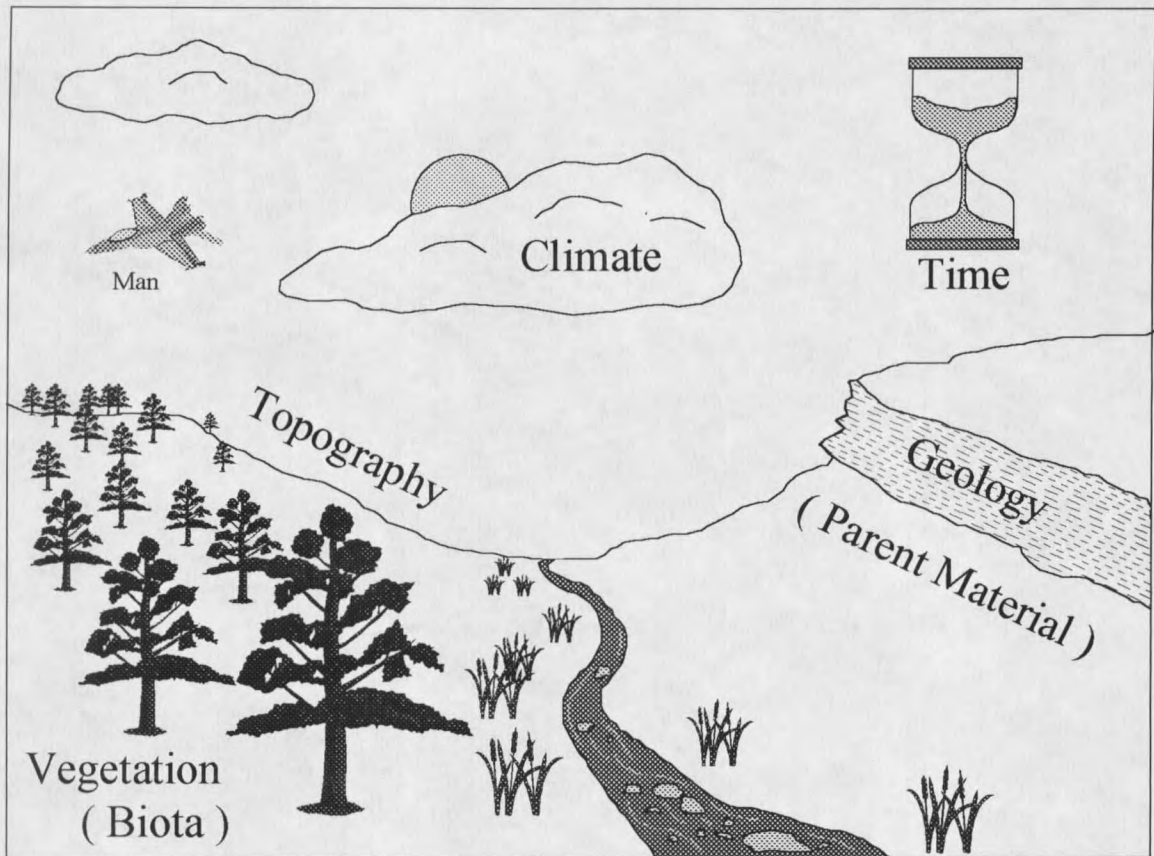


Figure 2.2. Schematic diagram of the five soil forming factors: (1) climate, (2) parent material, (3) living organisms including man, (4) topography, and (5) time.

Arnold (1988) described the soil scientists' predictions in terms of the scientific method.

Predictions are made based on a hypothesis of how soils are distributed on the landscape. If these predictions are verified by sampling then the hypothesis is considered to be correct and the soils are mapped based on this assumption. If sampling fails to support the hypothesis, then more sampling must be done to modify the hypothesis or develop a new one. In any event, it is the predictability of soil patterns on the landscape, the soil-landscape continuum, that enables soil scientists to map soils and provides the underlying strength of soil survey. Good soil mappers are always testing and updating their models of the soil-landscape continuum.

The second paradigm of soil survey is that of soil taxonomy. While this paradigm does not necessarily conflict with the idea of a soil-landscape continuum, its application to soil mapping often does. Man has a basic tendency to group similar things together (Quine, 1969). The soil taxonomy paradigm simply says that all soils can be described and classified within one comprehensive system of soil taxonomy. Every soil fits within a class and there are no gaps between adjacent classes.

2.2.1. Assumptions of Soil Survey

A model can only be as accurate as the accuracy of its underlying assumptions. There are a number of assumptions inherent in soil survey maps. The first is that discrete units exist on the landscape. A soil scientist draws a line on his or her soil map separating two map units (Fig. 2.3). The line implies that the two map units are distinctly different, that when you cross the line, you have passed from one population of soil pedons into a different population of pedons. Even though the soil scientist drawing the line might know it is "soft" in terms of how distinctly the boundary actually exists, users of soil survey information generally assume the line separates distinct entities.

Discrete boundaries do exist in nature. If you walk from a bedrock controlled upland onto a floodplain you will almost certainly cross over a very distinct boundary on the landscape. Terrace edges and many glacial features are also characterized by distinct landform boundaries. Distinct boundaries may be defined by geologic contacts between contrasting rock formations or created by geologic faults. On the whole, however, discrete boundaries in natural landscapes are more often the exception than the rule.

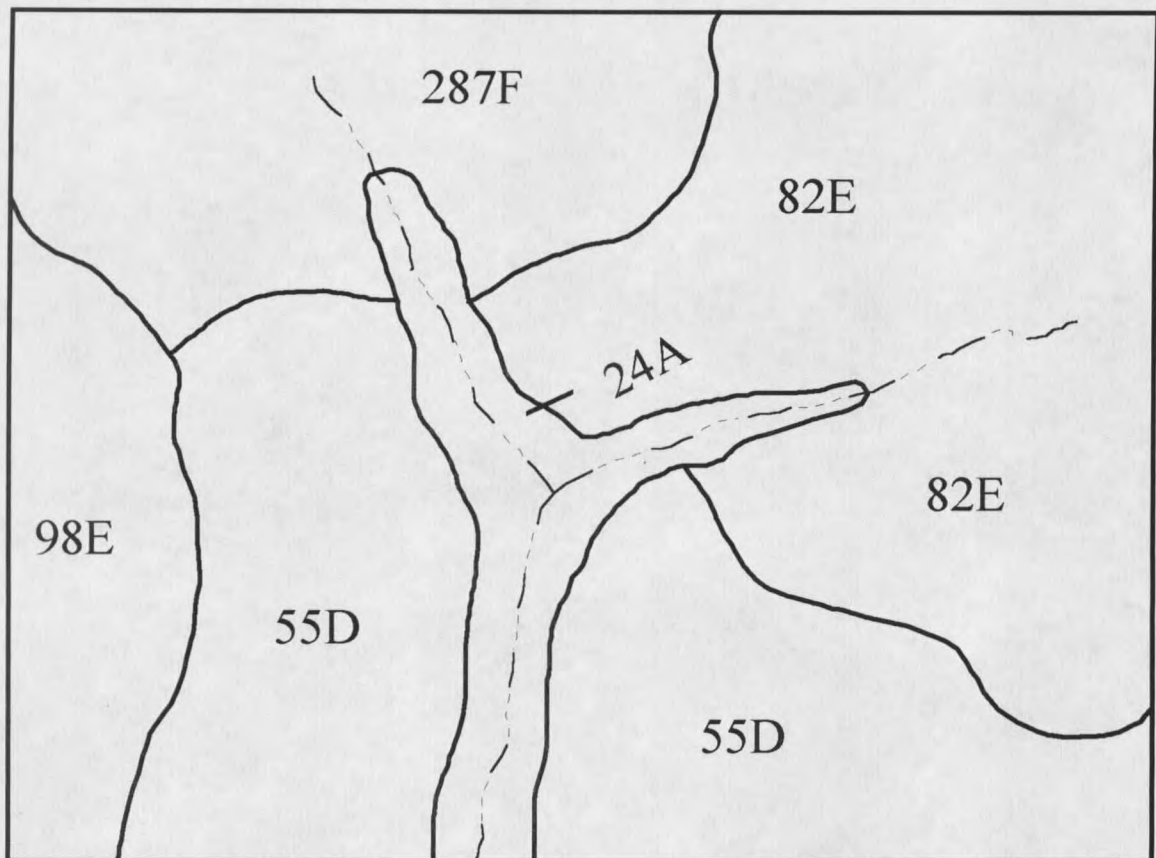


Figure 2.3. Example of a standard soil survey map with soil map units identified by map unit symbols and adjacent map units separated by discrete soil boundaries.

Landform positions grade from one to another, ridge to shoulder slope, shoulder to sideslope, sideslope to footslope, etc. Concave landform positions give way to convex positions across a hillside. Soil properties gradually change in response to these differences and the resulting changes in the balance of soil forming processes. Climate changes slowly across long distances while microclimate changes more rapidly in response to topographic features. Both change in gradations and not in discrete steps. Plant communities also tend to grade into one another, forest into shrubland, grassland into forest, etc. Their boundaries are not static, but rather move back and forth during the time it takes a soil to “form”. Climate also changes over time. Plant

communities respond to changes in climate and cycles of succession and disturbance. All the above are examples of how soil forming factors change gradually over space and time. These gradual changes make boundaries between different soil types "fuzzy" at best and have sparked the current interest in the use of fuzzy set theory to define soil boundaries (Burrough, 1989; Burrough et al., 1992; McBratney and deGrujter 1992; Odeh et al., 1992).

The second assumption of soil survey follows from the first. In order for discrete units to exist, soil properties must vary together at common scales or at least be synchronized with respect to scale. Soil pH must be changing at a similar scale as soil texture as is soil depth and so on across the landscape for many different soil properties. This is best shown by example. Figure 2.4 illustrates a common sequence of geologic materials and associated soils found in the unglaciated sedimentary plains of eastern Montana. Classifications for the three soil series used are given in Table 2.1 while selected soil properties for each series are in Table 2.2.

Assuming map scale allows these soils to be mapped as consociations (map units comprised of a single soil type), a soil boundary would be drawn on the map between the Cabbart and the Ethridge series. Another soil boundary would be drawn between the Ethridge series and the Delpoint series and so on across the landscape. In changing from the Cabbart to Ethridge map unit, the map infers a change in surface soil texture from sandy loam to clay loam. Control section clay content changes from less than 35% to more than 35%, soil depth changes from shallow (10 to 20 inches over soft sedimentary beds) to very deep (greater than 60 inches) and the depth to lime increases from the surface to 10-20 inches deep. Surface pH would be expected to decrease although some overlap exists in the pH range of the two series. The ochric epipedon of the Cabbart series would be replaced by a mollic surface for the Ethridge series and the lack of subsurface diagnostic horizons (Cabbart series) would be replaced by an argillic

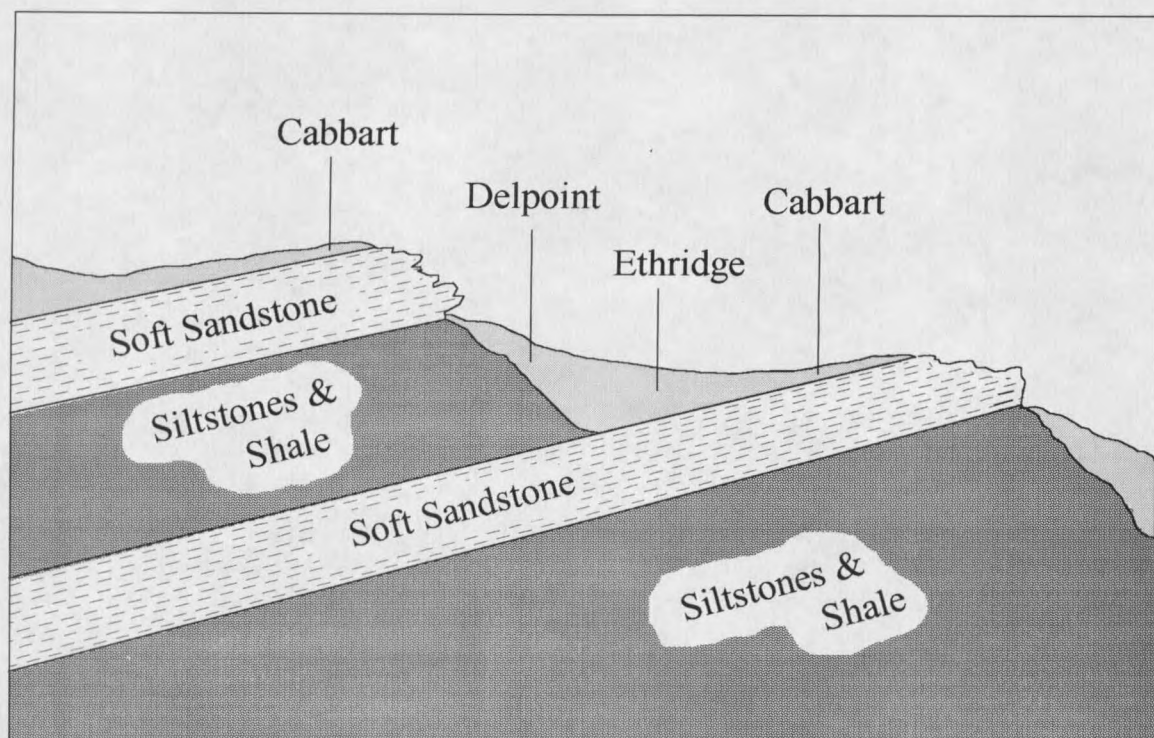


Figure 2.4. Diagram of a typical sequence of geologic parent materials and associated soil series in the unglaciated sedimentary plains of eastern Montana.

Table 2.1. Classification of soil series shown in Figure 2.4.

Series	Classification
Cabbart	Loamy, mixed (calcareous), frigid, shallow Aridic Ustorthents
Delpoint	Fine-loamy, mixed Aridic Ustochrepts
Ethridge	Fine, montmorillonitic Aridic Argiborolls

Table 2.2. Selected properties of soil series shown in Figure 2.4.

Series	Soil Depth	Surface pH	Surface Texture	Con. Sec. Clay %	Diagnostic SS Horizon	Diagnostic Epipedon	Depth to Lime
Cabbart	10-20	7.4-9.0	SL	18-35	none	ochic	surface
Delpoint	20-40	6.6-8.4	L	18-35	cambic	ochic	0-20
Ethridge	> 60	6.1-7.8	CL	35-45	argillic	mollic	10-20

horizon (Ethridge series). Slopes groups would change as well. All the above soil properties and others would need to be varying together at a common or synchronized scale across the landscape in order for the soil "type" to change along a common or discrete boundary in the landscape. Similarly, soil properties would be expected to change together along a common boundary between the Ethridge and Delpoint soils and between the Delpoint and Cabbart soils. This pattern would continue across the landscape in response to changes in geologic parent material until an additional change in one or more of the soil formative factors was encountered. Similar examples can be drawn from any soil survey map. The soil survey model of how soils are distributed on the landscape inherently assumes all soil properties are varying together at a common scale. This implies an unrealistic amount of correlation among all the soil properties that constitute a soil series at a landscape scale. Regional and microscale variations and skewed variations among different soil properties tend to be discounted.

A third assumption of soil survey requires that the range of individual soil properties falls within specified limits. Thus, a fine-loamy soil has a range in clay content from 18 to 35 percent in the control section. A mildly to moderately alkaline soil horizon has a pH range from 7.4 to 8.4 and so on for many different soil properties within different horizons. The data distributions within these classes are unspecified and largely unknown. Class boundaries originate from both the hierarchical taxonomic system and from the current methodology for making soil interpretations. Ranges in soil properties are constrained by both Soil Taxonomy and soil interpretive classes. The need to clearly distinguish each soil series from every other further restricts the ranges of soil properties for a given soil "type". This third assumption implies that the central tendency of each data distribution is well within the class limits. Field experience indicates that the central tendency for many soil properties often falls on the fence between classes, not only at the soil series level but

all the way up through the classification system. Imposing the limits of soil taxonomy and interpretive limits on soils from without frequently divides natural soil bodies (Nettleton et. al., 1991; Swanson, 1991) if indeed such natural soil bodies exist.

2.2.2. Soil Series and Modal Concepts

The “modal” pedon represents a concept unique to soil survey. A soil profile description is considered modal for a soil series or map unit if it best fits the typical condition found in the field based on the soil scientist’s judgment. Modal in this context does not infer any kind of statistical relationship to other samples within the class. The modal pedon must fit within the series and classification limits of the soil it represents. The class in which the modal pedon fits then becomes the standard by which interpretations are made for that soil and provides the mechanism by which information at one location is transferred to another.

The transfer of information from one location to another based on a modal concept forms the basis for nearly all soil survey work and has been identified as one of the major sources of inaccuracy in standard soil surveys (Nettleton et. al., 1991; Yost et. al., 1991; Rowgowski and Wolf, 1994). Inaccuracies arise as modal concepts identified at one location are applied to other locations. They are compounded by both taxonomic and interpretive constraints that force the modal concept to fit within class boundaries. Force fitting modal concepts into class boundaries, in turn, creates the major source of bias in all soil survey pedon databases. Similar difficulties occur at the map unit level, where a map unit concept, set-up at one location, is often applied to many other portions of the landscape based on limited sampling or observations.

From an analytical standpoint, the soil series exists within the realm of multivariate analysis and multidimensional space (Fig. 2.5). Each series concept encompasses specific ranges

for many different soil properties as a function of depth within a soil profile. For a given soil body, the degree to which all soil properties fall within corresponding class ranges at specified depths determines the likelihood that a point sample will exactly fit within a given taxonomic class or series. Once again, there is an underlying assumption of near perfect correlation among many different soil properties. The assumption is also extended to accessory soil properties, i.e.: those properties not explicitly used in the classification. Seyfried et. al. (1992) found that on a regional basis (state of Florida), soil classification, for soils previously sampled and classified as "modal" pedons, did a good job of partitioning 80 to 90 percent of the variability in soil properties even for selected accessory properties. Thus, if a profile accurately fits within a taxonomic class, there appears to be a reasonably good probability that other accessory soil properties will follow suite.

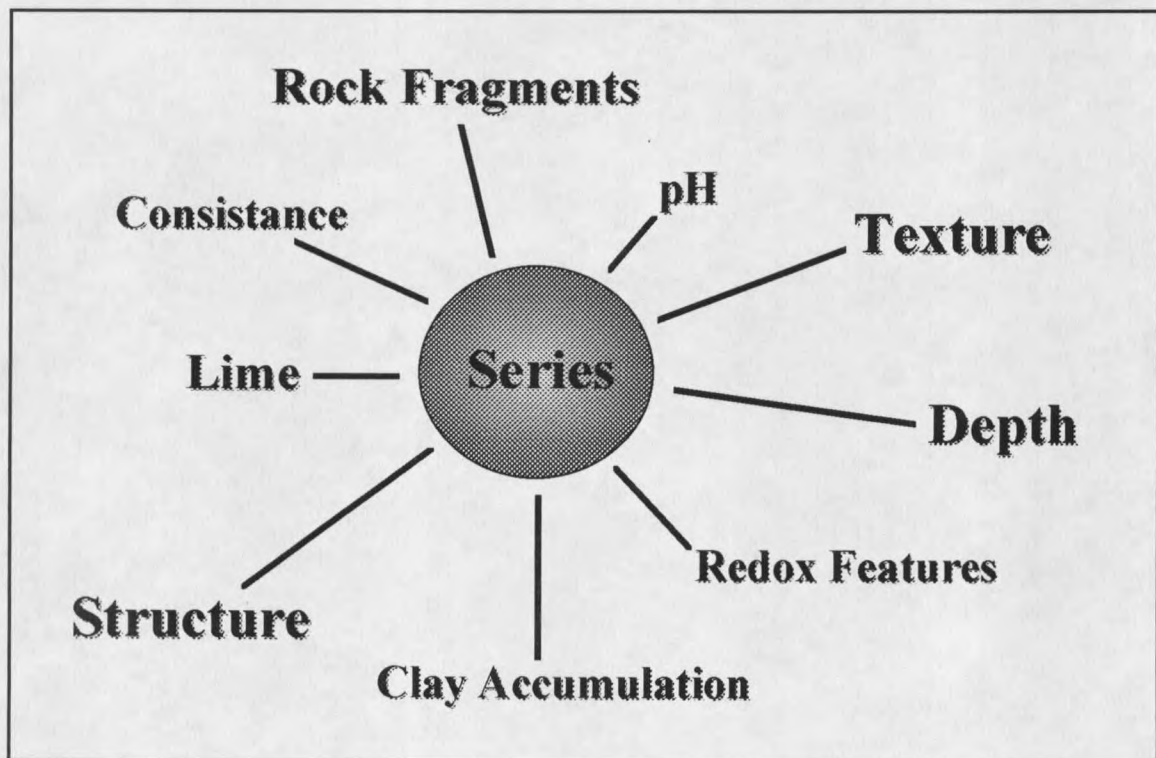


Figure 2.5. Graphic representation of the soil series in multidimensional space. In reality, many other soil factors and their distributions with respect to depth would be included in the concept of a soil series.

2.2.3. Soil Survey Accuracy

A much more difficult task requires an assessment of how well the “modal” pedons or those profiles selected as typical within a map unit represent the total population of soil pedons within the map unit. Here the results are much less favorable. Both spatial and temporal variations in the soil cause point samples to often not fit the typical or modal concept assigned to a given soil series or map unit (Nettleson et. al., 1991). Swanson (1990) goes as far as to state, “it is sometimes difficult to find a pedon that falls within the series range of characteristics, even in the area where the series was originally described”. Presumably, this would be due to the constraints of taxonomic and interpretive class limits.

Hartung et. al. (1991) found that old mapping in Nebraska correctly identified the classification of point samples along transects only 26, 15 and 16 percent of the time, respectively, for three separate map unit consociations. Somewhat better results were reported by Beckett and Webster (1971) in a review of the available soil variability data at that time. They concluded that, “On average, some 50 % of the randomly chosen sites within a mapped series or type are occupied by soil profiles which match the definition of the profile class for which the unit is named”. Powell and Springer (1965) in another early study reported that 60 to 70% of the soil profiles they examined in map units for 3 soil series in the Piedmont region of Georgia correctly fit the map unit series. The problem of fitting soil classes extends even to soil profiles submitted to the National Soil Survey Lab as “typical” profiles. Only 25% of the 1477 pedons submitted to the lab between 1978 and 1988 fit the family classification for which they were sampled (Nettelton et. al., 1991). While “modal” pedons can be classified within the system of soil classification, the degree to which these concepts accurately portray the variability of soil profiles within segments of the landscape remains highly suspect.

Clearly there are some limitations to how standard soil surveys represent the distribution of soils on landscapes. Concepts of discrete units, common scales and the application of a rigid classification limits create inaccuracies when applied to real landscapes. The more diverse the landscape, the more troublesome these become. The net result is "few fits". Based on soil classification alone, soil survey does a poor job of modeling the distribution of soils. The likelihood that any given point sample will directly match the mapped classification drops off sharply as landscape complexity increases.

2.2.4. Accuracy Depends on Landscape Diversity

Soil survey maps do provide a reasonably good representation of soil spatial distributions in areas where only one or at most two of the soil formative factors vary across a given segment of the landscape. For example, geologic parent material, vegetation type and the time available for soil formation are relatively constant over large areas of eastern Montana. Changes that do occur in these factors generally occur in discrete jumps, such as from grassland to forest or from shale to sandstone. Climate remains fairly constant across most of this area although temporal variations occur. Much of the soil mapping in eastern Montana attempts to capture the variability associated with topographic relief in relatively homogeneous areas with respect to other soil formative factors. As a result, soil maps provide a reasonable representation of the distribution of soils in these areas. Difficulties might still exist in finding an exact taxonomic fit for certain soil series but from a functional standpoint the "modal" concepts work reasonably well.

Mountainous regions of southwestern Montana represent a different situation. There all of the soil formative factors may be varying across a given segment of the landscape. They generally vary at different scales. Thus, it becomes increasingly difficult to find uniform facets or discrete

units on the landscape. Transitions comprise more of the total area than do the discrete units and the likelihood of a "modal concept" developed at one location accurately portraying soil properties in another portion of the landscape is greatly reduced. When two, three or four soil formative factors begin to vary across a given portion of the landscape, the basic assumptions of soil mapping no longer fit the spatial patterns of soils on the landscape. As a result, mapping quality, or the likelihood that any given point sample accurately fits the modal concept of a map unit, goes down. A reduction in map quality, especially that based on taxonomic purity, occurs irrespective of the skill or perseverance of the soil mapper. Even in eastern Montana, areas with mixed geologic materials, like the Hell Creek or Judith River Formations, result in lower map unit purity.

2.2.5. Considerations for Use of Soil Survey Maps

Soil survey maps provide a range of values for many different soil properties at any point in the landscape. They do not give precise point estimates. The central tendency (mean, median, etc.) and the data distributions for soil properties are unknown within class boundaries. The distributions for many soil properties inevitably range outside class limits. This may also be true for the central tendency of some soil properties, especially those properties not explicitly used within the classification system. The accuracy of soil survey maps depends to a large extent on the complexity of the landscape. As landscape complexity increases, basic assumptions inherent to all soil survey maps no longer fit real conditions.

Soil survey maps represent the professional judgments of the soil scientist(s) who made them. The skill of the individual mappers in this sense plays a major role in the quality of the final product. Although they are often hampered by the limitations of scale and inaccurate model assumptions, skilled soil scientists can consistently produce soil maps that accurately reflect the

major land use potentials and limitations of the soil resource. Soil survey, in this sense, represents more of an "expert system" than it does a linear, mathematical model. On the other hand, inherent difficulties in soil maps can be greatly compounded by the careless sampling of an individual soil mapper or by the use of dissimilar procedures among mappers (Beckett and Webster, 1971). The use of subjective judgments to combine similar soils into map units greatly increases the likelihood of individual differences in mapping quality.

Soil Taxonomy provides a tremendous medium to communicate, compare and contrast soils as they occur in natural environments. "Soil Taxonomy is less an arrangement of kinds of soils than it is a language that facilitates our communication about soil by providing terms that encode our experience and understanding of soil differences." (Holmgren, 1988). There are no inherent contradictions between the soil-landscape and the soil taxonomy paradigms.

Unfortunately, soil scientists have continued to use Soil Taxonomy explicitly as the basis for soil mapping. This predisposes them (us) to assess the accuracy of soil maps in terms of classification purity; a test we are sure to fail on certain landscapes. A more rational approach would be to assess soil survey maps in terms of interpretive value as demonstrated by Powell and Springer (1965).

Finally, soil surveys are scale specific. Most countywide soil surveys are on a 1 to 20,000 or 1 to 24,000 scale. They were never intended to provide site specific estimates of soil properties. Small areas, up to 5 acres, of uniquely different soils are generally not recognized at this scale except as spot symbols or as map unit inclusions. Regional variations are only indirectly identified in map unit descriptions since the same soil series or modal concepts are often used across large geographic areas.

2.2.6. Soil Survey as a Model

Soil survey methods represent a semi-quantitative model of the distribution of soil properties on landscapes. Both input and outputs tend to be ranges of values. Results or final outputs are static, representing only one expression or "realization" of how soil properties are distributed. It is a "knowledge-based" model, however, developed with substantial emphasis on the deterministic patterns of soil formation. The "expert" knowledge of soil mappers provide the greatest strength to this approach. Expert, in this context, refers to judgments made by field personnel based on experience that could be encoded into an expert system. Unfortunately, some of the underlying assumptions of soil survey maps do not match the characteristics of many native landscapes. The accuracy of model outputs are limited as a result.

2.3. Statistical Interpolation - Geostatistics

Statistical interpolation methods provide an alternative approach to modeling the spatial distribution of soil properties on landscapes. As stated previously, many different spatial interpolation techniques exist. All of these techniques attempt to predict values at unsampled locations based on the known values of surrounding sample points. Differences exist among techniques in how surrounding sample values are used, in the size of the search area and in some basic assumptions about the sample data. Laslett et al. (1987) provides a good review of the differences among a number of different spatial prediction techniques.

Discussion here will focus on geostatistics and kriging as the spatial interpolation technique most commonly used in earth sciences today. Geostatistical techniques are based on the theory of regionalized variables first developed by G. Matheron in 1963. Matheron's theory describes the occurrence of natural phenomena distributed in space (Matheron, 1963). The initial

development and application of Matheron's ideas came in the field of mining geology for the prediction of ore grades in gold deposits. Since that time, geostatistics has become an increasingly accepted tool in the field of soil science for interpolating spatially variable soils data from point samples.

2.3.1. Spatial Correlation

All geostatistical techniques depend on the concept of spatial correlation. Simply stated, samples located near each other are expected to more alike than samples spaced further apart. This can be best demonstrated by the example shown in Figure 2.6. Sample values in this example could represent any spatially variable attribute. For soils, the attribute might be depth to lime or thickness of the mollic surface, but could just as easily be any number of other soil properties. The area enclosed by the square represents an area over which we would like to know something about sample values at unsampled locations. The question mark enclosed by a solid line circle indicates just one location within the field where the sample value is unknown. Based on intuition, we would use known values from the three sampled locations to make our prediction of the unknown sample value. The question we must ask ourselves is how should each known value be weighted to make that estimate? Most of us would predict the unknown value to be somewhere in the neighborhood of 16 to 20, not 32. Why? Because the unknown location is spatially located close to where we have observed sample values of 16 and 20. In making this prediction, we have concluded that samples located nearby contain more information about the unknown value than samples located further away. We have assumed that highs are near highs and lows are near lows. Similarly, we could make predictions about sample values at the other locations indicated by question marks. In doing so, we will have intuitively used the concept of spatial correlation in our estimates. Whether

spatial correlation actually exists depends on the structure of the data and/or the underlying process(es) involved. Our intuition makes us believe that it ought to be true. The same principle can be applied to data in one, two, or three dimensions.

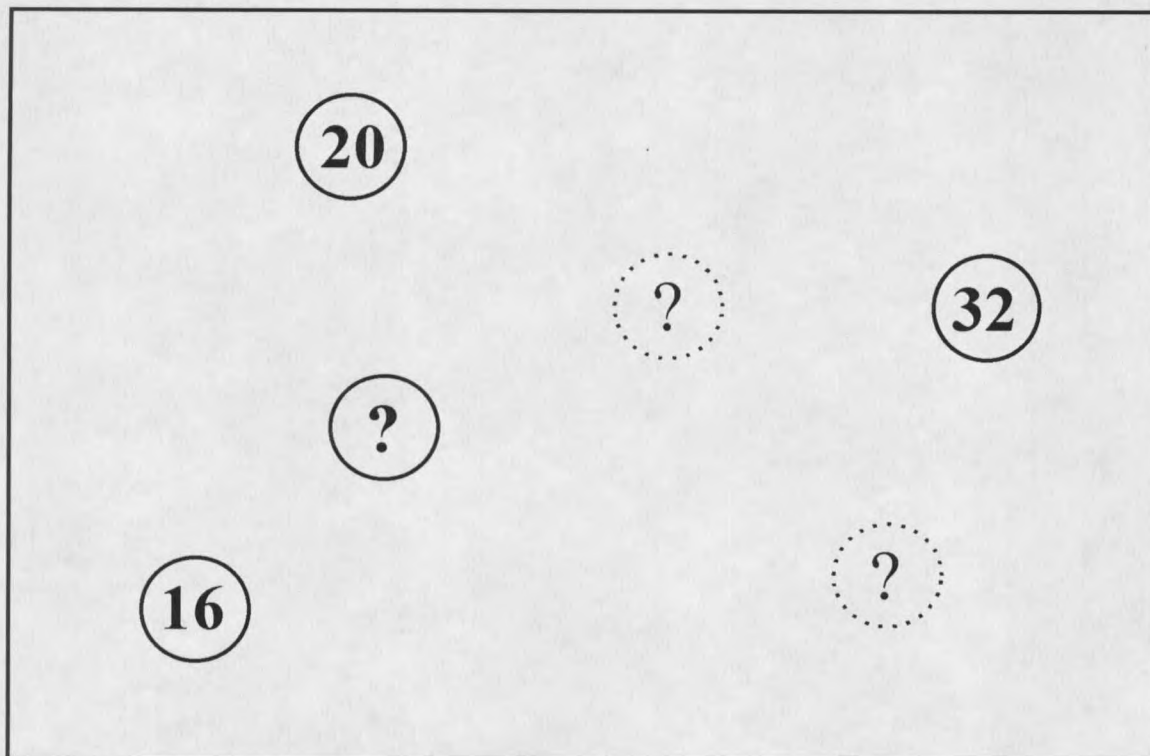


Figure 2.6. Example of spatial data distributed within a 2-dimensional field.

Geostatistics provides a more formal approach to what our intuition told us was reasonable. Instead of estimating an unknown value at one location, we usually want to estimate unknown values at many locations. Unknown points invariably outnumber known locations or sample points in all soil science applications. For most applications, we want information about an entire field based on just a few sample sites. The approach to spatial interpolation up to this point has been the same for both geostatistics and for soil survey techniques. The concept of “highs next to highs and lows next to lows” applies equally in both cases. In soil survey, when we sample a soil at one location on the landscape, we assume the profile described represents a significantly

larger surrounding area. Whether this is true or not depends on the structure of the data and the underlying processes of soil formation. Our intuition tells us it ought to be true. We pick our sample locations to avoid obvious transition areas where the relationship may not hold true. Given limited time and resources, our next sample will be in another portion of the field or in another area where we can see a change has occurred in one or more of the soil formative factors. We assume that our sample accurately represents all the pedons in the area surrounding our sample location based on observed similarities in soil formative factors.

Beyond this common starting point, however, geostatistical and soil survey techniques take very divergent paths towards spatial interpolation. The most significant differences relate to how each method represents the soil. While soil survey treats all soil properties at a point together as a “soil individual”, geostatistics in most common applications, treats each soil property as a separate variable, i.e.: a regionalized variable. Knox (1964) provides a good discussion of the concept of soil individuals relative to soil classification. Geostatistical and soil survey techniques also differ in that they are most often applied at different scales, geostatistical analyses are most often used at a field or microscale while soil survey techniques are more readily applied to more of a landscape or macroscale. Finally, geostatistical analyses depend on a different set of underlying assumptions about the behavior of soils data across landscapes. While soil survey maps assume that discrete soil boundaries exist, applications of geostatistics generally assume the opposite; that discrete soil boundaries do not exist within the area to be interpolated.

2.3.2. Application of Geostatistical Techniques

The application of basic geostatistical techniques involves three distinct steps: plotting the experimental semi-variogram, fitting a mathematical model to the semivariogram, and using the

selected semivariogram model to interpolate the data by kriging. Detailed accounts of the theory and application of these techniques can be found in Matheron 1963, Journel and Humbredts 1979, and Burgess and Webster 1980. In addition, a number of good textbooks on the subject have been published (Clark, 1979; Ripley, 1981; Isaaks and Srivastana, 1989). Many variations and refinements of the basic geostatistical techniques have evolved since 1963.

Most applications of geostatistics in soil science have as their goal, the generation of kriged soil attribute maps. These maps can be viewed as continuous statistical surfaces of a soil attribute over the map plane (Burgess and Webster, 1980). They are similar to topographic maps but unlike their topographic counterparts, kriged maps are based primarily on derived data. The ability of the estimator to accurately interpolate values at unsampled locations is crucial for the resulting map to accurately represent reality.

Kriging has been described as an optimum interpolator because it provides estimates that are both unbiased and have minimum variance. Like soil survey techniques, kriging can be viewed from a modeling perspective. The goal is to model the spatial distribution of soil properties across landscapes. Outcomes are not truths about the soil but rather approximations of those truths. Geostatistical analyses, like all other models, are based on a set of simplifying assumptions. Although the assumptions are quite different from those of soil survey mapping, they have the same potential impacts on the accuracy of model outputs.

2.3.3. Statistical Assumptions of Kriging

The primary assumption inherent in all applications of kriging is that sample values depend solely on their spatial orientation within the area to be kriged. Several statistical assumptions have to be met for this to be true. In the strictest sense, dependence on spatial

orientation implies "second order stationarity" in the data. This implies that the mean, variance and covariance of the variable to be interpolated remain constant within the kriged area. Few natural systems fit this strict assumption of stationarity. As a result, applications of geostatistics generally appeal to the less stringent assumptions of the "intrinsic hypothesis" or intrinsic stationarity (Vieira et al., 1982; Knighton and Wagenet, 1987; Laslett et al., 1987).

The intrinsic hypothesis has two parts. First, the population mean or expected value of the mean, $E\{Z(x)\}$, of the kriging variable is assumed to be constant within the kriging region.

$$E\{Z(x_i)\} \text{ is constant for all } x_i \text{ within area 'A'}$$

Thus, the mean does change as a function of location. Differences in sample values are assumed to result entirely from their location within the "regionalized" field plus an error term. The intrinsic hypothesis also requires that a finite variance exists for the differences between sample values at every separation distance. A finite variance exists for all sample values whose locations are one separation distance apart, a second finite variance exists for all sample values whose locations are two separation distances apart and so on for all separation distances. In practice, the relative locations between sample values can have both distance and directional components. The variance of differences between sample values for a single attribute as a function of separation distance is called the semivariance. The intrinsic hypothesis requires the relationship between semivariances and separation distances to remain constant for all locations within the area to be kriged.

$$\text{VAR}\{[Z(x_i) - Z(x_i + h)] = E[Z(x_i) - Z(x_i + h)]^2\} \text{ for all } x_i \text{ within area 'A'}$$

If the above is true, then the semivariance between any two samples depends only on the relative direction and distance apart of their sample locations, plus an error term. The semivariogram provides a graphical representation of the variance-distance relationships in the data.

A third assumption of kriging is the expectation that the semivariogram model applies equally well to all portions of the kriged area. This assumption follows directly from the second half of intrinsic stationarity. If the variance-distance relationships remain constant over the kriged area, then the semivariogram of those relationships would apply equally well to all portions of the area. The semivariogram attempts to capture the underlying spatial correlation structure in the data. Good kriging predictions depend on a reasonably good fit of the semivariogram model to the underlying structure of spatial correlation in the data. It follows that the semivariogram model must then fit equally well in all portions of the field to provide equally good predictions across the entire field.

To summarize, kriging assumes a constant population mean and constant spatial correlation structure in the data. Several authors have suggested that kriging appears to be fairly robust with respect to some trends in the data, i.e.: shifts in the population mean (Yost et. al., 1982; McBratney et al., 1991). A constant mean within the local area of estimation, as defined by the range of the semivariogram or "local stationarity" (Isaaks and Srivastana, 1989) is generally considered good enough. Strong trends in the data should be removed prior to kriging. This is most often accomplished by fitting a least squares trend surface to the data and subtracting trend surface values from the original data prior to kriging (Isaaks and Srivastana, 1989). Kriging is applied to the residual values and final results are transformed back by adding in the trend values after kriging. Changes in the correlation structure of the data, i.e.: where the semivariogram does not fit equally well to all parts of the field, can create greater problems.

Discrete boundaries on the landscape present the greatest potential problems for kriging soils data. A discrete boundary occurs where one or more soil formative factors changes abruptly. This invariably results in an abrupt change in population mean and in the spatial correlation structure of various soil properties. In essence, the intrinsic hypothesis implies that abrupt or discrete boundaries do not exist in the area to be kriged. While soil survey maps assume the presence of discrete boundaries, kriging assumes such boundaries do not exist. The kriging model treats individual soil properties as continuous variables. It assumes that the mean of each variable is constant within some allowable limits and that the variance-distance relationship behaves in a specified way. Different areas separated by discrete boundaries, if they are different enough, should be treated separately. The trade-off in terms of kriged results is between inaccuracies due to increased edge effects and inaccuracies due to a poor fit of the semivariogram model.

2.3.4. "Goodness of Fit"

As discussed above, accuracy of kriged estimates depend to a large degree on how well the underlying assumptions fit a particular data set. Accuracy also depends on the "goodness" of the computed semivariogram as described by Burgess and Webster (1980a). Goodness here refers both to how well the semivariogram model fits the experimental data and the degree of spatial dependence exhibited by the data. The graph of the experimental semivariogram for some data sets provides a clean fit to a semivariogram model with very little scatter in the data around the plotted line. In other data sets, a graph of the experimental semivariogram results in excessive noise or scatter of the data about any plotted model line. This would be comparable to obtaining a low r -squared value in linear regression. The poorer the fit of the semivariogram model, the less confidence we can have in our kriged results. A poor fit of the semivariogram model might occur

because the data set does not meet one or more of the underlying assumptions or it may be due to poor sampling techniques, inconsistent sample analysis, or some undetermined flaw in the data. A good fit of the semivariogram model increases the confidence we can have in the accuracy of kriged results.

The second part of Burgess and Webster's "goodness" in the semivariogram involves the degree of spatial dependence exhibited by the data. This, in turn, relates to concepts of range and nugget. Figure 2.7 shows a standard semivariogram model for many soil properties.

Semivariance, the measure of difference between sample values, is plotted as a function of separation distance between samples. The range of the semivariogram refers to the distance along the x-axis (separation distance) within which the data exhibit spatial correlation as indicated by the rising portion of the graph. Beyond the range, the semivariogram flattens out at a "sill". At least theoretically, the sill of the semivariogram equals the population variance. Samples spaced further apart than the range do not exhibit any spatial dependence between one another and so their variance equals the overall population variance. These samples are considered to be spatially independent of one another. As stated by Burgess and Webster (1980a), "Points closer together than the range are spatially dependent; points further apart bear no relation to one another, unless there is periodic variation in the soil". Kriged estimates should be based only on sample points within the range shown in the semivariogram. If all sample points for a given variable are located beyond the range of spatial dependence then the data are spatially independent and more traditional statistical procedures are appropriate.

The desirability of basing kriged estimates on sample points within the "range" of spatial dependence often limits the application of kriging techniques at the landscape scales typical of most soil surveys, 1:20,000 or 1:24,000. Spatial correlations for many soil properties are relatively

short. Utilizing this information often requires a more dense sampling than is possible for standard soil survey projects. Trangmar et al. (1987) reported ranges of only 3 to 4 meters for spatial correlations of sand percent, clay percent, and soil pH for highly variable soils in rice fields of the humid tropics. Obviously, if samples needed to be closer than 3 to 4 meters, sample density would have to be many times greater than time or budgets allow for most soil surveys.

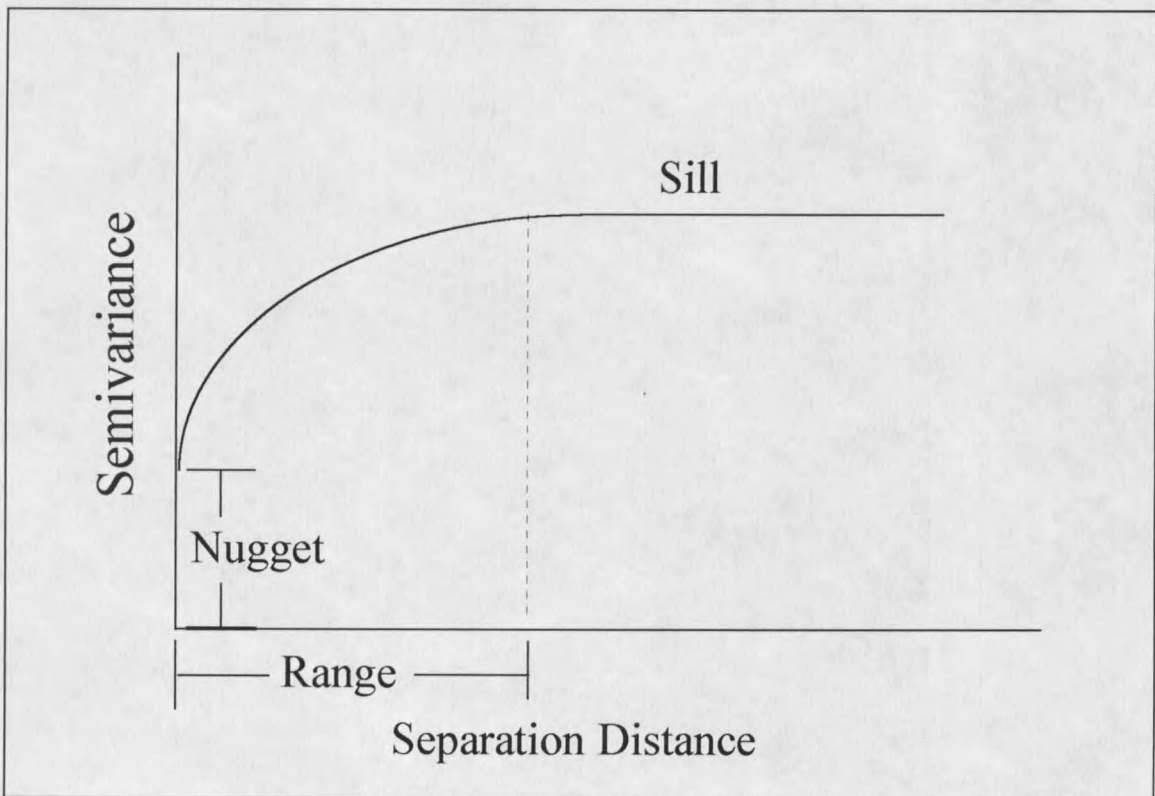


Figure 2.7. Diagram of a standard semivariogram showing concepts of range, sill, and nugget.

Other references in the literature report significantly larger ranges of influence; up to 10 kilometers for surface clay content in New South Wales, Australia (McBratney et al., 1991) and greater than 50 kilometers for selected soil chemical properties of Andepts on the island of Hawaii (Yost et al., 1982). This author's experience (unpublished data) suggests a significant range of spatial correlation up to 50 to 100 meters appears to be a reasonable expectation in field scale

studies for many soil physical properties in Montana. Actual ranges vary according to particular soil property in question and the characteristics of the landscape. These ranges would still require a much greater sampling density than is possible for most soil survey applications.

The nugget effect refers to a discontinuity of the semivariogram at the origin. The semivariance, in the idealized case, would reasonably be expected to equal zero at zero separation distance. Two measurements of the same variable taken at the same location should result in the same sample value. Unfortunately, this does not always hold true for soils data or other measurements taken of natural systems. Measurement errors and short range variations at distances less than the sampling interval result in semivariograms with a nugget effect. The nugget is the y-intercept of the semivariogram when it does not equal zero.

Soils data often exhibit short range variations at distances less than the sampling interval (Webster and Burgess, 1980). These variations show up as large "nugget" effects in corresponding semivariograms, the presence of which results in a large standard error of the estimate (Burgess and Webster, 1980a). Thus, large nugget values for the semivariogram can also reduce our confidence in kriged estimates. In the extreme case of spatially independent data, the semivariogram has only the horizontal line of a sill or "pure" nugget effect. The variable in question might actually be distributed in a spatially independent manner or the distances between sample locations are greater than the range of spatial dependence. In either case, assumptions of data independence can be made for the data set and more standard statistical procedures applied. Kriging estimates in the extreme case of a pure nugget semivariogram should be considered no better than any other local estimates of standard statistical indices.

2.3.5. Scales of Applicability

Many soil mappers and soil survey administrators discount the possible contribution of geostatistics to soil survey, citing short spatial correlation distances and prohibitive sampling densities. A more reasonable approach to soil spatial variability might conclude that spatial variabilities in soils occur at many different scales, dependent on the landscape, the soil property in question, and the degree of refinement with which the soil property is measured. We often refer to local, landscape and regional scales in soil survey. Other terms used, such as: micro, meso, and macro-scales, refer to similar concepts. All are over simplifications to some extent, implying distinct classes of variability. Soil survey generally works at a landscape scale but data can be aggregated to a regional scale depending on the level of detail required. Information at the local scale is either lacking or poorly represented. Geostatistics can in all likelihood be applied at any scale. The major limitation to its application at a landscape scale relates to the fact that the method provides information about the degree of variability at the local scale, i.e.: the "nugget effect". Beckett and Webster (1971) reported that up to one half of the variance in soil properties within a one hectare field may already be present within any one meter squared in it. The same level of soil variability exists at the local level irrespective of the method used to model that variability. We simply choose to ignore it in standard soil survey maps. The difference in scale of applicability between soil survey and geostatistical techniques may at times be more one of perception than reality.

2.3.6. Kriging as a Model

Kriging provides us with a valuable analytical tool for interpolating soils data. Like soil survey maps, kriging results are based on a fairly restrictive set of assumptions about the nature

and distribution of soils. The degree to which these assumptions hold true, largely determines the accuracy of outputs. Goodness of fit in the semivariogram can also effect the quality of interpolated results. As a model, kriging provides very precise estimates of soil properties. When used in conjunction with GIS, additional benefits can be obtained through range modifications in the legend to develop various realizations of results. The kriging model, however, does not take advantage of expert knowledge or understanding to make predictions. The same can be said for all statistically based interpolation techniques. Statistical interpolations are based only on numerical information and so are highly empirical. Even if additional facts are known, they cannot be used unless they can be numerically correlated to the variable being interpolated (Yost et al., 1991).

2.4. Future Directions

Both soil survey and geostatistical approaches have significant limitations with regard to their widespread use in accurately mapping the spatial distribution of soil properties at local scales. Traditional soil mapping techniques cannot be expected to provide precise site specific estimates of soil properties no matter how detailed the work. Geostatistical approaches often require a prohibitive amount of sampling and ignore valuable non-quantitative information. Efforts to improve our ability to map and understand the spatial variability of soils will inevitably focus on improvements to both these methods. The goal should be to combine strengths of both; to bring quantitative preciseness into soil survey methods and to add understanding and expert knowledge to statistical interpolation techniques.

2.4.1. Improvements to Soil Surveys

The strength of soil survey comes from its underlying knowledge base and deterministic approach to modeling the distribution of soils on landscapes. Soil surveys provide valuable soil resource information for the management of land resources. They are designed to be used at a landscape or regional scale. It should not come as a surprise when they are found lacking at site specific scales. It is only when we try to extend soil survey information beyond its original intended purpose that difficulties occur. Attempts to provide site specific estimates of soil properties, to quantify soil spatial variability and to assign confidence limits to map unit compositions all run contrary to the underlying assumptions and methods used to develop standard soil survey maps.

Soil scientists have traditionally lumped soils data into abstract soil classification classes, i.e.: soil series, rather than recording site specific soil attributes at most sample locations. This practice dates back to before the development of electronic databases and geographic information systems. The use of abstract concepts, such as the soil series, was the only means feasible to keep track such large and complex data sets. Applying rigid classification limits inevitably subdivides areas of similar soils that might be defined by a specific combination of soil forming factors. Experience by the author agrees with the comments by Swanson (1990) that because of our taxonomic bias, we often "end up choosing sites for descriptions and transects to fit our predetermined concept of a soil series or we may simply not report or record data for soils that do not fit the series". As a result, the point data soil mappers have collected has not been objective and cannot provide objective estimates of soil attribute variability, data distributions or confidence limits.

Findings reported by Yost et. al. (1991) of reduced sampling variance associated with soil survey measurements realistically apply to all soil survey datasets. Their assertion was correct that samples collected by the SCS (NRCS) were to support the mapping effort and so were selected to identify properties of dominant soil series in the landscape and not to measure all the variability of a specific property over the landscape. This biased sampling makes soil survey data suspect. Uncertainty in reported soil survey values has generally been studied using standard statistical methods based on assumptions of random, independent, and normally distributed samples. Seldom do any of these statistical properties apply to soil measurements (Yost et al., 1991). Of these limitations, the bias in collection of soil survey data, affecting which sample sites are selected and which observations are recorded, represents the greatest obstacle to accurately assessing soil variability within map units and across landscapes.

2.4.1.1. Data Collection and Analysis

Efforts to improve the quality of soil survey data need to start by retraining field soil scientists to select unbiased sample sites, to collect precise soils data and to analyze that data with appropriate techniques. The continued development of NASIS, the National Soil Information System, will provide the database management capability for these changes. In NASIS, each soil series within a map unit is assigned "representative values" (rv's) for all quantitative soil properties. The representative value approximates the central tendency of a soil property, such as: clay content or mollic epipedon thickness, but unlike statistical measures representative values allow for the input of professional experience and judgment in assigning values. All of the representative values for a particular soil concept must fit within the classification and series limits of the soil series used. A significant change has been incorporated in that now the range of

values for soil properties in map unit components can extend beyond both classification and series limits of the soil series used (personal communication - Mike Hansen, Data Set Manager - Northern Rockies MLRA Office). Representative values must still fit within class boundaries but not the range of values for specific soil properties. This represents a loosening of the soil taxonomy paradigm and a definite step in the right direction. While it is a positive step, NASIS alone will not overcome the problems of biased sampling.

2.4.1.2. Soil Survey Mapping

Ideas expressed by Knox (1964) and Swanson (1990) for the use of soil-landscape units and by Gessler (1990) for statistical clustering of landscape variables to define map units offer promising future developments in soil survey mapping. Some of these ideas are already being tested in ongoing soil surveys in Montana. A goal of soil survey should be to move away from the use of "subjective clustering" techniques currently embodied by standard soil survey practices. Map unit concepts, which are already informally linked to soil forming factors, need to have information about local landform, geologic material, vegetation and climate made a formal part of the mapping unit. This will provide significant progress towards improving the quality of soil survey maps. Map unit delineations can then be drawn based on observable patterns of landform, geologic material, plant communities, and patterns on aerial imagery. The distribution of soils within these delineations is then characterized in a concurrent but independent step from drawing map unit boundaries.

These ideas do not represent a radical departure from the way many soil scientists have mapped soils in the past. It does provide a more consistent approach to landscape-based soil mapping and moves soil mapping closer to the concepts of the soil-landscape continuum. The

same or even greater levels of detail in soil maps can be obtained by using soil-landscape units as obtained by a soil taxonomy driven approach. In some instances, areas that were arbitrarily separated in the past based on soil taxonomy and/or limited soil profile observations would be combined in this approach. In other instances, areas that were combined based on taxonomic class may be split into separate landscape-based map units. Representative values for soil components in this approach will be based on actual pedon descriptions and not series concepts.

Additional steps are needed to fully implement a soil-landscape based approach to soil mapping. While all soil profiles can be classified at the family level, hybrids between soil series will need to be recognized as central concepts for map units. These hybrids may overlap the range of characteristics of two or more soil series. Thus, the central concept for a soil component in map unit 'X' may contain soil attributes in common with series 'A' and some in common with series 'B'. The central concept should reflect existing soil conditions, even if existing rules of soil correlation would not allow for creating a third series, separate from the other two. This will largely eliminate the problem of "few fits" and the major cause of biased sampling. Ranges of characteristics for soil components can then be based on available data and the experiential knowledge of soil mappers. These ranges will inevitably overlap soil taxonomy class boundaries as allowed by NASIS. A second requirement will be to complete development of data driven soil interpretations programs that can be run for site specific soil profiles.

2.4.1.3. Advantages

The soil-landscape approach to characterizing soil components offers a number of advantages. First, as stated above, it would eliminate the problem of "few fits" at the series level and would greatly reduce the main cause of biased sampling in soil survey field documentation.

Modal concepts for a map unit would be local, data based and not tied to a modal concept from another location.

Adopting a more formal approach to soil-landscape map unit delineations will create many other advantages. The process of "data snooping", or biasing results based on available sample data, which is inherent in standard soil survey map delineations would be eliminated. Data snooping goes hand in hand with Gessler's (1990) concerns about subjective sampling and the overall concern of biased sampling. Soil-landscape concepts allow for the application of terrain modeling and image analysis techniques to help make landscape partitions; not only as pre-mapping tools but as actual criteria in the production of soil maps. Use of GIS coverages, however, should in no way be mistakenly substituted for field mapping in the production of detailed, order one, order two or even order three, soil survey maps. Less detailed, order 4 or order 5, soil survey maps can be generated directly from GIS coverages as demonstrated by Rodman et al. (1997) in the production of a soil survey for Yellowstone National Park. In either case, map unit concepts can be quantified in terms of landscape elements generated by terrain analysis, i.e.: elevation, slope, aspect, slope profile, slope curvature, contributing area, wetness index, etc., as well as by the more standard climate, landform, parent material and vegetation factors. Future map unit delineations will need to be based on such quantifiable land attributes, and the information on which mapping decisions are made needs to be reported as part of the soil survey report.

Finally, there are significant advantages in sampling strategies that can be applied to formal landscape-based map units. Ten randomly located samples collected from separate delineations of a single map unit may be analyzed as if they were taken along a single transect in one delineation. Statistically such an approach can only be considered valid provided independent

criteria are used to identify and delineate map units from those used to characterize the distribution of soils within map units. This approach is especially needed in rough, broken country where limited access, inability to use mechanical equipment, and rocky soils make soil sampling time consuming and difficult. The same advantages can be applied to easily sampled landscapes as well. Problems of insufficient sample data to characterize map units are greatly increased on rough terrain. They can also occur on easily accessible landscapes. Ambitious plans for using soil sampling transects may be logistically impossible in rough terrain but even on gentle landscapes, questions remain about the representativeness of transects and spatial independence of samples taken along transects. The key sampling issues are obtaining random samples within delineations or within components of those delineations and identifying delineation boundaries independent of sample values.

Aggregating data from many locations based on independently identified map unit delineations has the potential to provide increased sampling efficiency in soil survey data collection. Statistical assumptions of random, unbiased and independent samples can all be met while concerns about non-normal data distributions can be handled analytically by using bootstrap distributions (personnel communication - Dr. Martin Hamilton, Montana State University). The net result would be the ability to use standard statistical procedures to obtain valid descriptive statistics of soil properties within map units, including confidence intervals, without concern for violating the statistical assumptions of procedures used.

2.4.2. Enhanced Quantitative Methods

No matter how advanced standard soil surveys become, they will still have many of the same shortcomings for providing site specific estimates of soil properties. These shortcomings

pose real problems when soil survey maps are input into geographic information systems for use in subsequent spatial analyses. The quality of computer model outputs cannot exceed that of the inputs on which they are based. The same holds true for GIS analysis. The "propagation of errors" in subsequent GIS analyses will ensure that errors from input data layers will be transferred to outputs (Heuvelink et al., 1989). Oftentimes relatively small errors in input data can result in substantial output errors. Extreme care must be taken to insure the quality and accuracy of data layers used in GIS analyses or to at least make users aware of input data limitations and their effect on subsequent analyses. Questions of scale are another important concern.

Use of soil survey data as inputs to other computer models, such as modeling the transport of water or solutes through soils, present many of the problems described above. Model outputs depend on the accuracy of site specific estimates of soil properties or at least on a certain probability that values for selected soil properties fall within specified limits. Many dynamic soil properties, like saturated hydraulic conductivity or soil diffusivity, are not measured directly in soil mapping and can only be approximated from pedotransfer functions of other measured soil properties, yet transport model outputs are sensitive to the accuracy of these inputs. Often from an environmental standpoint, concerns relate more to extremes in the range of soil properties for a map unit rather than to the central tendency or representative value of components. Finke et al. (1996) reported map unit impurities as the primary cause of extreme values in measured levels of water and solute transport through soils that were not predicted in computer simulation models based on representative (modal) profiles. The same limitations apply when standard soil survey data are used as inputs to other soil and environmental modeling efforts.

There will continue to be a growing need for more site specific soils information than can be reasonably obtained by standard soil survey techniques. At the present time, much of the

interest in this area has been related to generating soil maps for site specific farming. Inevitably, the same level of detailed information will be required to address other environmental and land use concerns. While a small country like the Netherlands may be able to use a strategy of intensive random sampling throughout the country to upgrade soil survey maps (Finke et al., 1996), such a comprehensive approach would be prohibitive for most agricultural areas in the United States. Quantitative techniques, like kriging, will increasingly become a part of the complement of tools used by soil mappers in the future. Our strategy today should be to develop methods where the soil surveyor's expert knowledge can be incorporated into quantitative techniques. In essence, to combine the strengths of both soil survey and quantitative approaches (Figure 2.8).

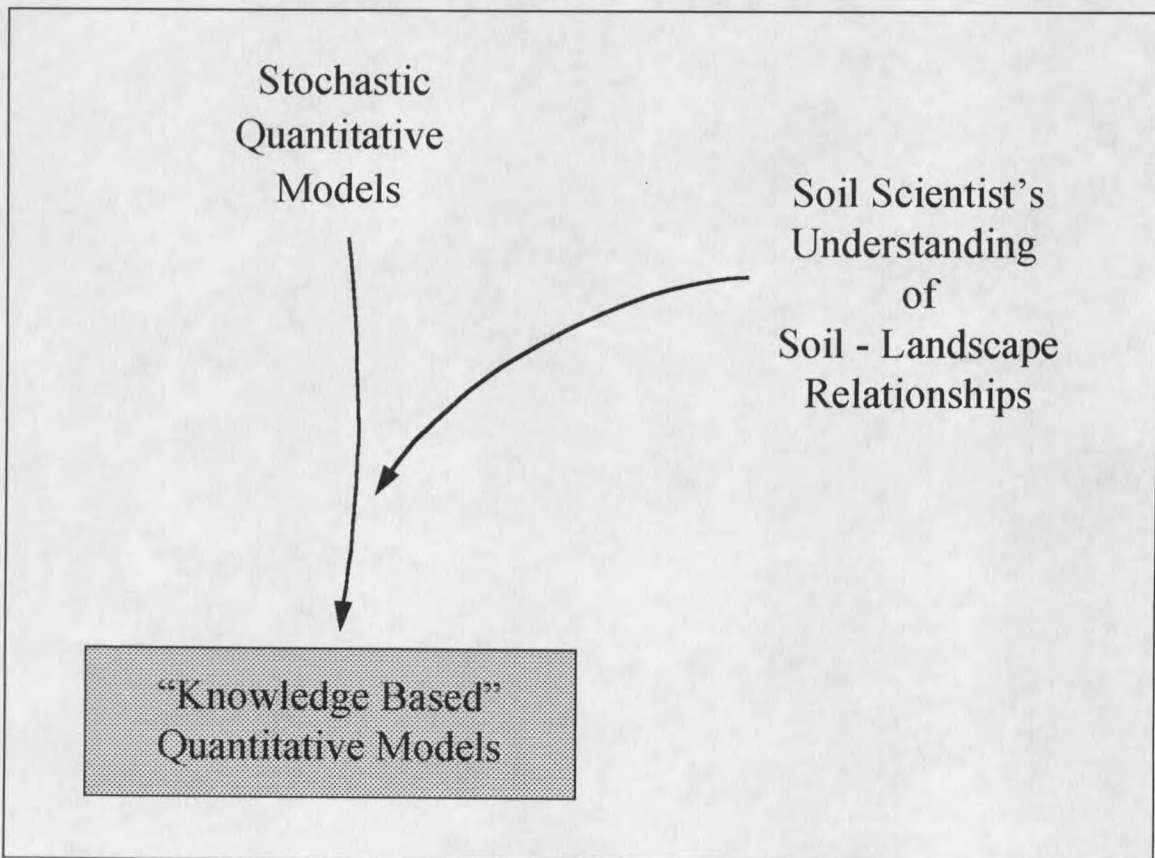


Figure 2.8. Generalized approach to improved estimates of soil properties at unsampled locations.

2.4.2.1. Soil Survey as "Prior" Knowledge

Several approaches have been studied recently that fit within the scope of enhanced quantitative methods for predicting soil properties. The first group includes the use of soil survey information to stratify sample areas into more or less homogeneous areas for geostatistical analysis. Yost et al. (1991) proposed a 3 stage sampling scheme where the first "qualitative phase" would partition the landscape in a manner similar to soil survey maps. This "prior" information would then be used for subsequent sampling and spatial analyses. McBratney et al. (1991) used region partitioning to improve cross-validation results for kriged pH values. Predicted values were only slightly improved by kriging hill and plain regions separately from those obtained by kriging the combined area. The value of splitting the region was partially lost by the creation of additional edge areas which inherently have increased variances (uncertainty) associated with kriged values (McBratney et al., 1991). Soil survey knowledge in both cases was used as prior information for subsequent geostatistical analysis.

In a modification of the above approach, Rogowski and Wolf (1994) used a combination of soil survey and geostatistical techniques to estimate the variability of bulk density and hydraulic conductivity within map unit delineations. This was accomplished by combining separate coverages of soil survey modal values and kriged estimates of soil properties within a GIS. The "predicted" value for each raster cell was the average between the modal and kriged values. While they do achieve a measure of spatial variability within the original map units, there appears to be little gained by averaging "modal" concept values with interpolated data, given that the point data available for each delineation will in most instances provide a more accurate representation of local soils than the use of modal concepts.

2.4.2.2. Application of Terrain and Image Analysis

The second category of enhanced soil prediction methods, relies on the use of digital terrain models and/or digital photogrammetry to predict soil properties at unsampled locations. In this approach, information similar to that used by the soil mapper about terrain attributes or patterns on aerial photographs are encoded into continuous spatial coverages within a GIS. What's often lacking is information needed to combine this wealth of data into meaningful relationships about the distribution of soil properties. Terrain models based on digital elevation data provide a continuous set of terrain attribute data across the landscape. Moore et al. (1993) make the argument that climate generally exerts influence on soil development on a scale larger than the local landscape scale and that differences due to parent materials are most often identified effectively by standard soil survey techniques. They hypothesize, that on a "meso" or landscape scale, information about topographic attributes can be used to predict the spatial variability of soil attributes. Interestingly, the above statement fairly well matches a statement made earlier in this chapter about soil mapping in certain areas of eastern Montana. Presumably, the geologic material would have to be relatively homogeneous within selected land segments and other sources of soil variation such as disturbances by animals or other soil degenerative processes would have to exert limited influence. Moore et al. (1993) quantified relationships between terrain attributes and measured soil properties through a series of regression equations. Thus, knowledge of the relationship between soil and terrain attributes is at least partially imbedded in subsequent interpolation procedures. Wilson et al. (1994) used a similar approach to examine relationships between selected soil properties and both terrain attributes and remotely-sensed spectral data. Use of more appropriate interpolation methods than linear regression would enhance the future applicability of these methods. The general approach, however, of using terrain attributes or

digital imagery to spatially interpolate related soils data appears to have merit. The spatial pattern of predicted values certainly appears more realistic than patterns based on soil survey maps alone. Unfortunately, no independent data sets were available to assess the accuracy of regression results from either of these studies.

Moore et al. (1993) also used terrain attributes to spatially distribute the range of soil survey map unit values for A-horizon thickness and soil pH within delineations. Despite questionable assumptions used regarding the soil survey data, the results obtained were comparable to those from regression analysis. The greatly reduced data requirements of this second approach represents a significant advantage. The method is "highly dependent on obtaining realistic estimates of the range of values of soil attributes" within delineations (Moore et al., 1993) and depends on reasonable estimates of the data distribution within that range. This missing information is often part of the soil mapper's "expert" knowledge used to produce soil survey maps that gets lost upon completion of standard soil surveys (see below: Application of Expert Systems) because it is not saved as part of the final product.

Gessler (1990) used a digital elevation model coupled with digital image processing techniques to partition landscapes in the "driftless region" of Wisconsin. By this approach, he replaced the "subjective clustering" of data inherent in the production of soil survey maps with a more analytical approach. Geostatistical analyses and kriging were then used within a specific delineation to model the thickness of surface loess deposits across the area. Results showed more detailed variations in loess thickness than indicated by standard soil survey maps but at a cost of a much higher sampling density.

Gessler's approach was expanded substantially in a proposed iterative multi-stage plan presented by McSweeney et al. (1994) for modeling soil horizons as a component of a digital

terrain model. Their approach appears extremely elaborate and data intensive from a soil survey point of view but it certainly illustrates the hidden complexity in a seemingly simple goal: to model the distribution of soils across landscapes.

2.4.2.3. Cokriging Approaches

Cokriging represents the geostatistical approach by which information about one variable (soil or otherwise) can be used to enhance predictions of a second variable. The variable or variables used to improve interpolations are generally attributes that can be easily measured or attributes for which there is an abundance of available data. In the ideal situation, information about the supporting variable exists at all locations. Outputs from digital terrain models or digital image analysis provide such continuous variables. The variable to be kriged is generally an attribute that is either more difficult, more time consuming, or more costly to measure. Often there are substantially fewer data points for the second variable. Information about soil properties fall into this second category. Despite initial promise with this technique (McBratney and Webster, 1983; Vauclin et al., 1983), relatively few applications of co-kriging have since been documented in the soil science literature.

McBratney and Webster (1983) first showed how cokriging and supplemental information about sand and clay contents could be used to make improved spatially variable estimates of percent silt. In a separate study, Vauclin et al. (1983) demonstrated that cokriging provided the greatest advantage over kriging and classical regression techniques when the fewest number of known sample points were available for the kriged variables. They used correlated data of percent sand to help make kriging estimates of $1/3$ bar and available ($1/3$ bar - 15 bar) soil water content. Stein et al. (1988) found similar results interpolating data on soil water deficits. Mean high water

table values were used as the cokriging variable. Cokriging outperformed kriging in every instance but the greatest advantage occurred when the number of known sample points for soil water deficit was reduced from 400 to 160.

The degree of correlation between the kriging and the auxiliary or cokriging variable affects results. Yates and Warrick (1987) suggest an absolute correlation value of $r = .5$ as the cutoff for when the additional complexity of cokriging may be justified. Kriging predictions of gravimetric soil water content were effectively improved by cokriging using the strongly correlated auxiliary variable of soil surface temperature while only marginal improvements were made over kriging estimates when the less correlated percent sand data were used as an auxiliary variable.

In all of the above cases, cokriging provided some incremental improvement over kriging. The trade-off is between increased prediction accuracy and the level of computational complexity. Improvements can be made in both the accuracy of interpolated results and the amount of data required for the kriging variable. The level of improvement, however, generally falls short of what would be needed to incorporate these techniques as standard soil modeling procedures. Using combinations of two or more variables to create a separate cokriging variable may offer some additional improvement. Using continuous variables in cokriging, such as terrain model outputs, also offer potential improvements in the applicability of this approach. Overall, the best soil modeling application of cokriging appears to be as an accessory tool to other approaches.

2.4.2.4. Expert Systems

Most of the knowledge and experience used by skilled soil mappers fits more appropriately within the realm of expert systems than linear mathematical models. Clues that enable the soil mapper to locate specific soil types or predict potential soil boundaries are all part of the field soil

scientist's expert knowledge base. This knowledge, on which soil survey is based, can be captured within an expert system for a specific soil survey area and linked with quantitative submodels. Even capturing some of the soil mappers expert knowledge during the production of a soil survey would improve any subsequent quantitative analysis. Currently, most of the underlying knowledge gets lost once the soil survey maps are completed because it is not recorded. Only hints remain of the understanding used to produce soil maps, which are hidden in the maps themselves. Information lost includes: much of the knowledge about soil and vegetation relationships, local topography effects on soil properties, the inherent variability in local geologic materials, and ideas about the range and pattern (distribution) of soil variation within selected map units. Future predictions of soil properties on landscapes could be enhanced through the use of expert systems that would take advantage of this information. The first step in this direction would be to encode much of the soil scientists' expert knowledge for an area as part of the soil survey product.

To date, only limited applications of expert systems have been made in mapping soils. Zhu et al. (1994) used fuzzy set theory and an expert systems approach to predict the distribution of four similar soil types on granitic parent materials in western Montana. Expert systems approaches were also used by Skidmore et al. (1991) and Rodman et al. (1997) to map soils based on information available within geographic information systems. In all these examples, expert systems were used to predict soil classes, either within distinct soil boundaries or within fuzzy boundaries. It would seem to be more beneficial to use expert logic towards predicting specific soil properties rather than soil classes. Keck and Lenneman (1993 - unpublished) provided some preliminary work in this area by developing a prototype expert system to predict the depth to groundwater and suitability for septic systems in Gallatin Valley, Montana, based on landform and

vegetation characteristics of local landscapes. Undoubtedly many other applications of expert system technology to map soil properties will be developed in the future.

2.5. Conclusions

We have just begun to scratch the surface on developing new ways to assess soil spatial variability. New tools like GIS, GPS, and expert systems provide options never before imagined for the inventory and management of land resources. At the same time, increasing demands to produce more food and more fiber and to accommodate more people on limited land resources will continue to stretch our ability to sustainably manage those resources in the future. Intensive land use is the driving force behind the need for more detailed land resource information, including more accurate representations of how spatially variable soil properties are distributed on landscapes. Site specific farming and environmental protection are just two examples where such information is crucial. New challenges abound. Exciting new opportunities will provide fertile ground for the continued development of unexplored ideas in this rapidly changing field.

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CHAPTER 3

NEW SOILS FROM OLD - RECONSTRUCTED MINE SOILS IN EASTERN MONTANA

3.1. Introduction

The total disturbance from coal mining in Montana exceeded 20,000 acres by mid-1991 and continues to grow at a rate of roughly 1200 acres per year (personal communication: Neil Harrington, Montana Department of State Lands). State and federal regulations require coal mining companies to reclaim strip-mined lands to a condition "as good or better" than what existed prior to mining. To ensure adequate reclamation, coal mining companies must post a substantial amount of bond money before the start of mining. All or part of this bond may be forfeited if reclamation does not meet the intent of the law in the view of state regulators. To date, final bond release has not been granted on a single acre of reclaimed strip-mined land in Montana. The increasing acreage of disturbed land and pending final bond release for many existing reclamation areas makes resource assessment of mine soils essential.

Most coal strip-mine reclamation, prior to the late 1970's, involved planting directly into regraded spoils (the geologic material moved from above the coal seam). Since then, salvaging and reapplication of the original soil on top of regraded spoils has become standard practice (Paone et al., 1978). The majority of coal mines in Montana, including the Rosebud Mine in Colstrip, use a two lift system for salvaging soils. Large scrapers lift the topsoil layer first, followed by a subsoil layer. The depth of soil salvaging varies, dependent upon premine soil conditions. When possible, the soil material is directly hauled to a reclamation area for spreading. Direct hauling saves the mining company both

time and handling costs and has added benefits of preserving the viability of seeds, root cuttings, and micro-organisms in the soil.

Soil salvaging and the reclamation process greatly influence the resulting soil resource. Mine soils are uniquely different from original undisturbed soils. Despite their differences, reconstructed mine soils can be described, classified, mapped, and interpreted for potential land use based on standard soil survey procedures.

Most previous studies on mine soils involved soils developing directly in regraded spoils. Schafer et al. (1980), reported that new mine soils developing in spoils at the Rosebud Mine had massive structure throughout, had nearly uniform calcium carbonate concentrations and were rapidly accumulating organic carbon in the upper few inches. Fifty year-old mine soils developed in regraded spoils had structure similar to native soils in the upper 20 inches. Organic carbon levels exceeded those in native soils in the top two inches but were lower than native soils at deeper depths. They estimate thousands of years would be required before carbonate distribution in the mine soils would reach levels comparable to the pre-mining conditions (Schafer et al., 1980). More recent work has examined 4 year-old and 11 year-old reconstructed mine soils in North Dakota (Potter et al., 1988). Mine soils exhibited a higher bulk density, fewer large pores, and a reduced ability to transmit water than native soils.

Several attempts have been made over the years to classify mine soils developing in spoils. Sencindiver in West Virginia first proposed adding a new suborder of "Spolents" to Soil Taxonomy in 1977 (Sencindiver, 1977). The first part of the name refers to soils formed in spoils while the second "ent" portion refers to the order Entisols or young undeveloped soils. Seventeen of 24 mine soil profiles examined in Pennsylvania by Ciolkosz et al. (1985) fit the criteria for Spolents. Indorante and Jansen (1984) proposed a separate mine soil classification system based on a conceptual model of reconstructed

mine soils. They defined the map units using knowledge of premine materials, mining methods, and reclamation practices.

Few attempts have been made to map mine soil resources based on soil classification. Mine soils were mapped at the family level of soil classification at two sites in West Virginia (Thurman and Sencindiver, 1986). Seven different soil family map units were used for an area of only 15 acres, indicating a large degree of variability in mine soil properties. Such detailed mapping would be impractical for all but the most intensive land resource inventories. The objective of this paper is to examine reconstructed mine soils at the Rosebud Mine based on standard soil survey procedures.

3.2. Methods and Materials

Soil studies were conducted at the Rosebud Mine in Colstrip, Montana during the spring and summer of 1988. The large open pit mining operation at Colstrip consists of 5 mining areas. Since the mid-1970's, when the Western Energy Company purchased the mine, coal has been removed and reclamation completed on approximately 4000 acres (personal communication: Bill Schwartzkopf, Western Energy Company). Native landscapes in the region are characterized by steep sandstone ridges separated by gently sloping valleys. Valleys are underlain by softer sandstones, siltstones and some shales. These strata belong to the Tongue River member of the Ft. Union formation which contains some of the most extensive coal reserves in the world (Schafer et al., 1979).

Standard soil survey procedures were used to inventory reconstructed mine soils at the Rosebud Mine. Soil pits were dug at numerous locations and transects used to assess the variability of soil properties across specific areas. Observations of mine soil properties included color, structure, texture, consistence, pH, carbonates, root distribution and the thickness of topsoil and subsoil replacement depths. Mine soils were classified to the subgroup level based on criteria in Soil Taxonomy (Soil Survey

Staff, 1975) and Keys to Soil Taxonomy (Soil Survey Staff, 1990). The suborder classification of Spolents proposed by Sencindiver was incorporated, although this amendment has yet to be accepted into Soil Taxonomy.

State law requires the mining company to collect data on replacement depth, soil texture, soil pH, and electrical conductivity (a measure of soluble salts) for both topsoil and subsoil materials in reclamation. These data, collected at roughly 300-foot intervals, provided additional information for soil mapping.

Mine soils were interpreted based on soil properties for land capability class, wind erodibility group, and range site using technical guides developed by the USDA, Soil Conservation Service and adapted for use in Montana soil surveys.

3.3. Results and Discussion

3.3.1. Soil Properties

Well developed granular soil structure was observed in the topsoil of most reconstructed mine soil profiles. Subsoil structure was often lacking or disrupted. As soil develops over time, individual soil particles aggregate together to form soil structure. The development of structure enhances aeration, water movement and plant root penetration. Much of the native soil structure in reconstructed mine soils has been disrupted or destroyed by heavy equipment used for salvaging and redistribution. Soils with high clay content tend to compact with repeated trafficking by equipment, especially if the material is moist during redistribution (Indorante and Jansen, 1984; McSweeney and Jansen, 1984). The rates of future structure development in reconstructed subsoils should be comparable to those reported by Schafer et al. (1980) for mine soils developing in spoils.

Abundant calcium carbonate (lime) exists in nearly all of the geologic overburden materials at the Rosebud Mine. Over time, carbonates have leached out of the surface horizons of many of the native soils in the area. Carbonates accumulate in subsurface horizons as secondary lime, often at shallow depths in semi-arid climates. In salvaging native soils, the topsoil lift most often mixes calcareous subsoil with non-calcareous surface soils. As a result, the majority of reconstructed mine soils at the Rosebud Mine are calcareous throughout.

Abundant calcium carbonate buffers soil pH at around 8.2. Most of the mine soils at the Rosebud Mine have a limited pH range of 7.6 to 8.4. A pH above 8.4 could indicate potential sodium affected soils. Few instances were encountered where the pH was higher than 8.4. Native soils of the Ft. Union formation are generally free of sodium or salt problems so saline or sodic conditions should not be expected in the mine soils. None of the soil samples analyzed by the Western Energy Company had electrical conductivity levels indicative of saline soil problems whereas only one site sampled in the field exhibited a sealed soil surface characteristic of sodium affected soils.

Native soils at the Rosebud Mine vary in depth to underlying sedimentary rocks. Spoil beneath the replaced soil materials presents less of a barrier to water movement or root growth than the original predisturbance sedimentary rocks. As a result, spoil must be considered as part of the soil profile. The mine soils, although varying in depth of salvaged material over spoil, are uniformly deep as a rooting medium.

Spoil at the Rosebud Mine resembles glacial till as a soil substrate. Both are comprised of relatively dense, unconsolidated geologic material containing many rock fragments. Bulk densities measured in recontoured spoils after reclamation ranged from 1.60 g/cm³ to 1.95 g/cm³ (Keck 1991, unpublished data). Inch per inch, mine soil tends to have less water holding capacity than native soil, due to compaction and limited soil structure. Overall, however, mine soils have greater water holding

capacity than many native soils because plant roots are not restricted by underlying, shallow sedimentary beds.

All soil properties described thus far could occur in any young soil developing in unconsolidated, calcareous material. The major difference between reconstructed mine soils and native soils occurs due to the layering of different soil textures during the reconstruction process. In mixed sedimentary rock formations, like the Ft. Union formation, sandy soils form from sandstones and clayey soils form from shales. Reconstructed mine soils are created from topsoil, subsoil and spoil, that originate from different locations. These materials may come from adjacent salvage strips or widely separate locations in the mining area. As a result, the texture of individual layers can vary substantially from one another with abrupt textural changes between layers. These abrupt changes in soil texture affect water movement through the mine soils and may result in increased lateral flow during wet periods possibly contributing to overland flow and accelerated soil erosion. The overall range of textures is no different in reconstructed mine soils than in native soils from which they were constructed. However, the pattern of abrupt texture changes both vertically and laterally within the reconstructed landscape are significantly different from local undisturbed landscapes.

3.3.2. Soil Classification

Reconstructed mine soils at the Rosebud Mine were classified into 2 soil orders, Entisols and Mollisols. The majority of mine soils fit within the classification of Entisols, young undeveloped soils which lack structure or other soil properties resulting from soil forming processes. Salvaged topsoil for some of the more sandy mine soils was free of calcium carbonate and relatively high in organic matter, causing them to retain a distinctly dark "mollic" surface horizon. The dark surface causes these mine

soils to be classified as Mollisols, indicative of fertile grassland soils. Classifications to the sub-group level are given in Table 3.1.

Table 3.1. Soil mapping legend and associated properties of reconstructed mine soils at the Rosebud Mine, Colstrip MT.

Symbol	Soil Classification	Depth to Spoil (in)	Range Site	Slope Group (%)	Wind Erod. Hazard	Capability Class
20A	Aridic Ustispolent	20-40	silty	1-3	high	4e#
20B	Aridic Ustispolent	20-40	silty	3-8	high	4e
20C	Aridic Ustispolent	20-40	silty	8-15	high	4e
20D	Aridic Ustispolent	20-40	thin silty	15-20	high	6e
24A	Aridic Ustispolent	20-40	sandy	1-3	high	4e
24B	Aridic Ustispolent	20-40	sandy	3-8	high	4e
24C	Aridic Ustispolent	20-40	sandy	8-15	high	4e
24D	Aridic Ustispolent	20-40	thin sandy	15-20	high	6e
31A	Aridic (Spolic*) Haploboroll	20-40	sandy	1-3	high	4e
31B	Aridic (Spolic) Haploboroll	20-40	sandy	3-8	high	4e
31C	Aridic (Spolic) Haploboroll	20-40	sandy	8-15	high	4e
31D	Aridic (Spolic) Haploboroll	20-40	thin sandy	15-20	high	6e
54A	Aridic Ustispolent	<20	sandy	1-3	high	4e
54B	Aridic Ustispolent	<20	sandy	3-8	high	4e
54C	Aridic Ustispolent	<20	sandy	8-15	high	4e
54D	Aridic Ustispolent	<20	thin sandy	15-20	high	6e
57B	Aridic Ustispolent	<20	silty	3-8	high	4e
57C	Aridic Ustispolent	<20	silty	8-15	high	4e
57D	Aridic Ustispolent	<20	thin silty	15-20	high	6e

All range sites are for the 10-14 inch precipitation zone of the eastern sedimentary plains.

Capability classes with an 'e' indicate soil erosion potential as the major limiting factor for crop production.

* Proposed addition to soil taxonomy of a 'Spolic' subgroup, identifying the manmade nature of these soils.

3.3.3. Soil Mapping

Soils form in native landscapes in response to the combined influences of geologic parent material, topography, climate, biota, and time (Jenny, 1941). These soil forming factors create patterns of soils occurring systematically across landscapes. Such patterns are used by soil scientists to map soil types on a landscape based on observations from relatively few sample pits. Reconstructed mine soils are, by comparison, manufactured. The placement of different materials depends not on natural

processes but on the details of a mine plan and the availability of material. Thus, the distribution of soil properties in mine soils cannot be predicted by "reading" the landscape. Mapping mine soils based on sampling alone would be a long and tedious task.

Mine soil data collected after reclamation by the mining company compensated for the lack of landscape predictability by providing a predictor of soil properties. Mapping the reconstructed mine soils was accomplished through a combination of field sampling and interpretation of existing data. The criteria used for differentiating map units included surface textures, slope classes, depth of soil material over spoil, and the presence or absence of a dark mollic surface. Approximately 2,000 acres of reconstructed mine soils were mapped employing this methodology. Figure 3.1 shows the soil map for the Area 'A' reclamation site. Map unit symbols are comprised of a base number indicating a soil type followed by a letter identifying the slope class. As in all soil surveys, soils in certain areas consistently fit within a single class while other areas may exhibit a substantial amount of variability within map units.

3.3.4. Soil Interpretations

Classifying and mapping mine soils is of limited value unless resulting soil classes can be translated to information about the suitability of mine soils for supporting various land uses. Soil interpretation refers to rating soils for their ability to support specific land uses. Criteria used to separate soil map units were based on soil factors that directly affect the potential use and management of the mine soil resource.

All of the mine soils at the Rosebud Mine were rated as having a high wind erosion potential based on criteria established for Wind Erodibility Groups in Montana (Soil Survey Staff, 1983). A soil's potential for wind erosion is determined largely by properties of the soil surface. Sandy loam surface

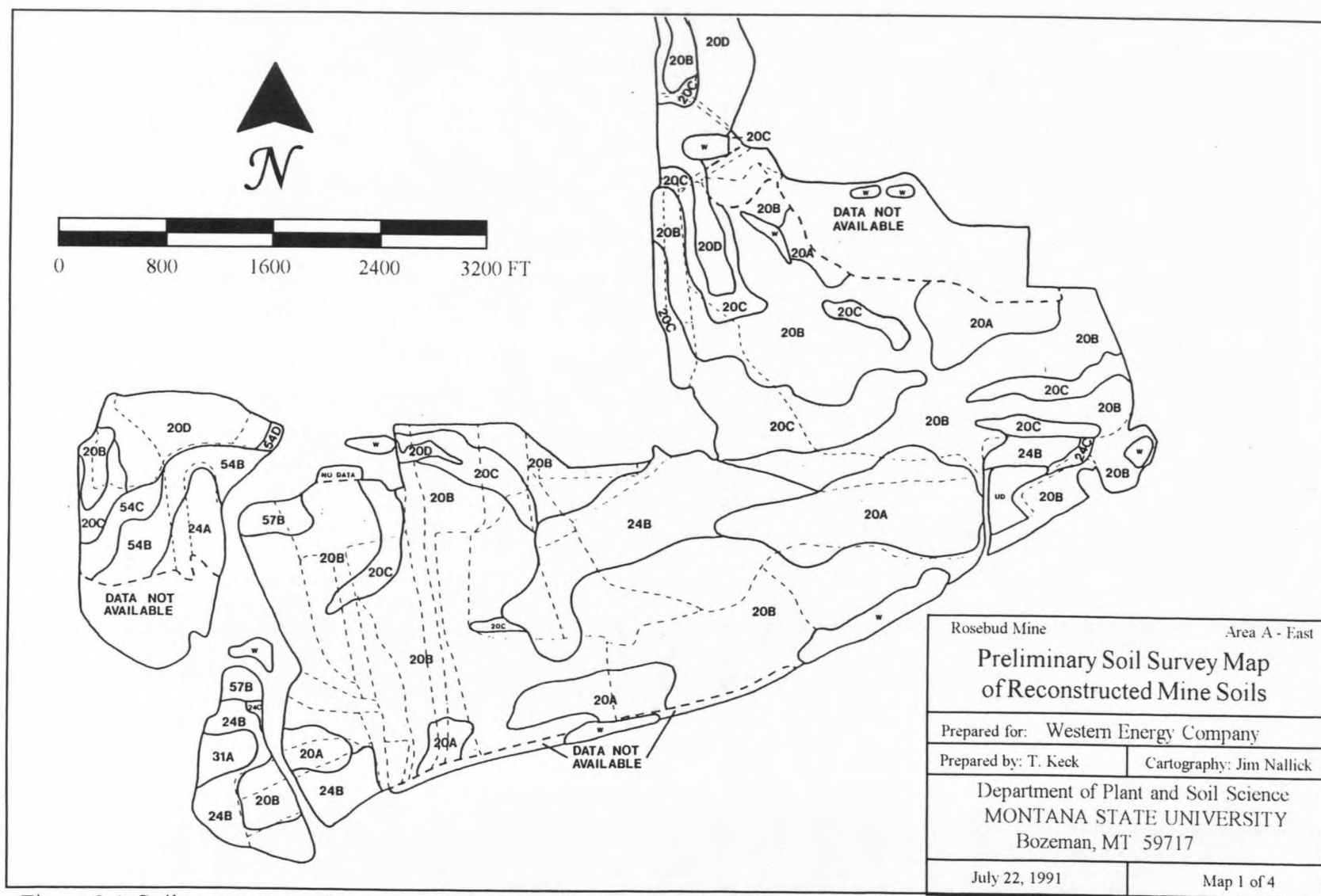


Figure 3.1 Soil survey map of reconstructed mine soils at the Rosebud Mine near Colstrip, Montana.

textures or high amounts of calcium carbonate in the surface result in high potentials for wind erosion. One or the other of these conditions exist in all of the reconstructed mine soils at the Rosebud Mine.

The land capability classification system rates lands for cropland suitability on a 1 to 8 scale (Soil Survey Staff, 1988). Prime agricultural lands fall within capability class 1 or 2. The best non-irrigated cropland in Montana rates as capability class 3 due to climate limitations. Higher capability classes have increasingly greater limitations to crop production.

Most of the reconstructed mine soils at the Rosebud Mine fit capability class 4 (Fig. 3.2). High wind erosion potential is the major limiting factor. Capability class 4 indicates lands suitable for cropping but with significant limitations which must be overcome for sustainable crop production. In the case of mine soils, conservation tillage should be a prerequisite for cropping.

Slopes greater than 15% caused some reclaimed areas to be rated capability class 6. State law restricts the maximum allowable slope steepness for coal mine reclamation to 20%, except under special permit. Map units with a slope class of 'D' indicate slopes of 15 to 20 percent and are rated as capability class 6. These units make up a relatively small portion of the reclamation. Figure 3.2 shows the proportion of mine soils by land capability class for Area A and Area B, respectively.

Range sites identify "complexes of soil and climate that have the capability of producing consistent quantities and/or species of climax vegetation" (Ross and Hunter, 1976). Range sites are defined based upon soil properties, precipitation zone and geographic location. Surface textures and slope classes determined the range sites for mine soils at the Rosebud Mine. This was due, in part, because other soil properties did not limit plant-available soil moisture and because areas of excess soil moisture, such as subirrigated soils, do not occur in the reclaimed areas.

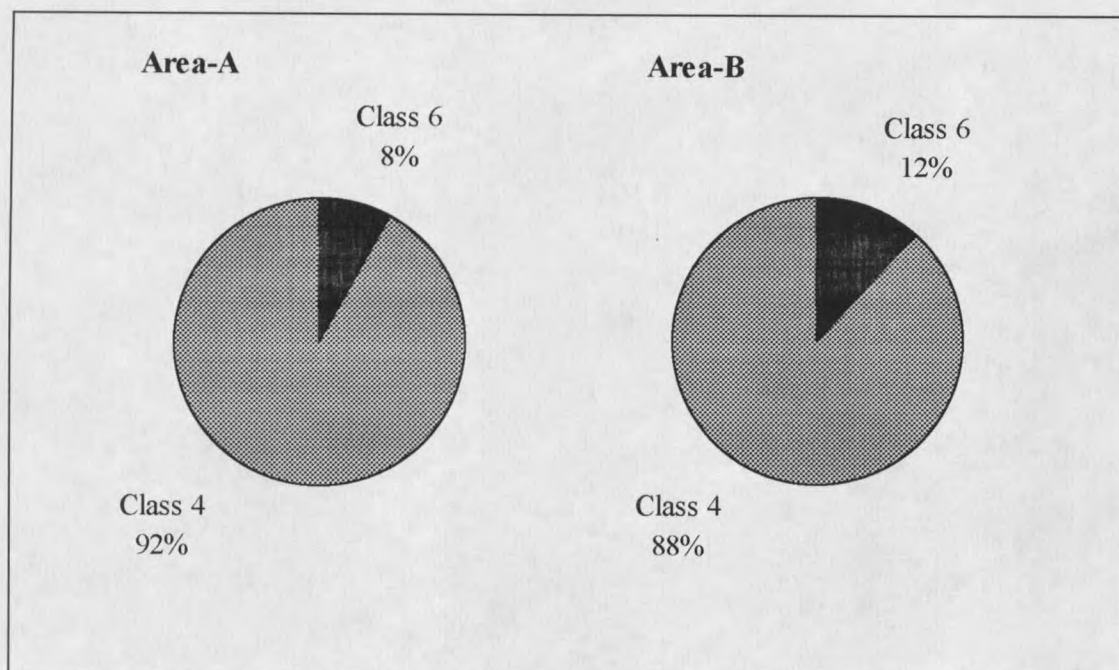


Figure 3.2. Proportion of land capability classes for reclamation areas A and B.

Mine soils with sandy loam surface textures fit the criteria for a sandy range site in the 10-14" precipitation zone of Montana's eastern sedimentary plains. Loam, clay loam and silt loam surface textures result in a silty range site. Slopes greater than 15% change the range site designations to thin sandy and thin silty, respectively. Figure 3.3 shows the proportion of each range site in Area A and Area B, while Table 3.2 lists the predominant plant species and production estimates for the range sites based on USDA, Soil Conservation Service technical guides. In 1991, measured postmine rangeland production for Area A varied from 1,563.5 lbs./acre to 1,879.2 lbs./acre (IMSINC, 1992). These figures compare favorably with the production estimates given range sites in native landscapes under good to excellent range condition (Table 3.2).

Table 3.2. Predominant plant species and estimated production under good to excellent range condition for selected native soils in the Colstrip area.

Site	Soil	Predominant Plants	Production lbs./acre*
Silty	Yamac loam	Western wheatgrass Bluebunch wheatgrass Green needlegrass	2,000-1,000
Thin silty	Delpoint loam	Little bluestem Western wheatgrass Needle and thread Bluebunch wheatgrass	1,400-500
Sandy	Busby sandy loam	Needle and Thread Prairie sandreed Little bluestem	1,800-1,200
Thin sandy	Twilight sandy loam	Needle and Thread Prairie sandreed Little bluestem	1,300-800

* Ranges in values reflect differences in herbage production between years of favorable and unfavorable weather conditions for plant growth. ** Data obtained from the USDA Soil Conservation Service in Montana.

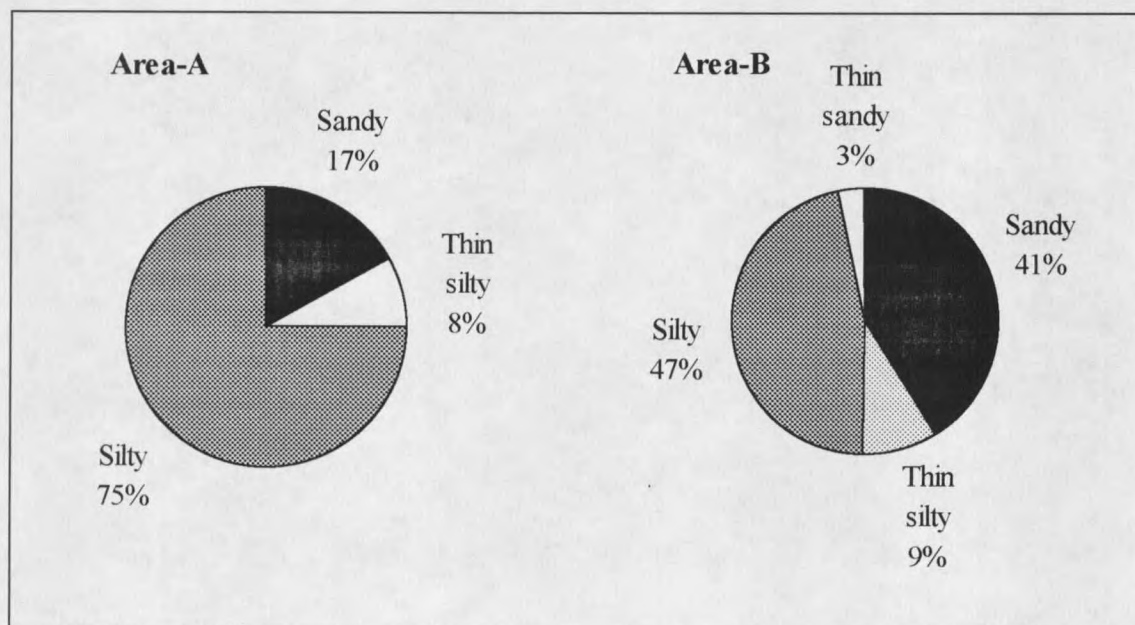


Figure 3.3. Proportion of range site classes for reclamation areas A and B.

3.4. Conclusions

Reconstructed mine soils are uniquely different from their native counterparts. Yet, mine soils share many common features with undisturbed soils and can be described, classified, mapped and interpreted following standard soil survey procedures. Mine soil properties reflect both original geologic parent materials and the reclamation process. They provide a uniformly deep substrate for plant roots with oftentimes greater water holding capacity than the original native soils. These soil conditions appear ideally suited for rangeland production of cool season grasses. Uniformity in the soil resource, texture variations notwithstanding, may make it difficult to reestablish the diverse plant communities which occur on more variable native landscapes. Mine soils may be used to a limited extent for growing hay or small grains. High wind erosion hazards limits even the best mine soils at the Rosebud Mine to land capability class 4. These soils are suitable for cropping if provisions are made to maintain vegetative cover for controlling wind erosion.

Reconstructed mine soils at the Rosebud Mine provide a unique land resource that appears ideally suited for range production of cool season grasses. This resource will become increasingly valuable in the future as grazing lands, wildlife habitat, and recreation areas. With time, soils may develop comparable to those existing in glaciated areas in northern Montana, but they will always remain different from surrounding native areas of the unglaciated sedimentary plains. Future plant communities developing on mine soils will reflect these differences as plants best adapted to the newly created conditions outcompete those less suited.

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CHAPTER 4

SPATIAL DISTRIBUTION OF SOIL ATTRIBUTES ON RECONSTRUCTED MINE SOILS

4.1. Abstract

Mining companies and regulatory agencies need clearly defined methods by which sample data of reconstructed mine soils can be interpolated to determine the spatial distribution and suitability of mine soils for reclamation. Objectives of this study were to model spatial distributions of mine soil attributes across reconstructed landscapes at the Rosebud Mine in southeast Montana based on existing sample data and to show the use of appropriate statistical procedures to account for possible spatial dependence in the data. Mine soils at the Rosebud Mine have been routinely sampled in an irregular pattern of 100 m sample intervals. The combined replacement depth of topsoil and subsoil material determined the depth of sampling. Western Energy Company analyzed topsoil and subsoil materials separately for replacement depth, soil texture, soil pH, and electrical conductivity. Mine soil attributes in all cases were spatially independent at the 100 meter sample spacing. Four soil attributes, topsoil percent clay, topsoil pH, subsoil electrical conductivity, and subsoil replacement depth were used to describe the spatial relationships found in the mine soil data. Application of kriging techniques to interpolate between data points was deemed unnecessary due to the uncorrelated nature of the data and lack of reasonable fit of any semivariograms. Trend surface analysis was used instead, as appropriate for the data. For topsoil percent clay, topsoil pH and subsoil electrical conductivity, a constant

surface through the overall mean was the best prediction of these properties at any unsampled location. A quadratic surface was fit to replacement depth data which exhibited a trend across the reconstructed landscape. This data set provides an example of how geostatistical techniques can be used to search for spatial dependence in data. In the absence of spatial dependence more traditional statistical techniques that rely on independent data assumptions can be used such as regression techniques.

4.2. Background

Colstrip, located in southeastern Montana, has a long history of open pit coal mining. In the 1920's, Northwestern Improvement Company mined coal in the area for the Northern Pacific Railroad (Schafer et al., 1979). Mining activity has been more or less continuous during the intervening years but accelerated in the mid-1970's, when Western Energy Company (WECO) purchased the Rosebud Mine. Since then, WECO has removed coal and completed reclamation on approximately 1,600 ha of land. The current rate of surface disturbance is 120 to 160 ha annually. Western Energy follows a reclamation strategy of using scrapers to salvage soil in two lifts, topsoil and subsoil, and then, to the extent possible, directly hauls the salvaged material to the other side of the pit where it is laid down over regraded spoils. The resulting soil resource has many properties inherited from the original undisturbed soils yet has some unique properties associated with the reconstruction process.

Native landscapes in the Colstrip area are characterized by steep sandstone ridges often capped by hard, erosion resistant, scoria. Ridges are separated by gently sloping valleys formed in softer sandstones and siltstones with some shales. All of these strata belong to the Tongue River member of the Fort Union Formation. This formation contains some of the most extensive coal

reserves in the world (Schafer et al., 1979). Native soils in the area vary in relation to differences in topography and geologic parent material. Topographic differences affect degree of soil development and soil depth while variations in soil texture relate almost exclusively to differences in geologic parent material. Abundant calcium carbonate is present in nearly all parent materials and soils. Most native soils in the area are classified as Aridic Ustochrepts, Aridic Ustorthents or Aridic Haploborolls.

4.3. Literature Review

Previous studies at the Rosebud Mine examined soil genesis (Schafer et al., 1979) and the spatial variability (Schafer, 1979) of pre-soil salvage mine soils developing in older spoil materials. No studies had been conducted on the younger reconstructed mine soils. Reconstructed mine soils have several properties that are uniquely different from both the older mine soils developing in spoils and the native soils in the area. Soil salvaging in two lifts results in mine soils made up of topsoil and subsoil material that originated from different sites, usually adjacent strips. This method of salvaging often results in abrupt texture differences between the topsoil and subsoil material due to the nature of mixed sedimentary parent materials. The range of textures found in the minesoils is no greater than their native counterparts, but the distribution of texture classes tends to be more mixed up both vertically in minesoil profiles and laterally across the reconstructed landscapes.

Reconstructed mine soils are more homogeneous than the native soils in other ways. They are uniformly deep as a rooting medium yet variable in the thickness of topsoil and subsoil laid down over spoil. Spoil material is not consolidated enough to act as a paralithic contact. Both roots and water penetrate readily into the spoil. Soil salvaging with scrapers destroys much of the

native soil's original structure and may result in compaction problems when materials are handled wet (McSweeney and Jansen, 1984). Calcium carbonates get mixed into both the topsoil and subsoil salvage lifts. Mine soils, as a result, are calcareous throughout and have little residual soil structure. They vary in the amount of soluble salts they contain and to a lesser degree in their pH.

There is a need to establish methodology by which soil sample data can be interpolated to assess spatial distribution and reclamation adequacy of mine soils on the reconstructed landscapes. State regulators use data on post-mining soil attributes to ensure that all reclaimed areas meet established soil suitability criteria and that adequate soil replacement depths have been maintained. If unsuitable material is encountered, then some mapping scheme is required to determine the extent of unsuitable areas. Reclamation at the Rosebud Mine has generally been viewed as a success based on the observed production of cool season grasses and forbs. Production measurements in 1991 ranged from 88.4 g m^{-2} to 126.6 g m^{-2} (IMS INC report to Western Energy Company, 1992, Rosebud County Soil Conservation Service Office). These production figures compare favorably with Soil Conservation Service production estimates for the best upland native soils in the region (Rosebud County Soil Survey, Rosebud County Soil Conservation Service Office). Yet, questions remain about the apparent lack of vegetational diversity and adequacy of the reclaimed soil resource to sustain future development of native plant communities. Final bond release has not been sought on any of the reclaimed land. This is due, in part, to the lack of a quantifiable set of criteria by which revegetation success can be measured for final bond release. Criteria for revegetation success could be based on establishment of suitable species best adapted to the newly created soil resource, or the reclamation process could be altered to provide soil conditions more suitable to a wider variety of plant species. In either case, some interpolation scheme is needed to provide site specific estimates of soil attributes over the region of interest.

Many different interpolation methodologies are available, including distance weighting, spline fitting, least squares methods, Gauss-Markov techniques, and geostatistics. Cressie (1987a) and Laslett et al. (1987) provide comparative studies of these techniques. Geostatistical and least squares methods offer an advantage in providing an estimate of interpolation error. The geostatistical interpolation method is referred to as kriging (Burgess and Webster, 1980) and the least squares method is referred to as trend surface analysis (Cliff and Ord, 1981). A discussion of the theory and implementation of these methods is beyond the scope of this paper. Discussions of kriging have been reported by Journel and Huijbregts (1978), Burgess and Webster (1980), and Cressie (1989a, b); similarly, trend surface analysis has been discussed by Cliff and Ord (1981) and Ripley (1981).

Spatial models and procedures are a relatively recent addition to statistics and soil science literature. Soil scientists who collect and map spatial data should take advantage of procedures that indicate when there is dependence between measurements at different locations. Analysis of semivariograms (Burgess and Webster, 1980) is the procedure used to establish the degree of spatial dependence present in data. If data behave dependently, then kriging would be the preferred method of interpolation for mapping. If data behave independently, then trend surface analysis may be the preferred method. The primary objectives of this research were to model spatial distribution of mine soil properties as they vary across reconstructed landscapes at the Rosebud Mine based on existing sample data and to show the use of appropriate statistical procedures to account for possible spatial dependence in the data.

4.4. Methods and Materials

Montana state law requires that for partial bond release coal mining companies collect soil replacement depth, texture, pH, and electrical conductivity data on reconstructed minesoils. Our statistical analyses were based on data collected by Western Energy's reclamation staff at the Rosebud Mine near Colstrip in southeastern Montana. We chose as a study site a contiguous area of approximately 120 ha of reclaimed land in the Area B portion of the mine. Reclamation at this site spanned a sequence of years from 1978 to 1984 forming a patchwork of reclaimed fields which collectively make up the larger area of reclamation. Samples were taken at approximate 100 m sample spacings along transects through the individual fields. A total of 55 sites were sampled in the study area (Fig. 4.1). Replacement depths were measured based on distinctive differences in color among the three materials: topsoil-brown, subsoil-light gray, spoil-dark gray. Topsoil and subsoil samples were treated separately at each site. The depth of soil replacement determined the depth of sampling. No samples of spoil material were collected. Analyses for soil texture, pH, and electrical conductivity were completed at Western Energy's reclamation soils laboratory. The Bouyoucos hydrometer method (Bouyoucos, 1962) was used for mechanical analysis of soil texture. The pH levels were measured with a pH meter from saturation extracts, and electrical conductivities were measured for the same extract, using a conductivity bridge. Discussion in this paper is restricted to four soil attributes: topsoil percent clay (%), topsoil pH, subsoil electrical conductivity, and subsoil replacement depth (cm). These four attributes represent the full range of spatial dependence exhibited by the minesoil data.

Data were plotted using the PC based program Surfer (Golden Software Inc., 1990). No assessment of the accuracy of interpolations was determined for these plots. They were intended

only to give a graphic representation of what the data looked like in 3-dimensional space.

Semivariogram analyses were completed for each attribute. Electrical conductivity (EC) data were log-transformed prior to semivariogram analysis while the rest of the data exhibited sufficiently symmetrical distributions that other transformations were not necessary. Semivariogram analyses were done using GEOSTAT (Knudsen, 1984) on an IBM 386 PC.

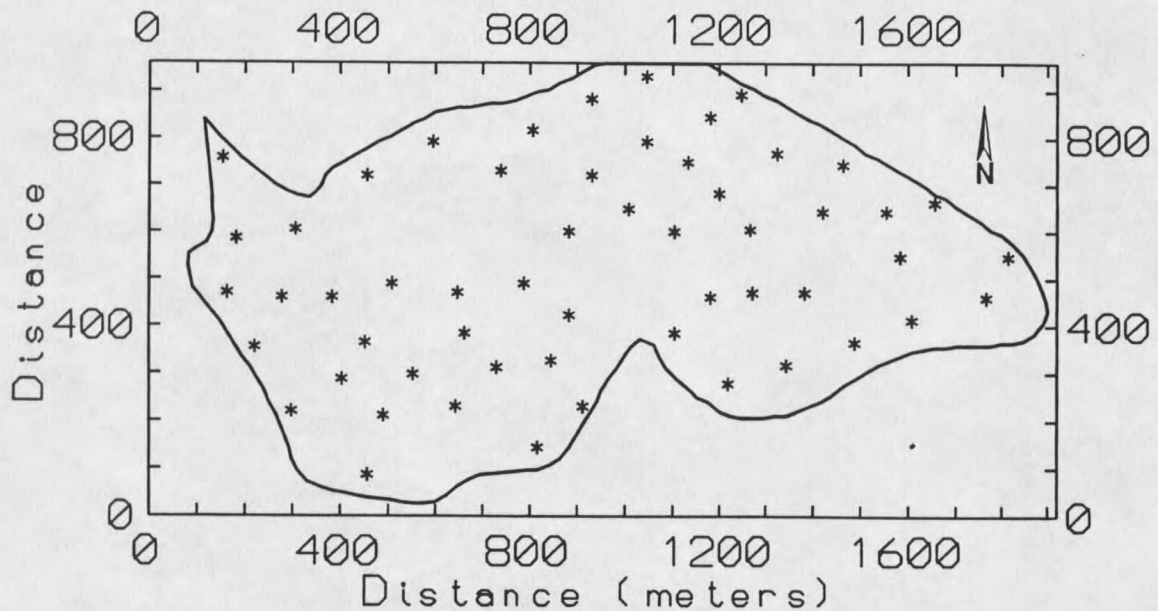


Figure 4.1. Locations of sample points within the Area-B study site.

We used trend surface analysis to interpolate the minesoil data instead of kriging, based on results of the experimental semivariograms and knowledge of the original soil resource and reclamation process. Trend surfaces were analyzed for each soil attribute, using successive reduced model tests of linear regressions. By this method, a three-dimensional surface was fit to the data. Trend surfaces were plotted using the Surfer program.

4.5. Results and Discussion

4.5.1. Assessment of Spatial Correlations

Summary statistics for the mine soil attributes are presented in Table 4.1. All soil attributes were spatially independent at the 100 m sample spacing used at the mine, meaning the data were not spatially correlated. This was true for directional and non-directional semivariograms. The data exhibited a substantial amount of "noise" or random variation about the sill of the semivariograms in all cases and showed no apparent range of influence (Figs. 4.2 and 4.3). Semivariograms of replacement depths indicated a trend in the data associated with a rising sill height at increased separation distances. Three-dimensional plots substantiated this (Fig. 4.4). Topsoil clay content, topsoil pH, and subsoil electrical conductivity showed no trends in the data. They did show a seemingly random pattern of interspersed high and low values. The plot of subsoil replacement depth, in contrast, had interspersed high and low values but also showed a noticeable trend of deeper soil replacement in the southwest direction.

Table 4.1. Summary statistics for mine soil attributes at the Area-B study site, Colstrip, MT.

	<u>Topsoil</u>		<u>Subsoil</u>	
	Clay content	pH	Replacement depth	Electrical conductivity
	%		cm	S/m
Mean	20.3	7.6	43.9	0.054
Median	18.0	7.7	34.0	0.040
Variance	41.3	0.035	552.1	0.016
25th quartile	15.5	7.6	27.0	0.040
75th quartile	26.0	7.7	236.2	0.050
Range (min.-max.)	6-32	7.0-8.0	12-101	0.03-0.26

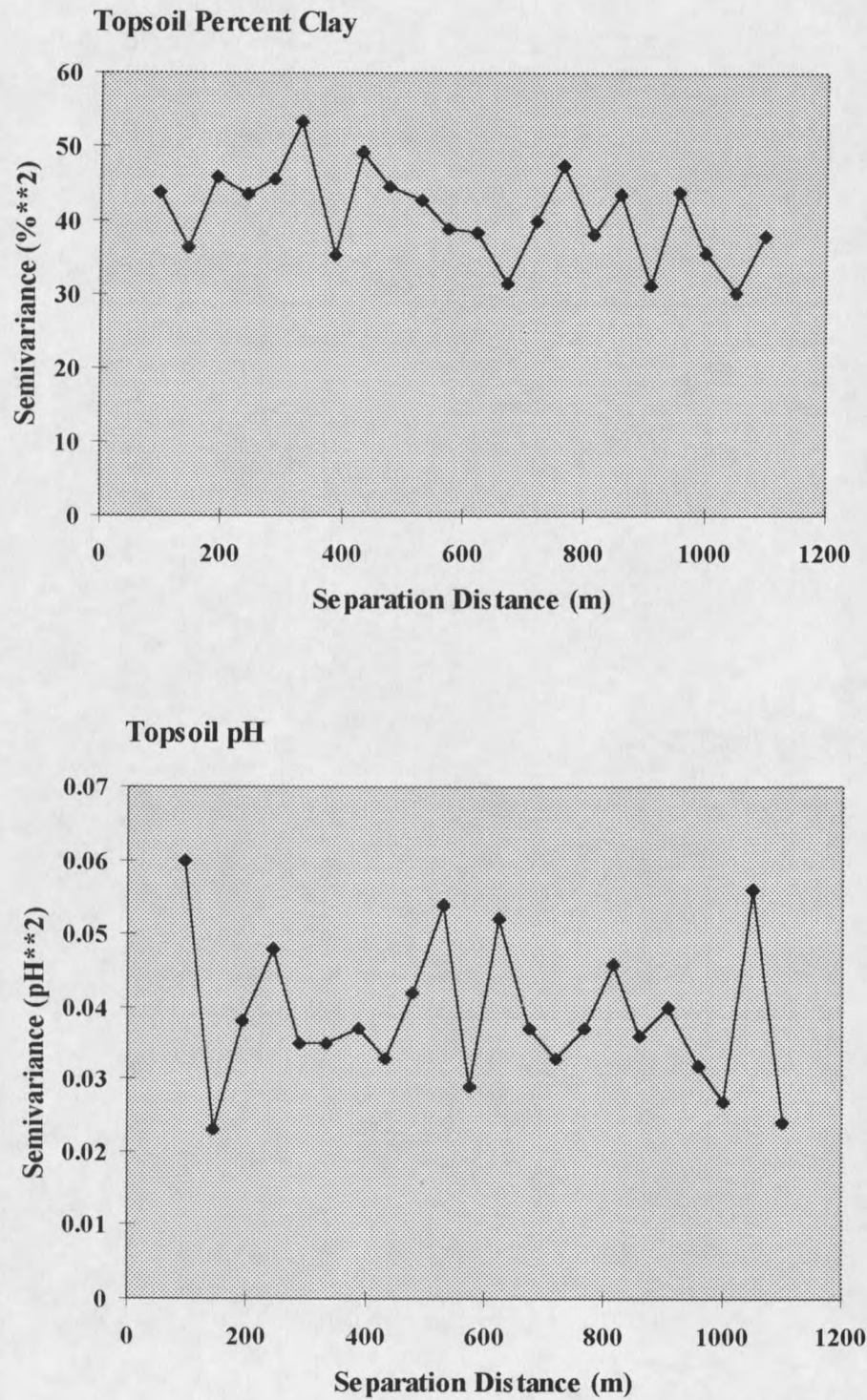


Figure 4.2. Experimental semivariograms for topsoil percent clay (top) and topsoil pH (bottom).

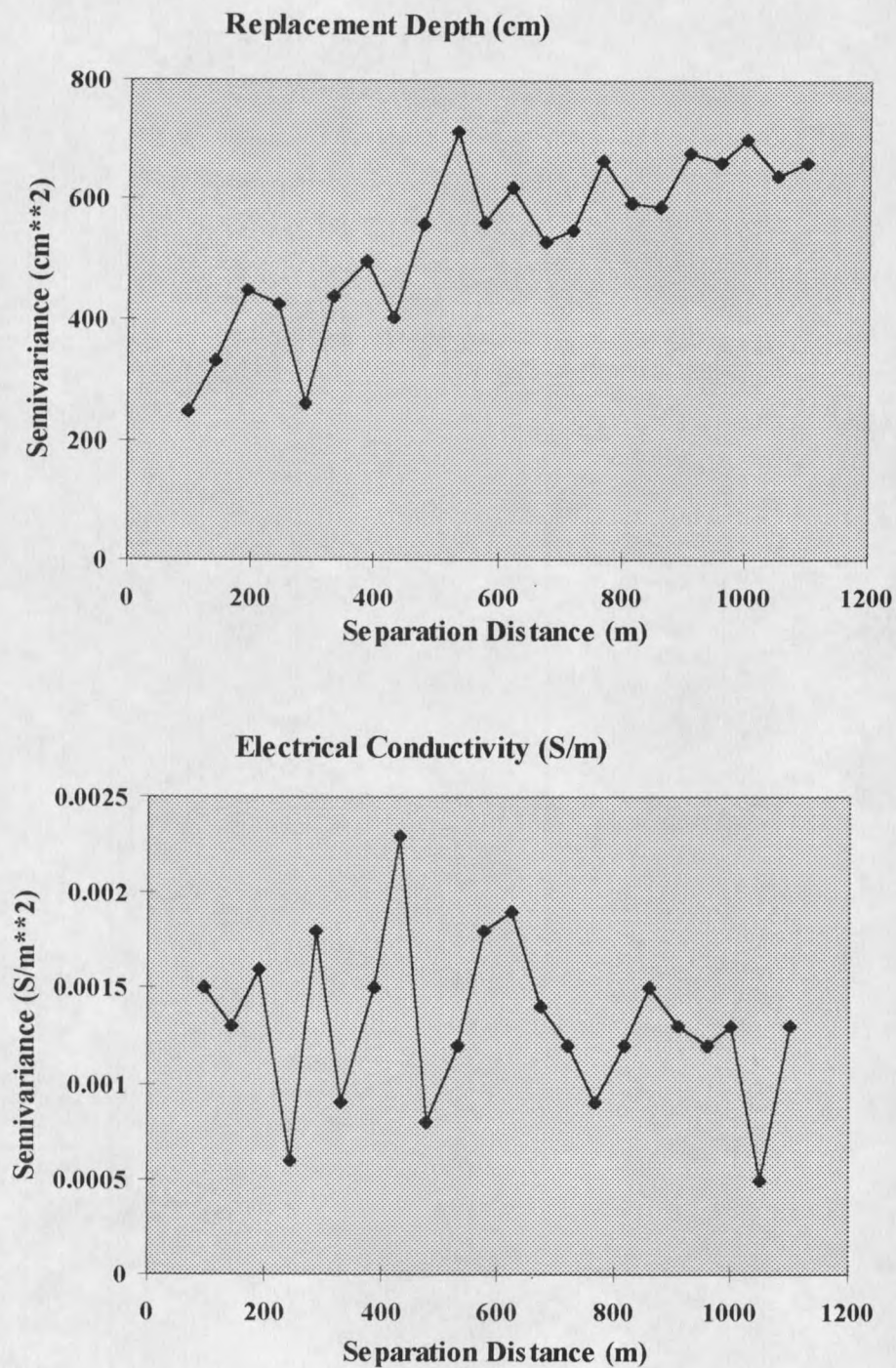


Figure 4.3. Experimental semivariograms for subsoil replacement depths (top) and subsoil electrical conductivity (bottom).

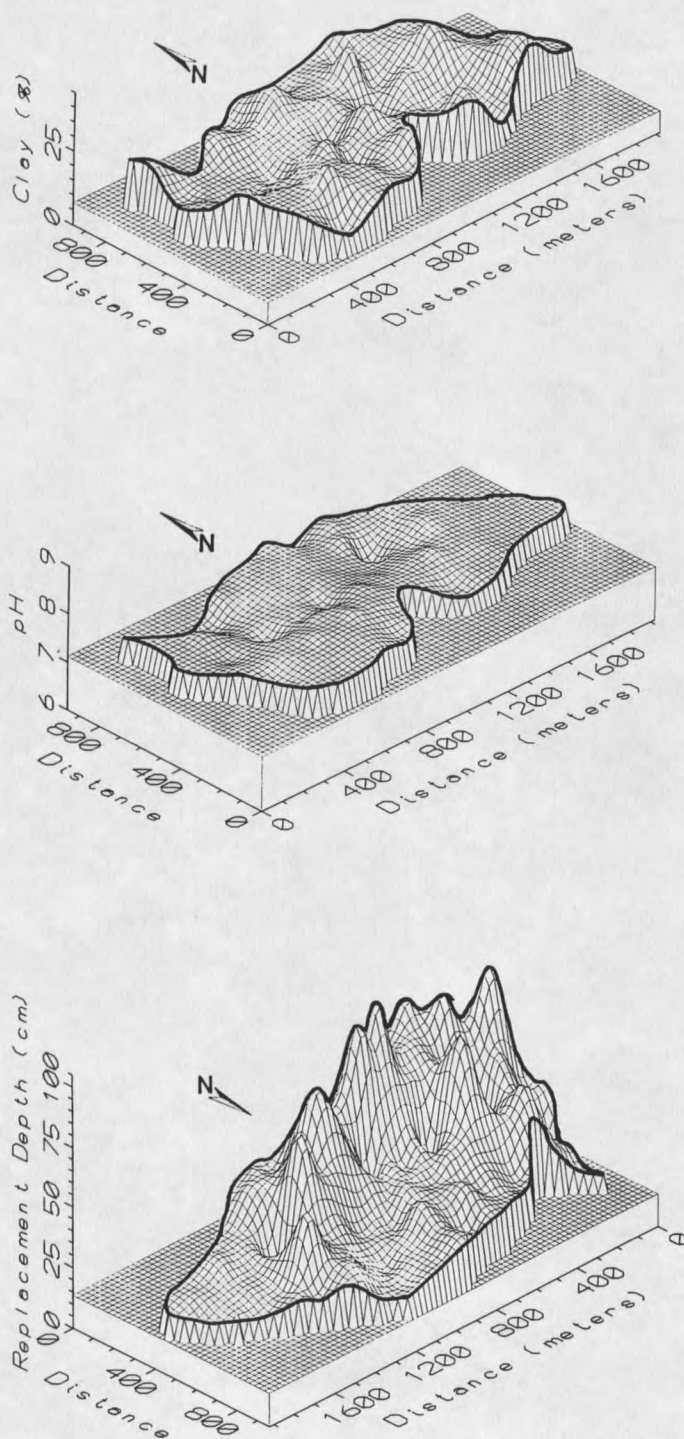


Figure 4.4. Data plots for: (A) topsoil percent clay, (B) topsoil pH, and (C) subsoil replacement depth. X and Y axes have been rotated 180° for Fig. 3C to display the data surface.

Large nugget effects or short range variations are typical in soils data (Webster and Burgess, 1980), even without disturbance. Stripping and laydown operations in mixed sedimentary parent materials often result in placement of dissimilar materials side by side or on top of one another. Variable soil conditions of pre-mined sites get further mixed during reclamation. Variations in reconstructed mine soil attributes, such as texture, pH and electrical conductivity, all occur within distances shorter than 100 m. A greater density of samples would be required if the goal were to use spatial correlation to improve interpolation estimates between samples.

Application of kriging techniques to interpolate between data points was deemed unwarranted for this mine soil data because of spatial independence between sample points and lack of reasonable fit of any semivariogram models to the experimental semivariograms (Figs. 4.2 and 4.3). Reclamation at the study site consists of a mosaic of individual reclaimed fields which together make up the larger area of reclamation. Source materials for different fields, reclaimed in different years, may have originated for widely separate salvage areas at the mine. Given the nature of mixed sedimentary rock parent material, field boundaries may have contrasting materials set side by side resulting in large semivariances at extremely short separation distances. Adjacent laydown strips within individual fields can also have contrasting materials. The discrete nature of individual reclamation fields within the larger area does not fit one of the underlying assumptions of kriging, as second-order stationarity may not exist even over local areas of estimation. This knowledge, of the original soil resource and the reclamation processes, supports the decision not to use kriging techniques. Instead, we choose regression techniques to model the distribution of soil properties.

4.5.2. Regression Analysis

Stepwise reduced model tests showed that a constant surface through the overall sample mean provided the best prediction of topsoil percent clay (Fig. 4.5), topsoil pH, and subsoil electrical conductivity at unsampled locations. Prediction intervals (Neter et al., 1985) for these were constant at all locations within the study area. The width of a given prediction interval varied as a function of inherent variability of the soil attribute in question. Thus, topsoil pH, which was largely determined by high levels of calcium carbonate throughout the mine soils, had a narrow prediction interval of $7.6 \pm .32$ ($\alpha = .10$), while topsoil clay percent had a wide prediction interval of $20.3\% \pm 10.9\%$ ($\alpha = .10$), reflecting the textural variability of the original geologic parent material. The upper limit of the prediction interval for subsoil electrical conductivity

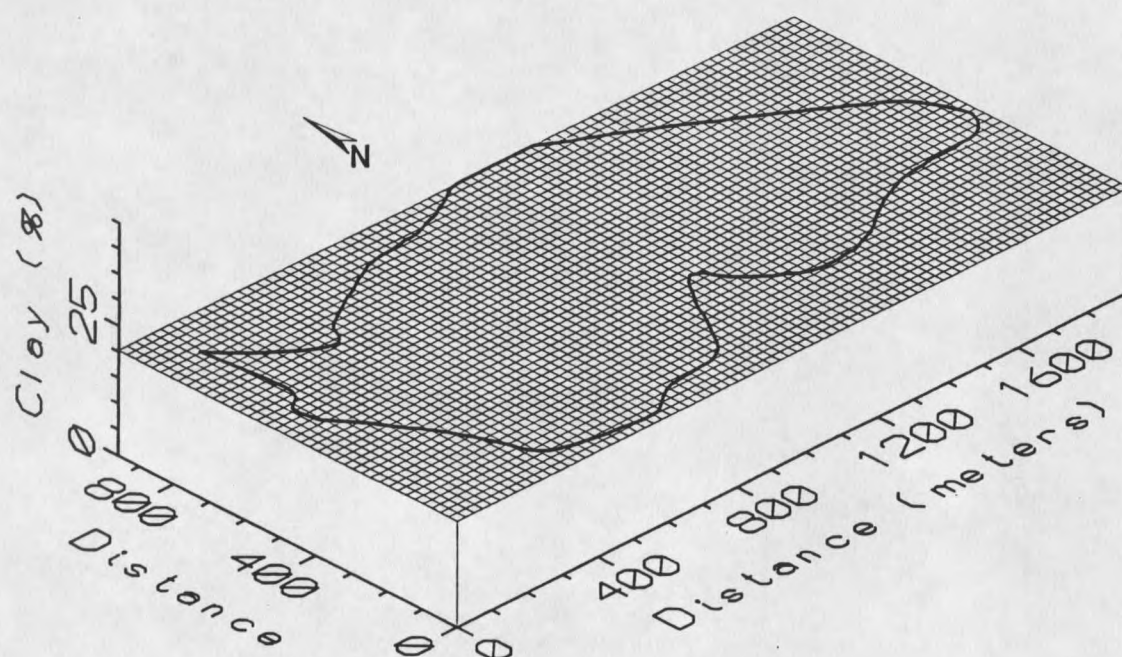


Figure 4.5. Constant trend surface of the overall mean provides the best estimate of topsoil percent clay at unsampled locations based on the current soil sampling strategy at the mine. Prediction interval = $20.3\% \pm 10.9\%$ ($\alpha = 0.10$).

equalled $0.254 \text{ S}\cdot\text{m}^{-1}$ ($\alpha = .10$) reflecting the inherent lack of salinity problems found in native soils of the Ft. Union formation. Even though the sample distribution was skewed, erratic high EC values of individual samples were still within the allowable limit of $0.4 \text{ S}\cdot\text{m}^{-1}$ considered suitable as coversoil material in reclamation by Montana Law (Montana Department of State Lands 1983).

A quadratic surface of $z = x^2 + y^2 + xy$ ($r^2 = .46$) was fit to the subsoil replacement depth data which exhibited a trend across the reconstructed landscape (Figs. 4.6 and 4.7). In this case, the prediction interval (Neter et al., 1985) varied as a function of location in the reconstructed landscape. The trend reflects changes in the balance of subsoil material available for reclamation over a sequence of years. The shallowest areas of subsoil replacement correspond to the earliest years of reclamation, 1978, 1979, and 1980. Increasingly greater replacement depths were used in subsequent years. These differences may be related to changes in suitability of salvage areas for deep subsoil salvaging or a shift in reclamation strategy at the mine. The quadratic surface provided "reasonable" predictions of replacement depths throughout the study area except along a couple boundary areas where unrealistically low predictions occurred beyond the outermost data locations. This difficulty reflects the extrapolation problems encountered in extending any interpolation method beyond the outermost data points. The surface did not account for the substantial amount of random variation in the data.

4.5.3. Future Sampling Considerations

If the mine soils were sampled with a closer grid spacing, spatial correlation at shorter separation distances may have been observed. Kriging could then be used to take advantage of that spatial correlation to improve predictions at unsampled locations. An associated kriged variance could be calculated for each location in the reclamation. Test studies would need to be done using

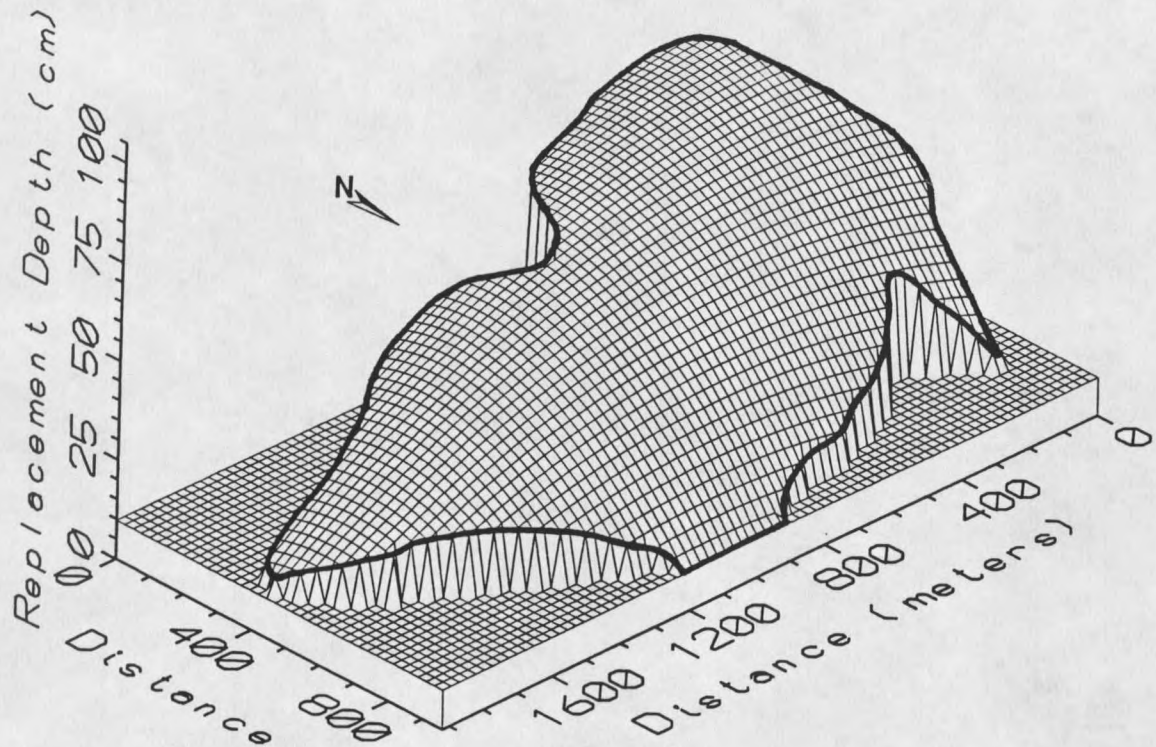


Figure 4.6. Trend surface for subsoil replacement depths $Z = X^2 + Y^2 + XY$ ($r^2 = 0.46$). X and Y axes have been rotated 180° to display surface.

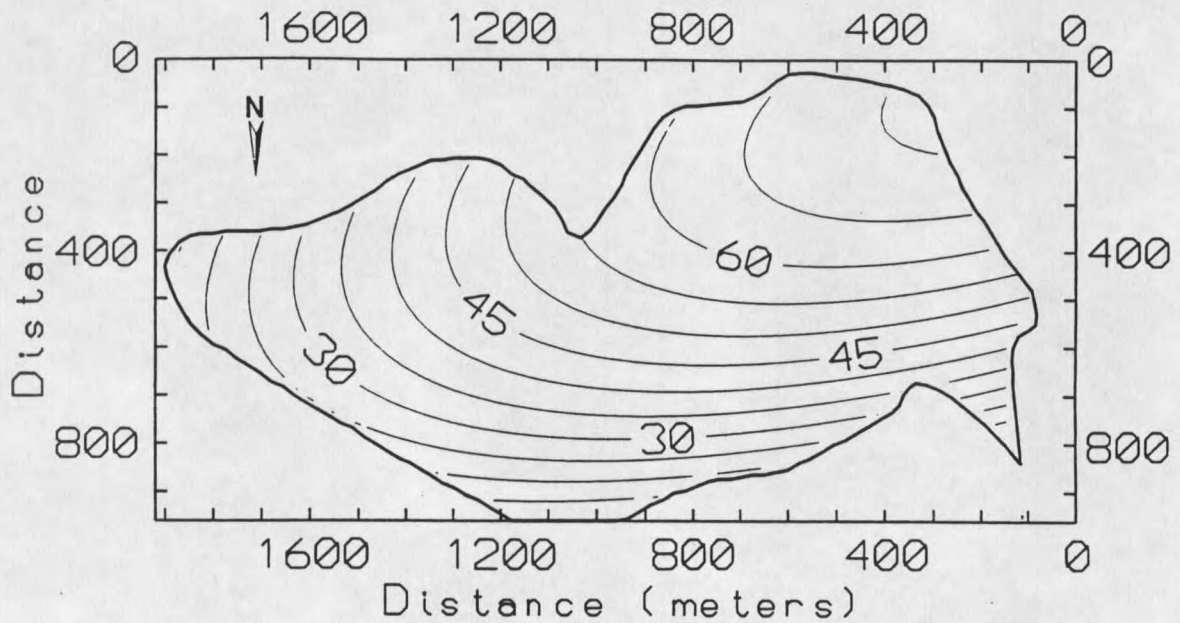


Figure 4.7. Contour map of the trend surface for subsoil replacement depth. X and Y axes have been rotated 180° to match orientation of surface plots.

short range grid sampling to determine optimum sampling density and individual fields may need to be treated separately to avoid making kriging estimates across discrete boundaries in the reclamation. Schafer (1979) found spatial dependence in soil properties of mine soils forming in spoils only over short ranges of 1 to 10 m. Although these ranges may be unrelated to those found in reconstructed mine soils, the density of sampling required to take advantage of such short range autocorrelation would be prohibitive. Ultimately, the intended use of the data will determine the density of samples required. Current sampling appears adequate if the goal of post-reclamation soil sampling is limited to ensuring suitable amounts and types of soil materials have been used. Prediction intervals ($\alpha = .10$) for all variables fit within the limits defined as suitable for reclamation. The native soils salvaged for reconstructing these soils all fall within the allowable levels for percent clay, soil pH and electrical conductivity (Montana Department of State Lands, 1983) so there is little reason to suspect problem areas. If the goal of reclamation officials or state regulators were to use kriging techniques to improve site specific estimates of soil properties, perhaps to identify microsites for vegetational diversity, then a greater sampling density would be required. Given the uncorrelated nature of the present data, trend surface analysis appears to be the best method available for interpolating minesoil attributes at unsampled locations.

Our assumption that the semivariogram for subsoil replacement depth represented a trend in the data and not any spatial correlation could come into question. The difference between a trend and spatial correlation is in a sense a difference in scale, trend representing larger scale spatial correlation. For this reason, we ran a semivariogram analysis on the residuals of the subsoil replacement depth data after subtracting off the trend surface. This resulted in the same type of semivariogram (Fig. 4.8) as was exhibited by the other mine soil properties without a trend; essentially random variation about a horizontal sill and no identifiable range of spatial correlation.

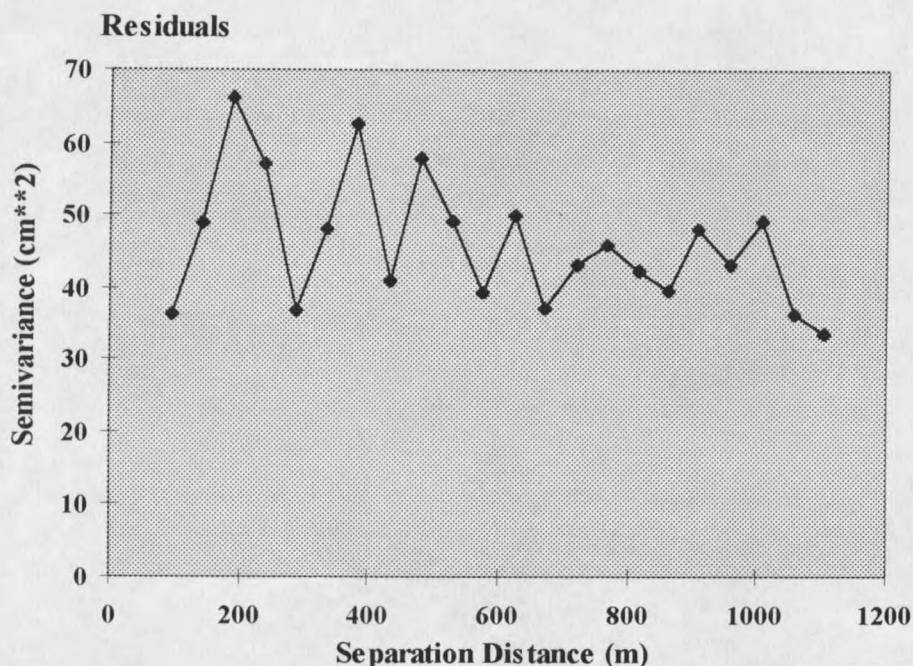


Figure 4.8. Semivariogram for residuals of subsoil replacement depth (cm) after subtracting the trend from the data.

4.6. Conclusions

Analysis of semivariograms provide an important first step in assessing spatially oriented data. This step should be taken before researchers pursue subsequent analyses. Mine soil data from the Rosebud Mine provides an example of how semivariogram analysis can be used to search for spatial dependence of data. In the absence of spatial dependence, more traditional statistical techniques that rely on independent data assumptions can be used.

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CHAPTER 5

GEOSTATISTICAL ANALYSIS OF MINE SOIL PROPERTIES

5.1. Introduction

In 1986, Dr. Peter Knutsen at the Montana School of Mines provided Western Energy Company with a geostatistical analysis of their characterization data on regraded spoils (Knutsen-unpublished data, 1986). Results from this study showed spatial correlation distances in regraded spoils ranging from 1,000 feet for sodium adsorption ratios (SAR) and electrical conductivity (EC) up to 4,000 feet for percent sand. His conclusions were that, given an allowable error bound of 20%, a sampling intensity of 1,000 feet between sample sites (1 hole/23 acres) "will provide as useful and reliable information as sampling every 300 feet". As a result, Western Energy was able to successfully make the argument to state regulators for reducing the standard sampling density on regraded spoils from one sample every 300 feet to one sample every 1,000 feet.

This "successful" application of geostatistics led Western Energy to fund a second geostatistical study at Montana State University. The goal of the second study was to assess spatial correlation in soils data collected for coversoil materials spread on top of the spoils, with the hope of finding similar results to justify a reduction in post-reclamation soil sampling (personal communication Bill Schwartzkoph, Western Energy Company). Western Energy, at that time, was collecting soil samples on an approximate 300 foot sample interval. Samples are taken of both topsoil and subsoil materials after the soils have been spread over the recontoured spoils. These samples are then analyzed in the lab for soil texture, soil pH and soil salinity to assess their

suitability for reclamation. Depths of topsoil and subsoil "replacement", are measured in the field at each sample location.

Keck et al. (1993) showed spatial correlations did not exist in the mine soil data at the 300 foot sample spacing. Thus, no justification could be found to further reduce sample spacing of the mine soils, at least not on the basis of any spatial correlations in the data. Data for topsoil replacement depths, soil texture, soil pH, and electrical conductivity all behaved in a spatially independent manner at the 300 foot sample spacing. This independence was attributed to the combined influences of double lift reclamation strategy used and the mixed sedimentary lithology of parent materials at the Rosebud Mine. A distinct trend existed in subsoil replacement depth data which could be reasonably modeled with a trend surface given spatial independence in the data. For other soil properties, a "constant surface through the overall sample mean provided the best predictor" of values at unsampled locations (Keck, et al., 1993). These results are believed to apply only to the special case, represented by mine soils, where analysis of semivariograms show a clear absence of spatial dependence in the data.

While the above results may have been disappointing to Western Energy, they raised some interesting questions for further study. Are soil properties in the reclaimed mine soils truly distributed in a spatially independent manner or do spatial correlations exist at shorter separation distances? If such correlations exist, could a more dense sample grid be used to obtain better predictions of how soil properties are distributed across the reconstructed landscapes? Such an approach, requiring an even denser sampling scheme, would generally not be viewed as a positive option for the mining company. However, much of the expense associated with soil sampling relate to laboratory analysis costs. Precise laboratory analyses for the reconstructed mine soils often seem out of place given the high, short-range spatial variability of mine soil properties and

lack of significant inhibitory or toxic substances in the soil materials. Could a trade-off be made substituting less precise field estimates for a higher density of sample points thereby providing better information at approximately the same cost? The current study was designed with these questions in mind.

Goals of the study were as follows:

- 1) Determine if a data set specifically designed for the application of spatial statistics would exhibit spatial correlations at shorter lag distances.
- 2) Test the possibility that a trade-off between precision in sample analysis and sampling density could provide better soils information for a comparable level of effort and expense.
- 3) Test the earlier hypothesis, that for the non-correlated or poorly correlated mine soil data, an estimate of the overall mean, or where appropriate a trend surface, provides the best estimate of soil properties at unsampled locations.

The working hypothesis was that a higher sample density and use of sample clusters would identify some limited spatial correlations in the mine soil data but that kriging would still perform poorly due to the inherent nature of the reconstructed soil resource.

5.2. Literature Review

The theory and general practice of spatial statistics has been covered in previous chapters. Questions of interest here relate to the potential accuracy of geostatistical interpolation procedures, specifically kriging. A number of studies have been conducted comparing the accuracy of kriging estimates to those of other spatial interpolation methods.

5.2.1. Comparisons Among Spatial Interpolation Methods

Laslett et al. (1987) conducted one of the first comparison studies among different two-dimensional prediction methods. They provide a concise discussion of conceptual differences among various techniques. Comparisons were made between predicted values and measured values of soil pH at the same study site. Overall, methods of ordinary kriging and Laplacian smoothing splines performed better than the other prediction methods tested. This initial work was followed by further comparisons of additional spatial prediction techniques using the same data set (Laslett and McBratney, 1990). Subsequent results showed, that for this data, geostatistical techniques provided better (more accurate) results than general interpolation methods, intrinsic random functions, or Laplacian smoothing splines. Universal kriging was the geostatistical prediction method used in the second set of comparisons.

Issaks and Srivastava (1989) generated a comprehensive set of spatial data from USGS digital elevation data for the Walker Lake area in California. These data provide a unique situation where known values exist at all possible sample locations. The Walker Lake data set forms the basis for numerous examples throughout their textbook, Applied Geostatistics, which includes comparisons between true and predicted results. For the comparisons made, ordinary kriging had the lowest standard deviation of errors, the lowest mean squared error, and the highest correlation coefficient between estimated and true values of all spatial prediction methods tested (Issaks and Srivastava, 1989).

A modified subset of the data by Issaks and Srivastava was used as a surrogate for soil contamination data by Weber and Englund (1992). In their comparisons of block estimates by various spatial "estimators", inverse distance methods outperformed both ordinary and simple kriging methods in reducing the mean squared error between estimated and true values. Inverse

distance methods also performed best in a measure they call the linear loss score which was based on a loss function of remediation costs and the estimated cost associated with contamination that remains after cleanup is complete. Some of the other spatial estimation methods used in the study, such as data means or rank kriging, performed quite poorly relative to inverse distance and standard kriging methods.

In yet another study, Weber and Englund (1994) created five separate data sets from digital elevation data in a manner similar to the Walker Lake data set. Two distinctly different types of data were created. Three of the data sets consisted of elevation values from the digital elevation data. These provided generally smooth, continuous surfaces and unskewed data. The other two data sets were generated from variances of elevation data. Plotted values of the variance data were spiky in appearance with discontinuous, noisy surfaces and highly skewed data. Comparisons were made among various inverse distance and kriging methods along with a simple spline-fitting method. In general, kriging methods either outperformed or were equal to the inverse-distance methods in terms of having the lowest mean square error. The spline method gave less accurate results than either kriging or inverse distance methods, especially at the lowest sample density. Differences among methods were greatest at the lowest sample density while increasing sample density tended to eliminate differences among methods.

The relationship between exponent values in the inverse-distance method and the effectiveness of this method to make predictions of different types of data was perhaps the most interesting outcome from the 1994 Weber and Englund study. The inverse-distance cubed approach provided estimates almost as accurate as any of the kriging methods for the smooth, continuous elevation data set while inverse-distance to the first power did much worse. This relationship was reversed for the highly skewed variance data. Inverse-distance to the first power

did as well or better than any of the kriging methods for the variance data while the inverse-distance cubed approach did much worse.

Further comparisons between kriging and inverse distance methods have been conducted by Gotway et al. (1996) for nitrate (NO_3^-) and soil organic matter. Data were collected at two research sites in central Nebraska with two data sets collected for each site, one prediction data set and one validation set. Results were similar to those reported by Weber and Englund in 1994. Ordinary point kriging performed as well or nearly as well as the best inverse-distance method in all cases. Inverse distance to the lowest power ($p=1$) provided the best estimates for the highly variable NO_3^- data. Inverse-distance to the highest power ($p=4$) provided the best estimates for the much less variable soil organic matter data.

The choice as to which spatial prediction method will give the most accurate estimates at unsampled locations appears to depend in large part on the properties and distribution of the variable studied. In all cases examined, kriging did nearly as well or better than other methods tested. In the majority of these cases, however, the semivariograms on which kriging was based exhibited "good behavior" with respect to low nugget values, significantly large spatial correlation distances (range), and a reasonable fit of the semivariogram model.

One exception to the above was a linear "black box" kriging approach included by Weber and Englund in their 1994 study. For example purposes, a linear model was used with zero nugget regardless of characteristics of the experimental semivariogram. This would represent the case of making extremely poor choices in modeling the semivariogram. Estimates based on this "black box" approach were equally accurate in predicting the smooth, continuous elevation data as the other three kriging approaches, each of which involved elaborate schemes for fitting semivariogram models by least squares methods. The other kriging approaches did outperform the "black box"

method for the more erratic variance data. In general, data from mine soil areas will be expected to exhibit erratic behavior similar to the variance data in the Weber and Englund study.

5.2.2. Fitting Semivariogram Models

Issaks and Srivastava (1989) in their textbook, recommend a trial and error approach to fitting semivariogram models based on the experimental semivariogram and using allowable "positive definite" semivariogram models. Many established practitioners of geostatistics have subscribed to just such an approach (Journel and Huijbregts, 1978; Clark, 1979; Englund and Sparks, 1991). In this regard, "a good graphical program can be tremendously helpful" (Issaks and Srivastava, 1989). Some variability in results may be introduced by the inherent subjectivity of model decisions. Englung (1990) found substantial variations among spatial estimates from 12 different geostatisticians working with two common data sets. Most of the variation, however, was related more to the choice of interpolation method used than due to differences in semivariogram model parameters of those using standard kriging approaches.

Most of the published geostatistical studies in soil science literature rely on more rigorous least squares methods of fitting semivariogram models. These methods model the experimental semivariogram by minimizing the squared difference between the model values and experimental semivariogram data points. Unfortunately, very good regression coefficients can be obtained by least squares methods and yet equations may still do a poor job of modeling spatial correlations at the most critical short lag distances. Revisions of the basic least squares techniques (David, 1977; Cressie, 1985) have been aimed at remedying this problem. No amount of rigorous model fitting, however, can overcome the limitations of poor sampling design or insufficient sample points at short separation distances.

No studies were found in the literature demonstrating the superiority of kriging estimates based on the use of robust least squares methods to model empirical semivariograms over those based on visually fitting semivariograms. It seems questionable that minor adjustments in semivariogram models or the increased complexity of using multiple nested models will have a significant positive impact on kriging estimates. This is especially true in light of studies that show inverse distance estimation methods, with no prior knowledge of spatial correlations built into the method, can at times provide as good or better interpolation estimates than kriging. Such attention to the details of model fitting assumes a higher degree of stationarity in the spatial correlation structure of the data than is often warranted, i.e.: the semivariogram model is assumed to fit equally across the area of estimation.

Much attention has been paid to the common lack of stationarity for the mean in soil science applications of kriging. Relatively little attention has been paid to the assumed stationarity of experimental semivariograms. In practice, kriging estimates, calculated from two different semivariogram models, may be almost identical (Englund and Sparks, 1992), assuming both models are reasonable. Estimates of the theoretical kriging variance or kriging standard deviation are much more sensitive to changes in the semivariogram model. Perhaps the best criteria for judging semivariogram models should be to test their validity against "real world" considerations of how the property in question would be expected to be distributed based on an understanding of the physical and/or chemical processes involved.

5.2.3. Estimation of Kriging Errors

Whether semivariograms are visually fit or selected by least-squares methods, often cross-validation methods are used to "verify" the semivariogram model. Cross-validation is a rather

ingenious means of generating pairs of true and estimated values by removing a single data point and kriging the remaining data to predict the missing value. This process is repeated for each data point in the data set until a complete set of predicted versus true values has been generated.

Criteria tests have been developed to assess the theoretical consistency of semivariograms on the basis of cross-validation results (Gambolatti and Valpi, 1979; Yost et al., 1982). Such cross-validation techniques provide valuable information but they can be extremely time consuming. They generate pairs of true and estimated values only at sample locations. Since sample points do not represent the total distribution of unsampled locations, cross-validation results generally do not reflect the actual performance of an estimation procedure. While negative results should raise serious questions about the appropriateness of procedures used, positive results do not guarantee successful kriging predictions (Issaks and Srivastava, 1989).

The ability to obtain a measure of interpolation error for each interpolated value has often been claimed as one of the major benefits of geostatistical techniques over other spatial interpolation methods. Once a semivariogram model has been selected, a kriging variance or kriging standard deviation can be calculated for any point in the estimation field based on separation distance and the orientation of surrounding sample points. These kriging error terms, however, are determined solely from the semivariogram model parameters. Departures between "real world" conditions and the underlying assumptions of kriging equations can have a major impact on the accuracy of predicted error terms (Englund and Sparks, 1991). As such, they cannot be used as a true measure of estimation error. Predicted kriging standard deviations invariably are lower than standard deviations obtained from comparing predicted versus measured values. The predicted standard deviations are too low because "they do not account for the uncertainty associated with semivariogram estimation and modeling" (Gotway and Hergert, 1997).

5.2.4. Trends in the Data and Anisotropy

Another area where divergent opinions exist among geostatisticians is in how to handle trends in spatial data. Even the distinction between spatial trends, changes in the expected value of the mean across the area of estimation, and anisotropy, a directional component in the semivariograms, appears to be blurred among certain geostatisticians (Gotway and Hergert, 1997). In many instances, ordinary kriging techniques appear to be quite robust with respect to general trends in the data (Yost et al., 1982; Cressie, 1987; Journel and Rossi, 1989; Laslett and McBratney, 1990) and anisotropic data (Laslett et al., 1987; Gotway and Hergert, 1997), provided reasonable stationarity of the mean is maintained within the local search radius, referred to as local stationarity. Difficulties arise when extreme trends exist in the data or when abrupt changes occur in the true mean. In such cases, even local stationarity does not exist.

Significant trends in the data can be handled a number of ways. In the traditional approach, the trend is modeled by a standard least squares method. The modeled trend is then subtracted from the data and ordinary kriging performed on the residuals. Results are back-transformed by adding the trend component back to the final kriging results. Several researchers have warned that residuals, after removing a least squares trend, are biased, thus adding some additional uncertainty into the semivariogram analysis (Olea, 1974; Gotway and Hergert, 1997). New methods of estimating trends, such as restricted maximum likelihood (Laslett and McBratney, 1990) and simultaneous estimation techniques (Gotway and Hergert, 1997) are believed to eliminate much of this bias. Universal kriging provides an adaptation to ordinary kriging whereby the trend is calculated automatically. Depending on how the technique is used, concern about biased residuals may still apply. Issaks and Srivastava (1989) warn against relying on automatic

methods unless the results are checked to see if they "have the support of common sense and good judgment".

Gotway and Hergert (1997) compared 5 methods for making spatial estimates in data with a strong trend or general anisotropy. Unfortunately, their comparisons were based largely on theoretical considerations and no data sets of actual versus predicted values were available to compare results. They appeal instead to the nature of physical processes responsible for systematic variations in the spatial data to obtain insights into how to best proceed with the analysis.

5.2.5. Example Errors in Spatial Interpolation

The concern with any spatial interpolation method is that estimates away from known sample locations may be largely inaccurate. Zinc concentrations in the Butte-Anaconda area provide a good example. White et al. (1997) developed a kriged map of zinc concentrations across the contiguous U S. Nearly three thousand data locations across the country were used in the analysis. A global trend was removed prior to kriging, semivariogram models were fit using least squares methods and adjustments made to increase accuracy at the critical short lag distances. The semivariograms behaved properly, and data were interpolated by punctual kriging techniques to a 10 by 10 kilometer grid (White et al., 1997).

The final kriged map shows a zone of low zinc values encompassing the Butte-Anaconda area including the Deer Lodge Valley. Predicted zinc concentrations in this region range from approximately 28 mg/kg to 56 mg/kg. Data on heavy metal and arsenic concentrations in soils have been collected at various sites in this region for the Deer Lodge and Silver Bow County Soil Surveys. Measured values for zinc concentrations in surface soils of this mining and smelting

impacted region ranged from 114 mg/kg to 1890 mg/kg. The study by White et al. (1997) illustrates how proper geostatistical techniques were followed throughout, yet in at least this one instance, completely inaccurate results were obtained. Data originally collected for other purposes may have avoided mining and smelting impacted areas producing a bias in the database or the limitations of scale and luck of the draw in selecting sample sites may have simply missed the area. Several data points from other mining impacted areas around the county were thrown out of the study as anomalies in the data.

There are several factors that can seriously impact the accuracy of kriged estimates. Bias in the database, limitations of scale, low sample density, and a poor fit of kriging assumptions to the "real world" situation appear to be the most important. A statistically rigorous treatment of modeling semivariograms and accounting for trends in the data may be well justified in many cases but they do not guarantee accurate results. Use of common sense and good judgment is perhaps the greatest insurance against poor results; along with obtaining an adequate amount and distribution of data points. Unfortunately, many geostatistical studies apply kriging as a "black box" solely on the basis of theoretical superiority over other spatial interpolation methods.

Indicator kriging provides an alternative, non-parametric and non-linear, approach to the estimation of spatial data (Journal, 1983). While subject to the same constraints as ordinary kriging, spatial correlation in the data and adequate sample density, indicator kriging provides results in terms of the probability of exceeding a specified cutoff value rather than as precise estimates of attribute values. Probabilities more accurately reflect the level of knowledge available in many situations.

Only few studies on indicator kriging have been published. Kim et al. (1987) demonstrated how indicator kriging could be used to obtain more accurate estimates of mean

recoverable gold reserves than results from ordinary kriging for highly skewed gold concentration data. Ordinary kriging under-estimated actual gold reserves in the study by over 25%. Results among individual point estimates appear more varied, however, in terms of which method provided the best predictions. In a separate study, an indicator kriging was used to generate local monthly estimates of the probability distributions of H^+ deposition in the northeast US (Bilonick, 1988). Even fewer studies have been published on applications of indicator kriging in soil science. Smith et al. (1993) recommended "multiple-variable" indicator kriging as a potential method to combine information about several factors influencing soil health into a single soil health index. Application of their approach has not gained wide acceptance at this time.

5.3. Methods and Materials

A study site was selected covering portions of two adjacent reclaimed fields in the Area-E portion of the Rosebud Mine at Colstrip, Montana. Mining was completed in this Area in the 1980's and final reclamation for the entire Area-E mine was nearly complete by 1990. Coversoils used at the study site came from soil salvage piles of topsoil and subsoil material that had been set aside for final reclamation when the mining pit in Area-E was first opened. The fields selected had been recontoured in 1989 and had subsoil and topsoil materials laid down during the summer of 1990. Sampling was conducted in the spring of 1991. A 50 meter grid was laid out covering an area of 400 by 750 meters. Irregular field boundaries caused some of the east and west boundary samples to be spaced only 25 meters from their closest neighbors in the east-west direction.

Four sample points in the interior of the study site were randomly selected as the center data points for sample clusters. Eight cluster samples were located around each of the four sample points selected. These were oriented along the primary east-west and north-south axes with 12.5

meter spacing between samples locations in the cluster (Fig. 5.1). A total of 174 sample locations in all were selected.

At each sample location, the thickness of soil replacement was measured in the field for both topsoil and subsoil materials. Slope and aspect of the recontoured surface were measured using standard field techniques. Separate soil samples were collected from the topsoil, subsoil, and top foot of spoil at each sample location for subsequent analysis in the lab of soil texture and soil organic matter. Bulk density samples were taken at two sample locations within each east-west row using a core sampling tool as described by Doran and Mielke (1984).

Soil and spoil samples, collected in the field, were later analyzed to determine percent clay, percent sand, and soil texture class. A hydrometer procedure adopted by Western Energy (Bouyoucos, 1962) was used to create texture standards for hand texturing. Comparison of test results for selected samples showed the Western Energy method gave comparable results to the more widely accepted modified Day procedure (Gee and Bauder, 1987). The Western Energy approach was retained because of the desire to use Western Energy's data as an independent data set for testing kriged estimates. Estimates of clay and sand percentages were made for all soil and spoil samples by standard hand texturing techniques (Soil Survey Staff, 1951) with close attention paid to reference samples covering the full range of textures encountered in the field. Additional hydrometer analyses were run for all of the samples collected in sample clusters. Soil organic matter contents were determined for all topsoil and subsoil samples using the Wakely-Black method (Sims and Haby, 1971).

A separate 100 meter grid of Western Energy's sample locations was superimposed over the experimental data grid. Western Energy data points were placed midway between experimental grid samples in the north-south direction along every other row to maintain the required 100 meter

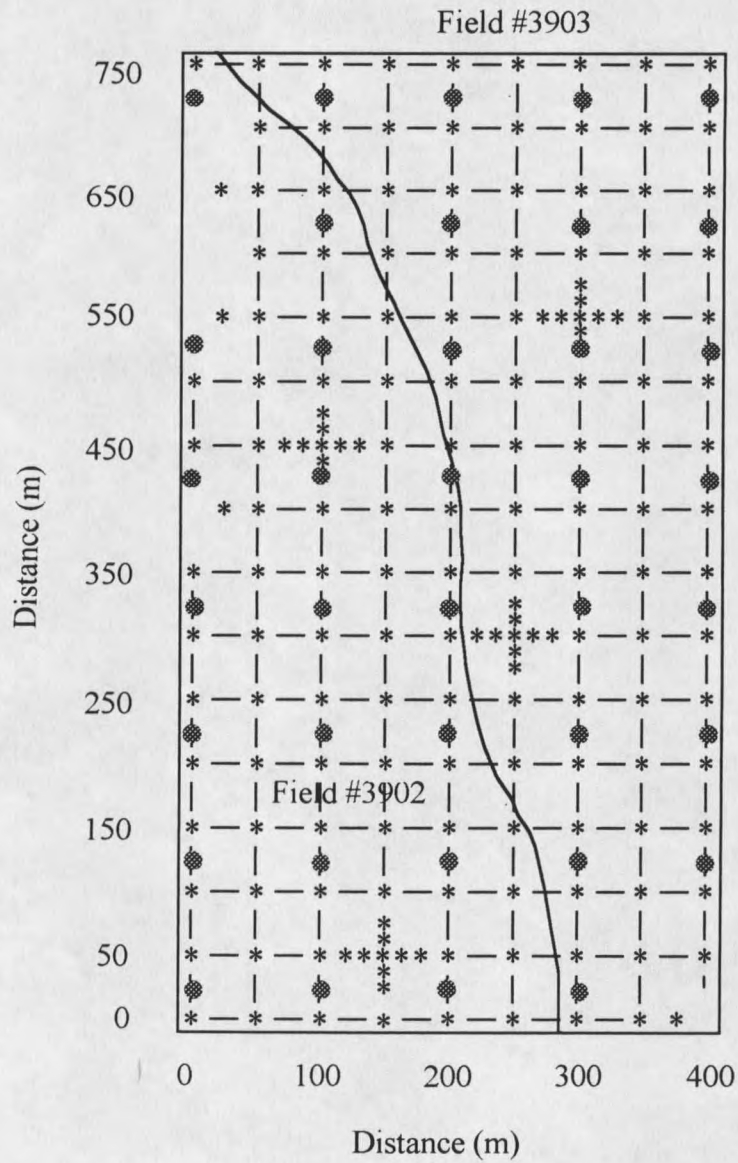


Figure 5.1. Locations of experimental data points (*) and the interspersed Western Energy sample grid (•). |

spacing (Fig. 5.1). Soil replacement depths were measured in the field by Western Energy personnel. Topsoil and subsoil samples were brought back to the laboratory for soil texture, soil pH, and electrical conductivity analysis as stipulated by the mining permit. This independent data set provided the measured values for subsequent comparisons of measured versus predicted data points.

Isotropic experimental semivariograms were run for the following soil attributes: topsoil replacement depth (cm), subsoil replacement depth (cm), total soil replacement depth (cm); topsoil percent clay, subsoil percent clay, and spoil percent clay; topsoil percent sand, subsoil percent sand, and spoil percent sand. The three non-spoil variables, exhibiting the greatest amount of spatial correlation, were selected for further analysis. Experimental semivariograms were re-run for subsoil replacement depth, subsoil clay percent and subsoil sand percent at a number of different lag spacings. Lags which provided the cleanest trace of experimental data for model fitting were used for final output and modeling of the semivariograms. The above step is comparable to adjusting class boundaries on histograms; it does not affect the basic data but adjusts the distribution of the data for display purposes. Directional semivariograms were run for the three selected variables in a north-south ($\pm 30^\circ$) direction, parallel to the direction of soil laydown, and in an east-west ($\pm 30^\circ$) direction, perpendicular to the direction of soil laydown. Semivariogram models in all cases were fit visually using the interactive model fitting module available in Geo-eas (Englund and Sparks, 1991).

Semivariogram models, fit to the isotropic data, were plotted on the directional semivariograms as a visual test of anisotropy. If data points in the first part of the directional semivariogram consistently fall below the model line on the graph then anisotropy in the spatial correlation structure is suspected (Englund and Sparks, 1991). Development of an anisotropic

semivariogram model for the subsoil percent clay data was accomplished by a modification of the method proposed by Englund and Sparks (1991). Model type and sill height for the anisotropic model were determined from the isotropic model. This utilizes the relatively greater stability of the isotropic model to determine these parameters. A new nugget value was then determined from the directional semivariogram exhibiting the greatest amount spatial correlation. This new nugget value became the basis for both directional semivariograms and adjustments were made in the range of spatial correlation to account for directional differences.

Ordinary block kriging (2x2 blocks) was used on subsoil replacement depth, subsoil percent clay, and subsoil percent sand data for comparison of kriged estimates with the Western Energy data. Isotropic kriging was run for all three variables while anisotropic kriging was only run for the subsoil percent clay data. Anisotropic kriging was accomplished solely by adjusting the major and minor ranges of the semivariogram model in Geo-eas as described by Englund and Sparks (1991).

Q-Q plots used to compare the Western Energy data with the experimental data indicated some distinct biases between the two data sets. As a result, the Western Energy data were scaled using a graphical approach and linear transformations to match the distribution found in the experimental data. The transformed data were used for all comparisons between kriged estimates and Western Energy measured values.

Results from isotropic kriging, anisotropic kriging, and the mean field values were compiled for all sample locations in the Western Energy data set. Comparison among methods were based on the relative mean squared errors between predicted and measured values and graphical representations of results.

$$\text{Mean Squared Error (MSE)} = 1/n \sum_{i=1}^n (x_i - \hat{x}_i)^2$$

x_i = measured values; $\hat{x}_i$ = predicted values

After examining results from the Western Energy data comparisons, a second test data set was generated from the experimental data. One data point was randomly selected from each of the interior rows in the grid and removed from the experimental data set. In the same manner, two data points were randomly selected from each data cluster. Isotropic semivariograms were rerun using the remaining sample points in the experimental data set for spoil percent clay, topsoil percent organic matter, and subsoil percent sand. These data were kriged using the isotropic models and results compared to the measured values in the test data set. Comparisons were again based on the relative mean squared errors between predicted and measured values and graphical representations of results.

In a final analysis, cutoff or threshold values of interest were selected for topsoil organic matter and spoil percent clay. The full experimental data sets for these two variables were transformed to indicator variables at each cutoff value. In creating the indicator variables, data points were set to one if the value at a sample location was less than the cutoff and zero if the sample value was greater than or equal to the cutoff.

$$\text{Indicator Variable (I)} = \begin{cases} 1 & \text{if less than the cutoff value} \\ 0 & \text{if greater than or equal to the cutoff} \end{cases}$$

Topsoil organic matter data were transformed at only one cutoff value (OM = 1%). Spoil percent clay data was transformed to a sequence of four separate indicator variables corresponding

to clay percentages of 12, 20, 28, and 36 percent. Semivariogram analysis was then run for each of the indicator variables and indicator kriging used to generate final maps.

5.4. Results and Discussion

One of the main objectives of this study was to assess potential benefits of a trade-off between higher sample density and the use of less precise field methods for sample analysis. If the increased accuracy of spatial interpolation procedures due to a higher sample density outweighed the lost accuracy of using field analyses rather than laboratory analysis, then the net effect would be better overall spatial information about the soil resource. Field tests exist for all of the soil analysis required in the mining permit for post-reclamation soils. These procedures include hand texturing techniques, pH determination by indicator dyes, and electrical conductivity (EC) with field EC meters. All of the above are standard soil survey procedures used by the National Cooperative Soil Survey Program to map soil resources throughout the United States.

Based on earlier results (Keck et al., 1993; Keck and Wraith, 1996), it was decided that soil pH and electrical conductivity were generally homogeneous within reclaimed fields at the Rosebud Mine, with ranges of measured values that fall within the suitability criteria for coversoils. Differences found in soil pH and EC would have limited impact on management decisions affecting the reclaimed soil resource. The range in soil textures was quite large, however, as would be expected for soils originating from mixed sedimentary beds of sandstones, siltstones, and shales. Further analysis focused on soil texture, including spoil substrates, and on soil replacement depths since existing variations in these factors appear to have the greatest potential impact on future management of the soil resource.

5.4.1. Soil Texture Comparisons

A necessary first step was to assess the accuracy of hand texture estimates relative to the hydrometer method used by Western Energy. Neither the hydrometer method nor hand texturing can be considered "truth" in terms of the actual clay or sand percentages of samples. Hydrometer methods have the advantage of providing more precise and consistently reproducible results and are recognized by the State of Montana as the standard for assessing mine soil suitability. Hand texture estimates provide much more rapid and therefore more cost effective results which can be obtained at the site. This allows for the analysis of many more sample locations given the limitations of time and budget. For the purpose of comparison, hydrometer results here have been considered as "truth" and are used as the standard for assessing the accuracy of hand texture estimates.

Error associated with the increased variability of hand texturing adds directly to any nugget effect in the analysis of semivariograms. Obviously, reducing this variability to the greatest extent possible is essential to obtain good spatial interpolation estimates. Good accuracy in field estimates can be obtained only if frequent use is made of texture standards to check results against known laboratory values (Soil Survey Staff, 1951). This becomes especially true when estimates are made for soils of varying parent materials. Hand estimates of soil texture have been the basis for millions of acres of soil surveys in the US and yet often times only limited use has been made of reference samples by soil survey crews. Inferred accuracies are often much greater than actual results (Keck, unpublished data).

Figures 5.2 and 5.3 show scatter diagrams of hydrometer analysis versus hand texture estimates for topsoil and subsoil percent clay and for topsoil and subsoil percent sand, respectively. The center diagonal line running from the lower left to upper right corners in each graph identifies

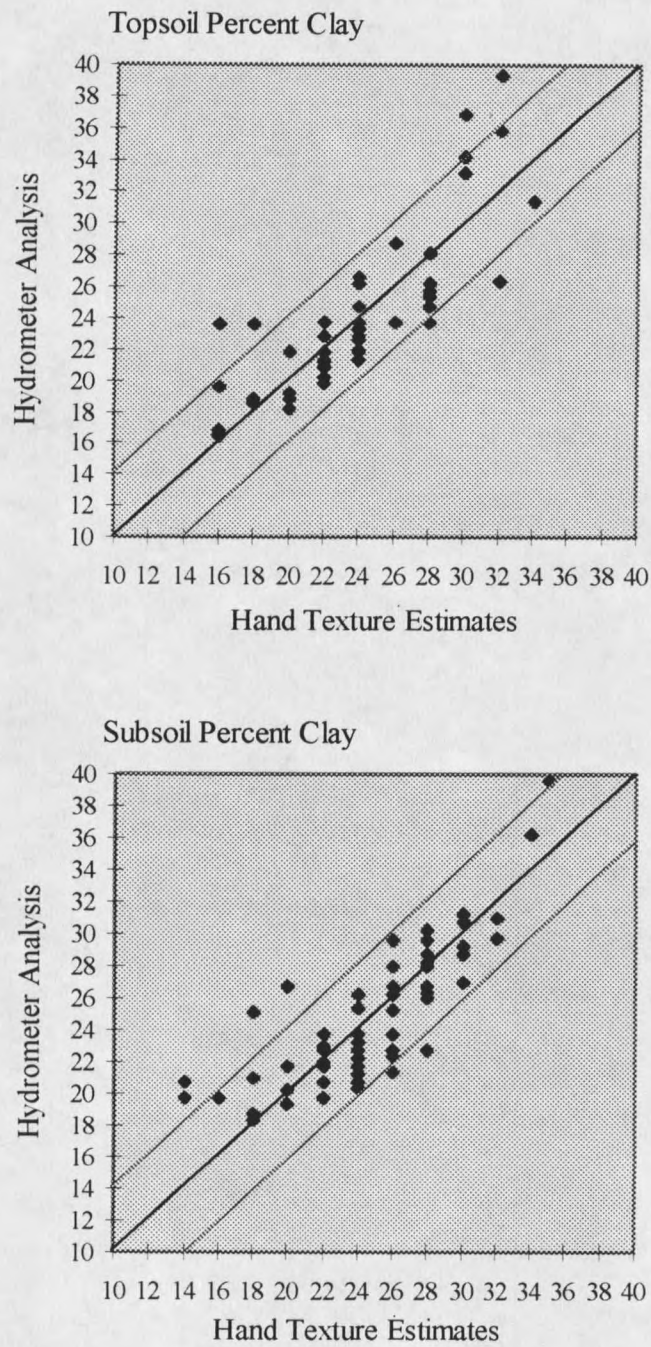


Figure 5.2. Scatter diagrams of percent clay from hydrometer analysis and hand texture estimates of topsoil and subsoil materials.

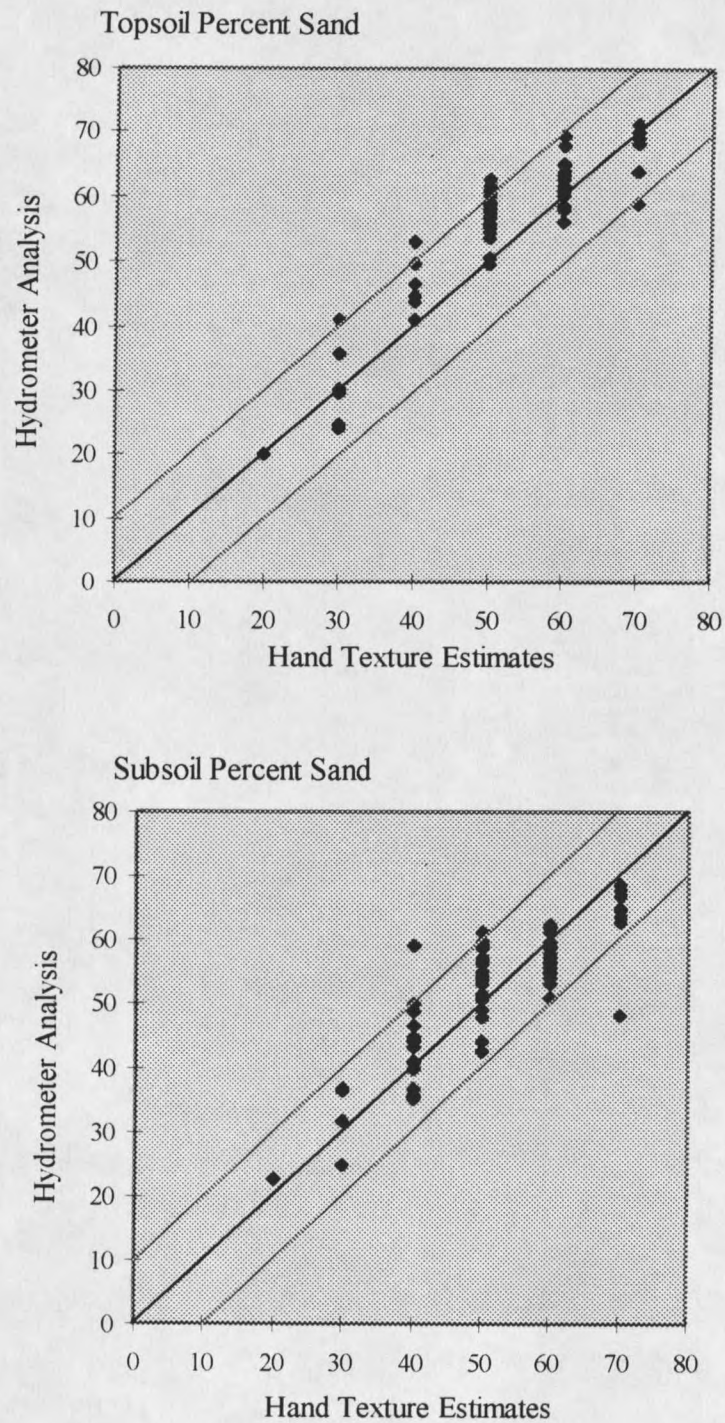


Figure 5.3. Scatter diagrams of percent sand from hydrometer analysis and hand texture estimates for topsoil and subsoil materials.

points of equal values for both x and y axes. If hand texture estimates were perfectly accurate at predicting hydrometer results, all the data points would align on this line. The other two diagonals on the scatter plots for percent clay represent an error bounds of $\pm 4\%$. Data points falling within the envelope of the two outer lines have hand estimates of clay content within 4% clay of the hydrometer values. Plus or minus 4% was the expected error of estimating clay contents by hand texturing. Data points outside this envelope exceeded the expected error.

Most of the percent clay estimates fell within the $\pm 4\%$ range, with only 7 out of a total of 68 topsoil samples and 7 out of 67 subsoil samples exceeding the expected error. This corresponds to roughly 90% for the hand texture estimates of percent clay falling within the expected range. Given the controlled manner in which hand texture estimates were determined, these results are somewhat surprising. Samples collected in the field were brought back to the lab where hand texturing was completed with frequent comparisons to known standards. Even under controlled conditions the expected accuracy was not completely supported by experimental results.

The scatter plot for topsoil clay shows a much greater scatter in the data at both the high and low ends of the scale. Better agreements between hand estimates and hydrometer results were obtained in the center of the range. This may be due to the greater number of samples and, as a result, more texture standards used for textures in the center of the range. Another possibility may relate to the samples used for texture standards. Samples used for the low and high clay contents were from subsoil materials. As a result, reference samples for the extremes in the range may not have adequately accounted for the influence of soil organic matter on field clay estimates for topsoil materials. The subsoil clay data do not show the same amount of difference between estimated and measured values at the high and low end of the scale, although the same general pattern exists.

The expected error bounds for sand estimates was $\pm 10\%$ sand. Standard soil survey procedures seldom require estimates of percent sand in field investigations since minor differences in sand content have little influence on either soil classification or use and management interpretations of soils. On this basis, the $\pm 10\%$ standard appears reasonable. Eight out of 68 topsoil estimates exceeded 10% sand expected error although none exceeded the threshold by much. While only three of the subsoil sand estimates exceeded the expected error, 2 of the 3 exceeded the threshold by a significant amount. Some bias was observed in the topsoil sand estimates with a tendency to slightly underestimate sand contents for samples in the middle of the range.

Table 5.1 provides summary statistics of means and variances for hand texture estimates, hydrometer analysis, and differences in results between the two methods. In all cases, the mean and variance were roughly equal between the two methods. The sample variance obtained from hand texture estimates was slightly less than for hydrometer analysis in the topsoil percent clay data while the opposite was true for subsoil clay and both topsoil and subsoil percent sand. The mean difference between hand texture estimates and hydrometer results for the same sample was between 1.9 to 2.0 % clay and approximately 5% sand.

Table 5.1. Summary of sample means and variances for hand texture estimates, hydrometer analysis, and differences in sample values between the two methods.

	Topsoil Clay	Subsoil Clay	Topsoil Sand	Subsoil Sand
	%	%	%	%
Number of Samples (N)	68	67	68	67
Hand Texture Mean	23.1	24.6	51.9	51.2
Hand Texture Variance	18.3	19.1	127.2	138.9
Hydrometer Mean	23.2	24.7	55.5	51.6
Hydrometer Variance	22.0	17.7	118.8	101.4
Mean Difference	1.98	1.91	4.93	4.76
Variance of Differences	2.91	2.95	13.91	14.78
Percent Hydrometer Var.	13.3	16.7	11.7	14.6

The last row in Table 5.1 indicates the relative percent of total sample variance represented by the variance of difference between methods. Total sample variance for these comparisons was based on the hydrometer data. Overall, the additional variance associated with using hand texture estimates equaled between 10 to 20% of the total sample variance of the data. As a result, nugget values of up to 20% of the sill would be expected in the semivariograms due to measurement error.

The level of variability introduced using field texture determinations would be within reason for assessing reclamation suitability of coversoils, provided adequate use was made of appropriate reference samples. A greater concern from a regulatory standpoint would be the potential bias that could be introduced into results if such methods were adopted as standard operating procedures.

Table 5.2 gives summary statistics for all 9 soil/spoil variables: topsoil replacement depth, subsoil replacement depth, total soil replacement depth, topsoil percent clay, subsoil percent clay, spoil percent clay, topsoil percent sand, subsoil percent sand, and spoil percent sand. Sample data distributions all approximated a normal distribution with only minor amounts of skewness observed in plotted histograms. Log transformations were not required in semivariogram analysis for any of the sample data.

Spoil percent clay exhibited a unique distribution with two distinct peaks, a larger one at approximately 28% clay and a second smaller peak near 12% clay. Each relates to the different parent materials in the area. Siltstones with some interbedded shales make up the majority of overburden materials. These correspond to larger peak in clay content while the smaller peak corresponds to the lesser amounts of sandstones which make up the remaining rock substrates in the overburden.

Table 5.2. Summary statistics for soil replacement depth, percent clay, and percent sand.

	Depth (cm)			Clay (%)			Sand (%)		
	TS	SS	Total	TS	SS	Spoil	TS	SS	Spoil
Num. Obs. (n)	174	174	174	174	174	174	174	174	174
Mean	13.0	15.0	28.0	23.2	24.5	25.1	54.1	51.4	49.8
Std. Dev.	4.83	6.12	7.32	4.15	4.57	7.75	10.54	12.51	16.00
Minimum	4.0	5.0	10.0	14.0	16.0	10.0	20.0	20.0	20.0
1st Quartile	10.0	11.0	23.0	20.0	22.0	20.0	50.0	40.0	40.0
Median	12.0	14.0	27.5	22.0	24.0	26.0	60.0	50.0	50.0
3rd Quartile	17.0	18.0	32.0	24.0	28.0	30.0	60.0	60.0	60.0
Maximum	28.0	39.0	51.0	40.0	40.0	42.0	70.0	70.0	80.0
Coeff. Skew.	0.57	1.03	0.489	1.10	0.60	-0.30	-1.05	-0.33	0.18

5.4.2. Experimental Semivariograms

Experimental semivariograms were plotted for each of the soil variables (Figs. 5.4, 5.5, and 5.6). In general, only weak spatial correlation structure was found in the soil data despite sampling at a closer grid spacing than required by the mining permit. The default lag interval, provided by the Geo-eas program for this data set, was used in all initial semivariogram plots. This facilitated quick comparisons of the experimental semivariograms at the start.

The experimental semivariogram for topsoil replacement depth (Fig. 5.4.) exhibited large semivariances at short separation distances associated with relatively large changes in laydown depth most likely occurring in adjacent strips or possibly adjacent haul loads. High semivariances at short separation distances also reflect the sensitivity of the semivariance statistic to erratic high values. Semivariances react similarly in this regard to other squared statistical indices.

Experimental semivariograms for subsoil replacement depths behaved in a more expected manner although only weak spatial correlation was found. The apparent nugget effect comprised a high proportion of the overall sill. Effects of erratic high and low sample values were still evident in high points on the semivariogram. The experimental semivariogram for total soil replacement

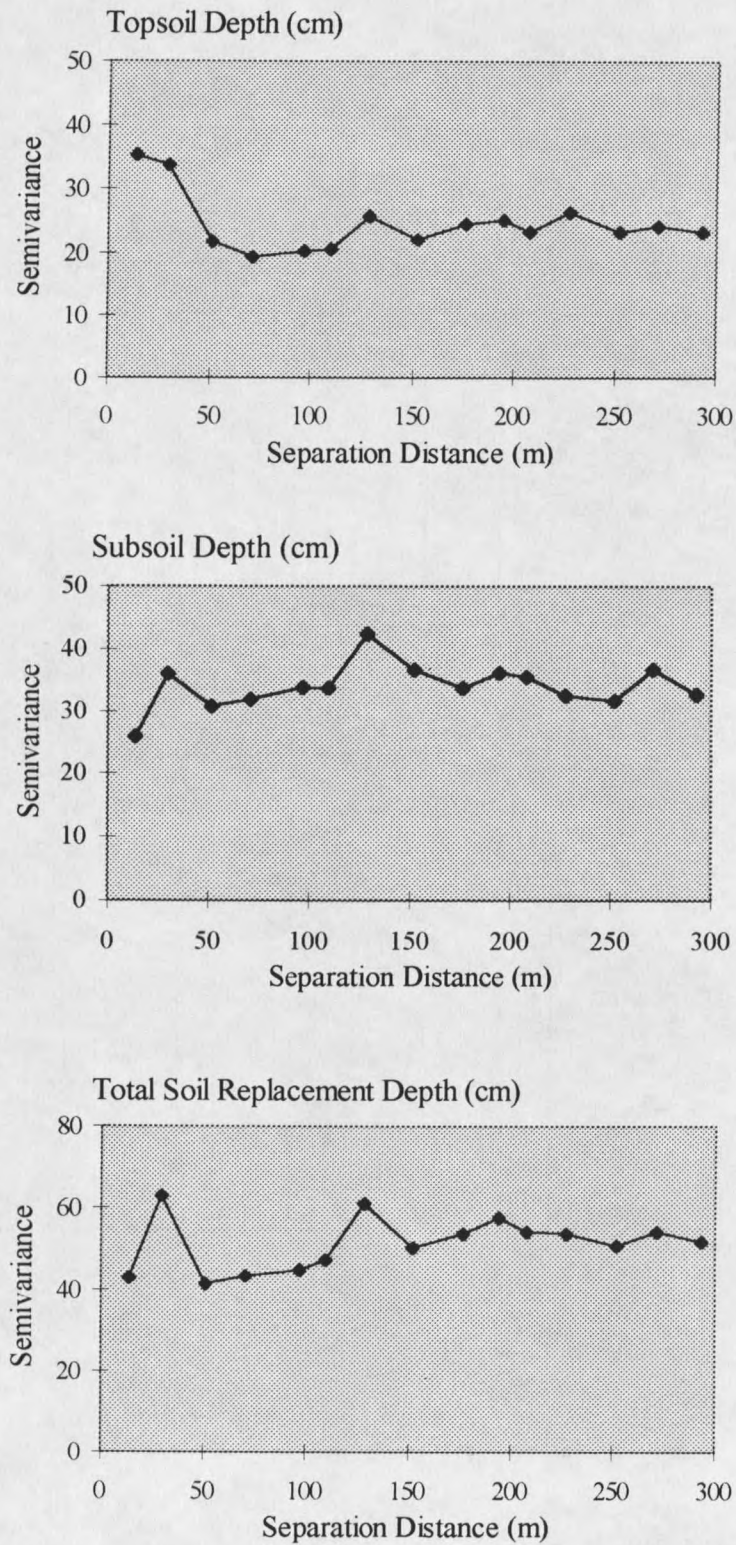


Figure 5.4. Experimental semivariograms for soil replacement depths: topsoil, subsoil and total.

depth was a composite of the first two, with little or no spatial correlation structure and evidence of erratic large differences in sample values apparent at several lag intervals.

The experimental semivariogram for topsoil clay (Fig. 5.5) indicated a pure nugget effect similar to the results reported by Keck et al. (1993). Weak spatial correlation structure can be seen in the plot for subsoil clay. Again, the high apparent nugget value relative to the semivariogram sill indicates questionable performance of kriging as a spatial interpolation procedure. Data for spoil percent clay showed good spatial correlation structure up to a separation distance of about 75 meters.

Similar patterns existed in the experimental semivariograms for percent sand (Fig. 5.6). Any apparent spatial correlations were restricted to very short separation distances of less than 25 meters for topsoil percent sand data. Reasonably good spatial correlation structure existed in the subsoil sand and spoil sand data. Since sand and clay are two of three components of soil texture, correlations in the data and data structure of these two variables were expected.

Three of the seven soil variables were selected for comparisons with Western Energy data (Sections 5.4.4 and 5.4.5). Western Energy does not sample spoil material in their coversoil sampling so direct comparisons could not be made for spoil clay or spoil sand percentages. The three soil variables selected were subsoil replacement depth, subsoil clay percent, and subsoil sand percent due to the greater amount of spatial correlation exhibited by semivariograms for these variables.

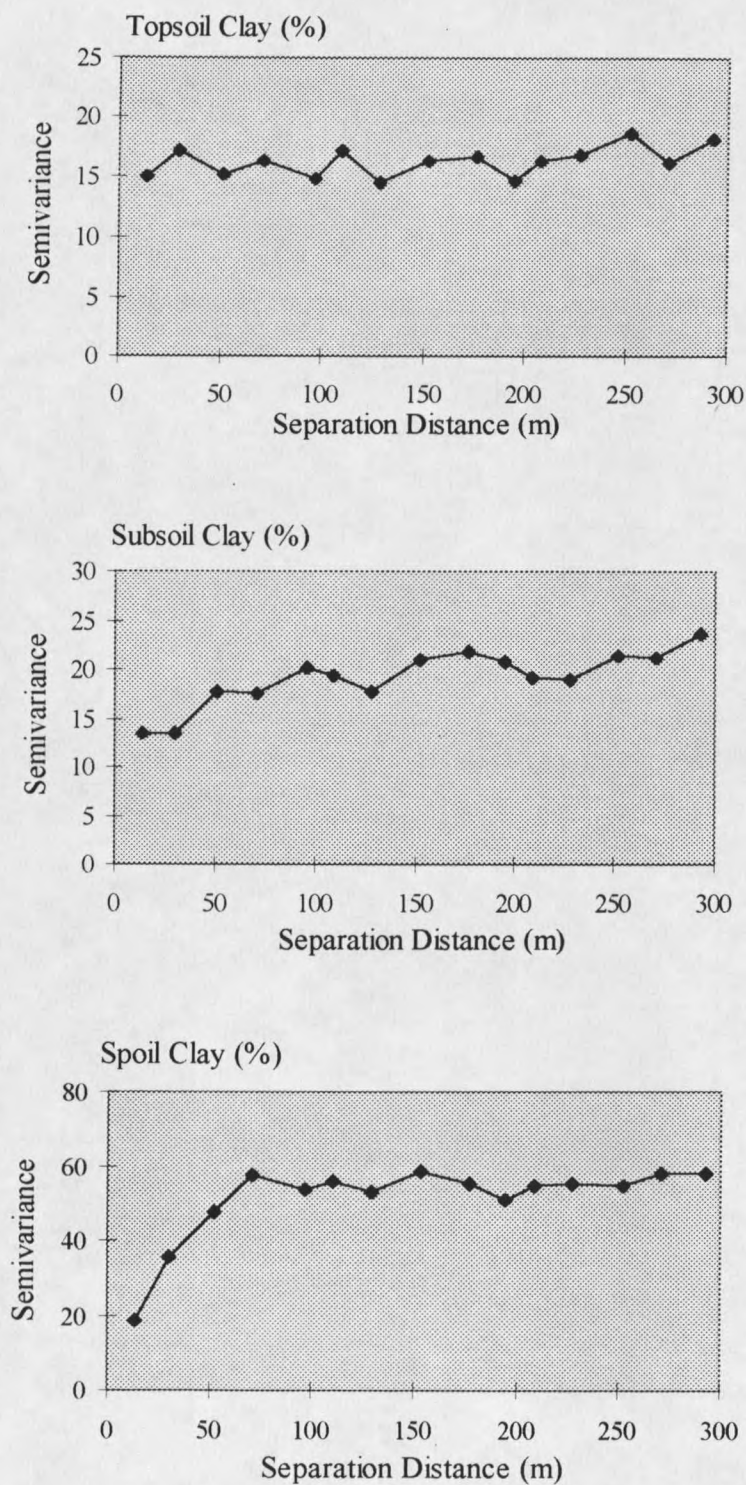


Figure 5.5. Experimental semivariograms for percent clay in soil and spoil materials.

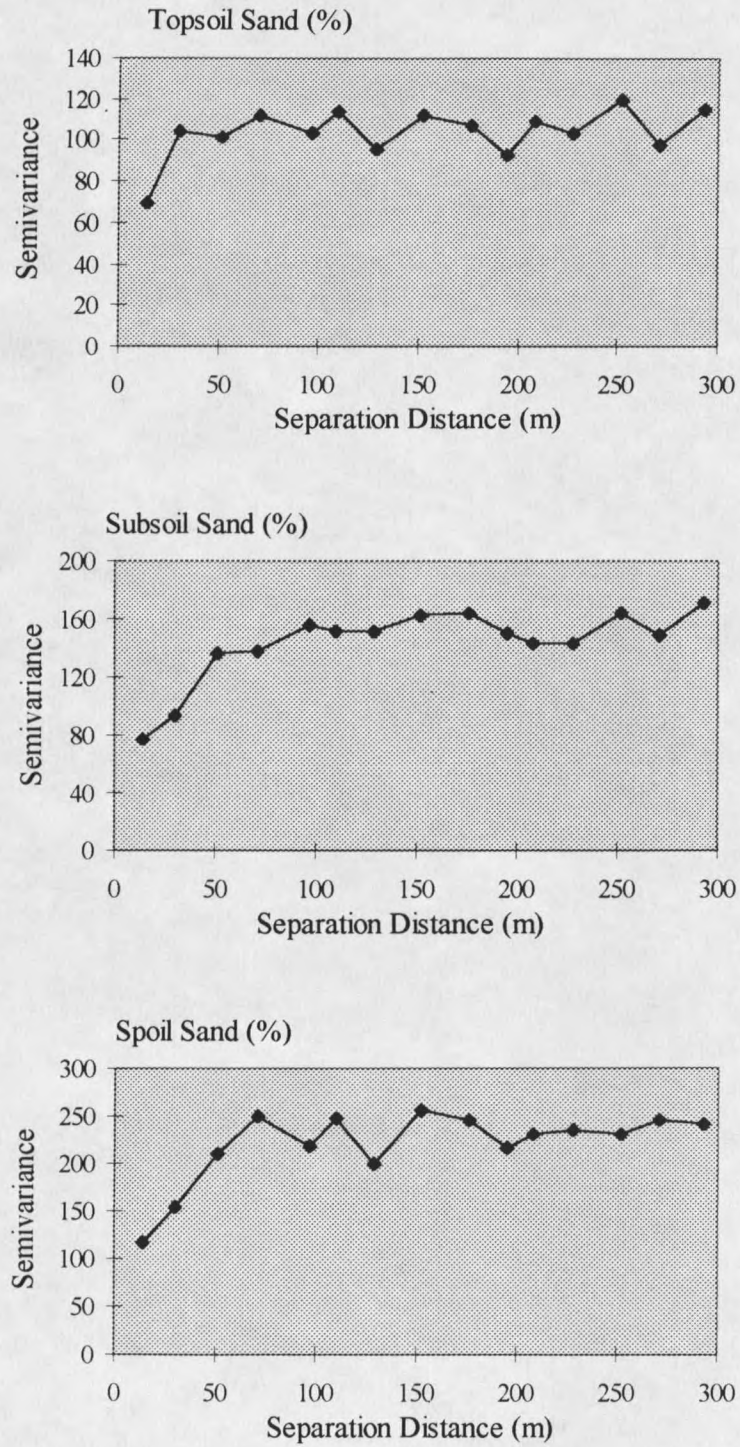


Figure 5.6. Experimental semivariograms for percent sand in soil and spoil materials.

5.4.3. Modeling Semivariograms

An exponential model provided the best fit for all of the experimental semivariograms modeled. Figures 5.7, 5.8, and 5.9 contain the experimental semivariograms, one isotropic and two anisotropic, for each of the three subsoil variables. Isotropic semivariogram models are superimposed over each plot of experimental data. Parameters for the semivariogram models are listed in Table 5.3.

Table 5.3. Parameters used to model the experimental semivariograms for subsoil clay, subsoil sand and subsoil replacement depth.

Soil Property		Lag	Model	Nugget	Sill	Range	Range	Sill/Nugget
		m		*	*	m	m	
Depth	(iso)	20.1	exp.	23.0	35.0	125	-	1.52
Clay	(iso)	30	exp.	10.0	21.5	175	-	2.15
Sand	(iso)	25	exp.	60.0	160.0	125	-	2.67
Clay	(aniso)	40	exp.	4.0	21.5	200	75	5.37

* Units for the nugget and sill are $(\text{cm})^2$ for soil replacement depth and $(\%)^2$ for clay and sand percentages.

Semivariograms for subsoil replacement depth (Fig. 5.7) were messy. The model does not account for several large, erratic semivariance values in the experimental data. Only weak spatial correlation structure was expressed by the data with a sill to nugget ratio of only 1.5 to 1. Semivariances for the first lags of the East/West and North/South directional semivariograms show a distinct anisotropic response at short separation distances. The East/West semivariogram has its highest point at the shortest separation distance indicating large sample value differences for samples located adjacent to one another in the sample grid. This direction runs perpendicular to the primary direction of soil laydown during reclamation. The North/South directional semivariogram, parallel to the primary direction of laydown, shows a corresponding low semivariance, below the model line, at the shortest separation distance.

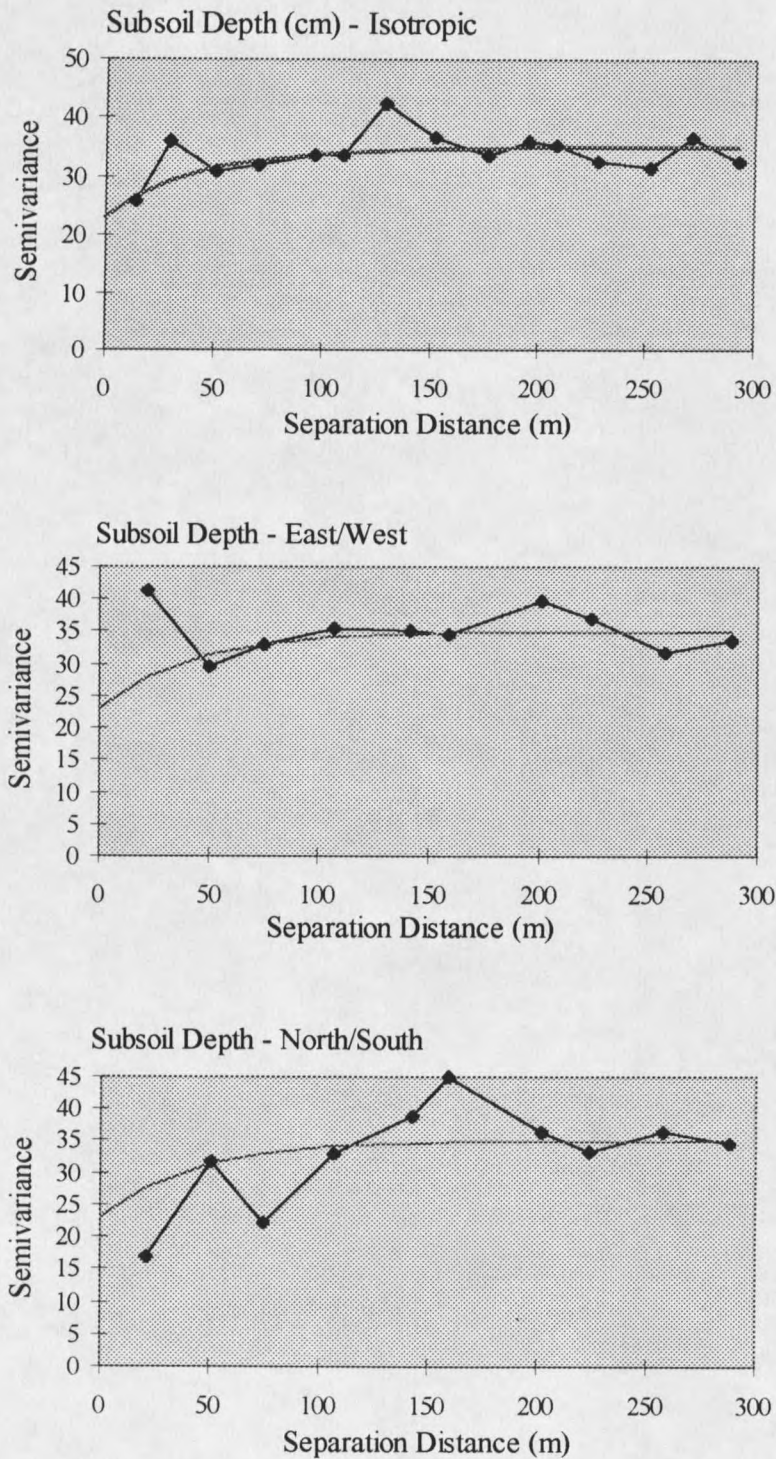


Figure 5.7. Experimental semivariograms for isotropic and anisotropic analysis of subsoil replacement depth data with the semivariogram model for the isotropic case plotted on each.

Semivariograms for subsoil clay (Fig. 5.8) exhibited the same general pattern of limited spatial correlation. The experimental semivariograms were much better "behaved" in terms of less noise around the model line and a range of 175 meters provided the best model fit. The sill to nugget ratio was 2.15 to 1. Data for the anisotropic East/West semivariogram (perpendicular to laydown direction) fit the isotropic semivariogram model reasonably well. In the North/South direction, the sample data for the first two lags fell below the model line indicating a potential directional component to the spatial structure of the data.

Semivariograms for subsoil sand (Fig. 5.9) behaved in a similar manner as those for subsoil clay although a greater degree of spatial correlation existed in the data. Similarities reflect the correlated nature of these two variables. The data provided a good fit of an exponential model to the experimental semivariogram which had a sill to nugget ratio was 2.67 to 1. Empirical evidence of the semivariogram suggests greater overall spatial correlation exists in the subsoil sand data than other soil variables tested. Analysis of the anisotropic East/West experimental semivariogram provided an almost exact trace of the isotropic model whereas in the North/South direction some possible anisotropy was indicated as the semivariance for the first lag fell below the model line.

A tendency towards anisotropic behavior in semivariograms was not totally unexpected. The primary direction for soil laydown in this area was North-South. It makes sense, that soil properties would be more similar over longer distances in the primary direction of laydown than at right angles to the primary direction of laydown. In the East/West direction, across the direction of laydown, dissimilar materials are more likely to be placed side by side in adjacent strips. These intuitive relationships were represented in the data but only as a weak tendency towards anisotropy.

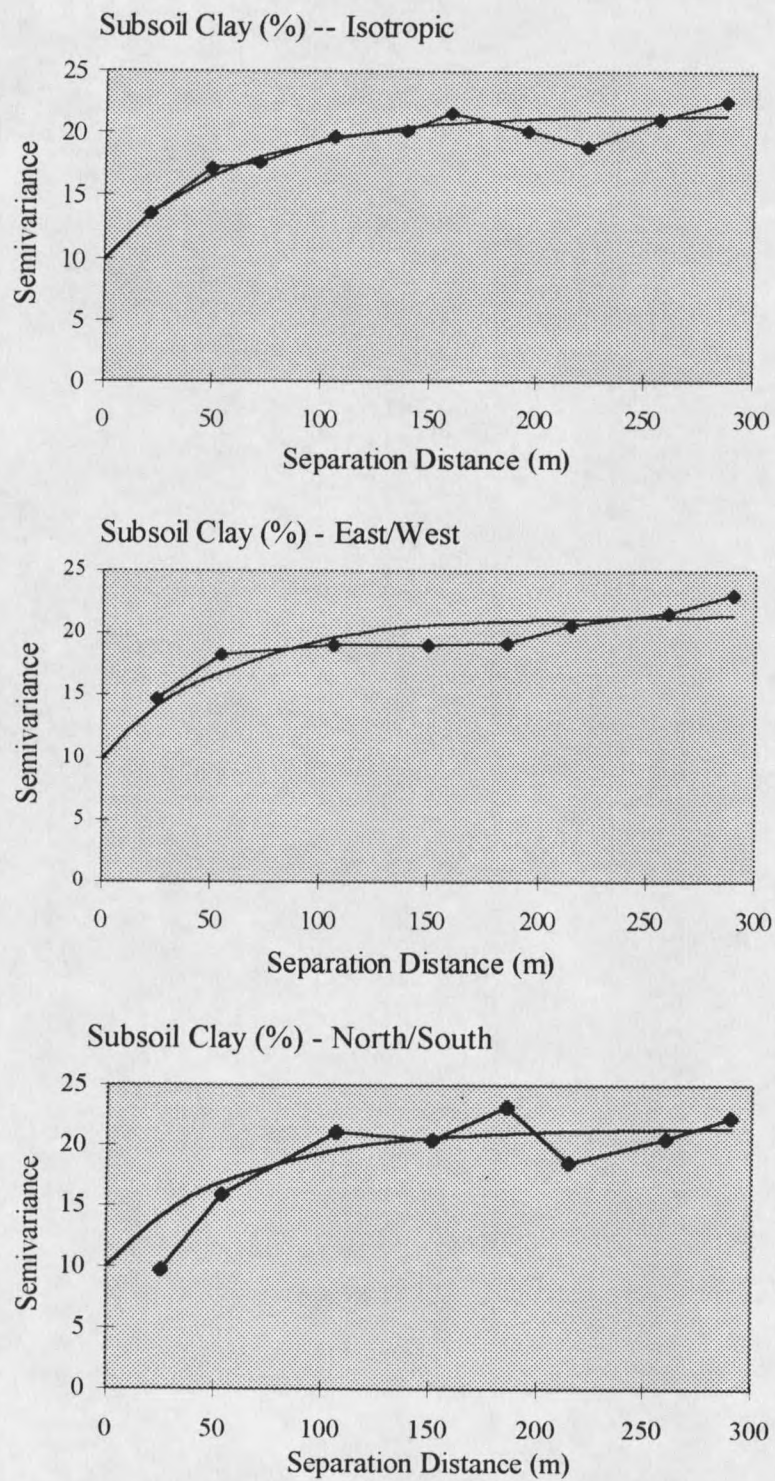


Figure 5.8. Experimental semivariograms for isotropic and anisotropic analysis of subsoil percent clay data with the semivariogram model for the isotropic case plotted on each.

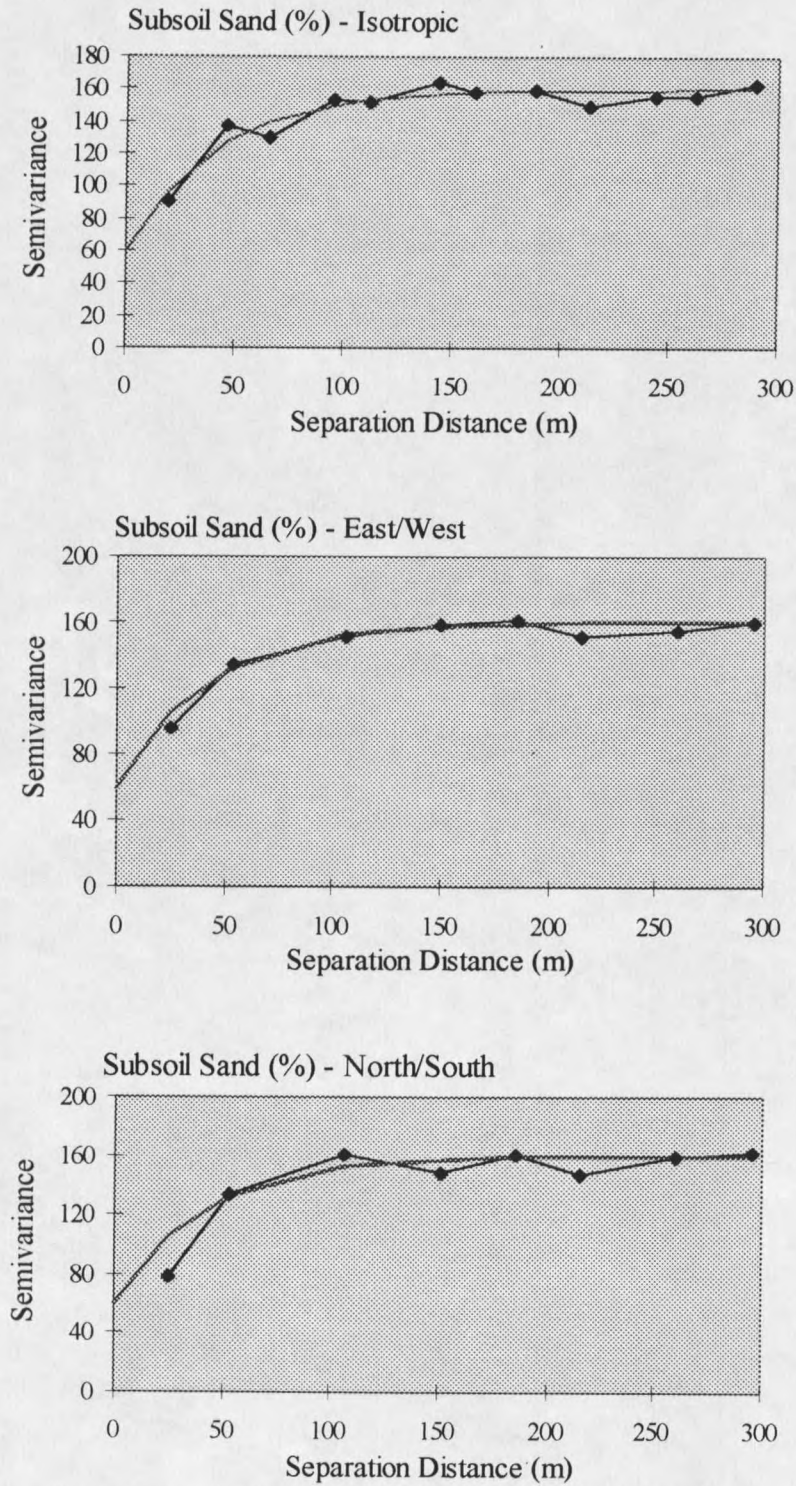


Figure 5.9. Experimental semivariograms for isotropic and anisotropic analysis of subsoil percent sand data with the semivariogram model for the isotropic case plotted on each.

Directional differences may have been more pronounced if the area had been reclaimed by direct haul methods rather than from coversoil materials stored in salvage piles.

An anisotropic semivariogram model was fit to the subsoil clay experimental data in a modification of the method outlined by Englund and Sparks (1992). The model type and sill height were set by the isotropic model for subsoil clay while a new nugget value was determined from the anisotropic semivariogram in the North/South direction. The model fit in this manner had a nugget value of 4 which was 18.6% of the model sill height. This corresponds to the approximate 10 to 20% of the sill expected minimum value for the nugget due to the variability of hand texture estimates. The exponential model with a sill of 21.5% and a nugget of 4.0% was then fit to the anisotropic data in both the North/South and East/West directions to obtain the range for each. A range of 75 meters was obtained for the East/West direction and a range of 200 meters was obtained in the North/South direction.

5.4.4. Comparison of Data Sets

Data collected by Western Energy provided an independent data set of measured values with which to compare kriged estimates. The two data sets must be reasonably equal for test results to be valid. Equal, in this sense, means the data were collected from the same population of soil properties, the same or comparable methods of sample collection and analysis were used, and no bias was introduced into sample collection or sample analysis of either data set.

The same methods of sample analysis formed the basis for both data sets. The hydrometer method, adopted by Western Energy, was used in the study to develop standards for hand texture estimates of percent clay and percent sand. In addition, up to a third of total analyses for soil texture were run by the hydrometer method. Field measurements of soil replacement depths for

both the Western Energy data and the experimental data were based on the same observed differences among topsoil, subsoil, and spoil materials. All samples were collected from the same two reclaimed fields. Based on the sample population and sample analysis, the two data sets should be identical; assuming no bias was introduced into the collection or analysis of either data set.

Q-Q plots between Western Energy data and the experimental data were run to test assumptions that the two data sets were equivalent. Figures 5.10a, 5.11a, and 5.12a show the relationship between sample distributions for the experimental data set and Western Energy data for each of the subsoil attributes tested. In each case, there appears to be some bias in the collection of data between the two data sets. Data distributions are narrower in all instances for the Western Energy data relative to the experimental data set. Regulatory thresholds for suitability may well provide a strong incentive for mining company personnel to bias results ever so slightly, to ensure that few samples as possible exceed allowable limits. Such biases may be as simple as selecting which handful of soil gets placed in a sample bag or inadvertently biasing judgments about the location of boundaries between soil layers.

Determining whether such potential causes of bias are real or imagined is outside the scope of this study. For comparison purposes, the presence of biased data required that one or the other data set be adjusted. A graphical approach was used to determine appropriate linear transformations for adjusting the Western Energy Data. Transformations used were as follows:

Subsoil Replacement Depth

$$WECO_{adj} = WECO_{int} + .5(WECO_{int} - 12)$$

Subsoil Percent Clay

$$WECO_{adj} = WECO_{int} + .24(WECO_{int} - 15)$$

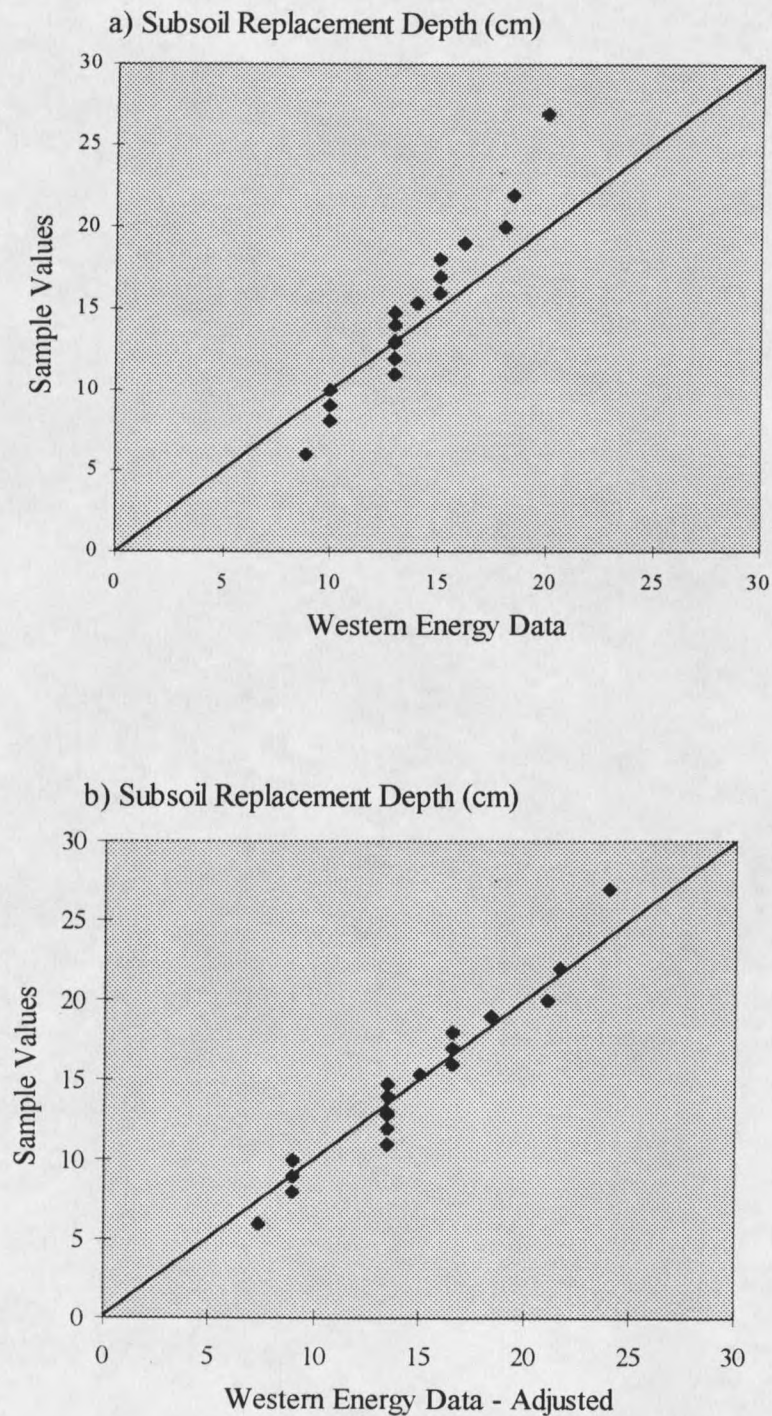


Figure 5.10. Q-Q plots comparing Western Energy data and the experimental data set for subsoil replacement depths: (a) initial data, (b) after scaling the Western Energy data.

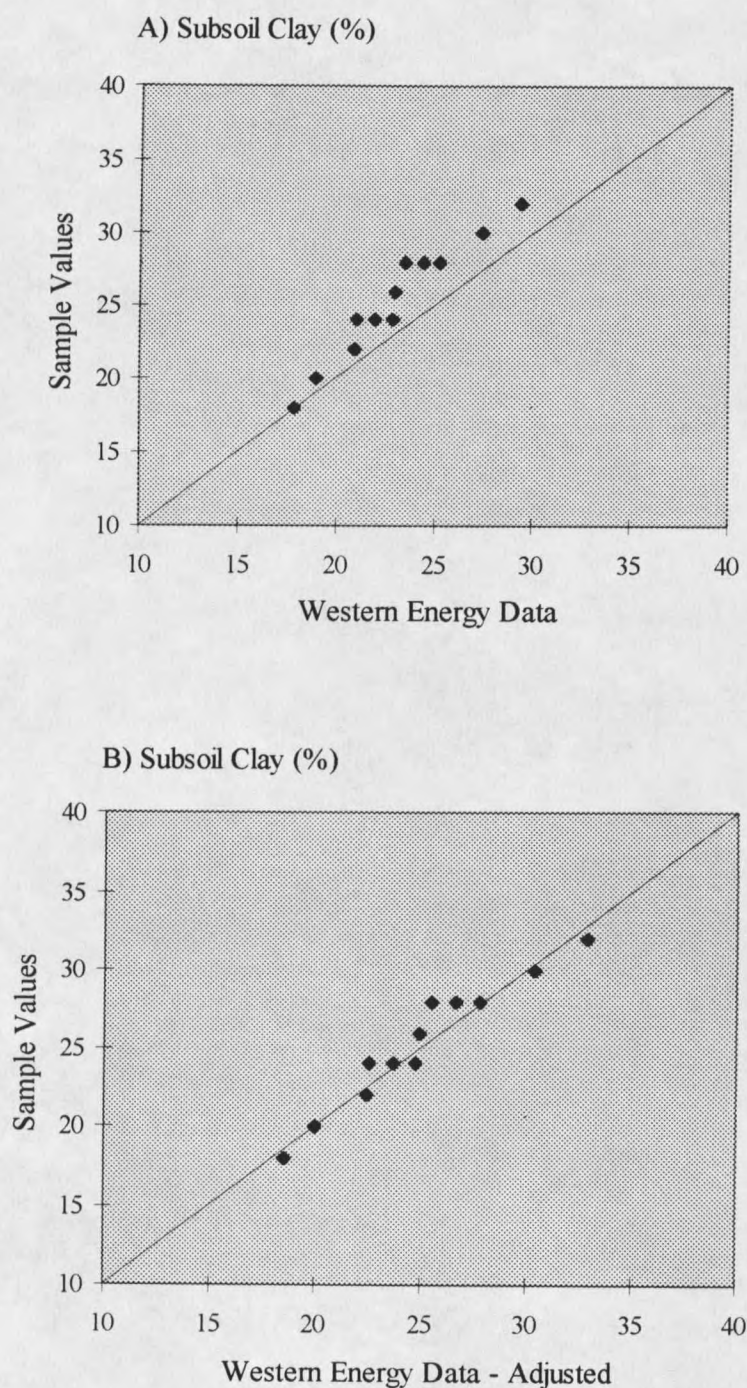


Figure 5.11. Q-Q plots comparing Western Energy data to the experimental data set for subsoil percent clay: (a) initial data, (b) after scaling the Western Energy data.

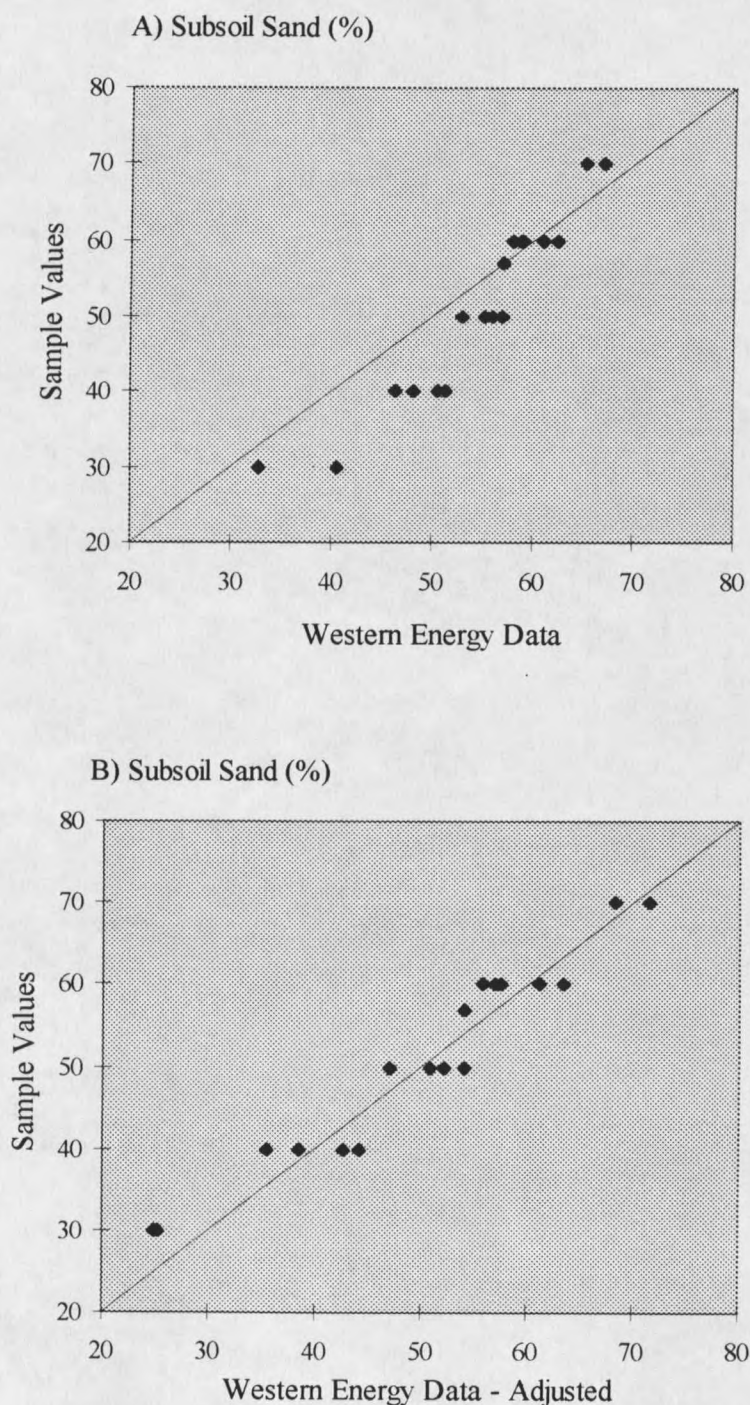


Figure 5.12. Q-Q plots comparing Western Energy data to the experimental data set for subsoil percent sand: (a) initial data, (b) after scaling the Western Energy data.

Subsoil Percent Sand

$$\text{WECO}_{\text{adj}} = \text{WECO}_{\text{int}} + .75(\text{WECO}_{\text{int}} - 61)^*$$

* Subject to a minimum constraint of 25% sand.

WECO_{adj} in the equations above refers to the final adjusted values for the Western Energy data while WECO_{int} refers to initial Western Energy data values. In each case, an approximate regression line from the q-q plot was scaled to match the diagonal equal values line of the graph.

The bottom portion of Figures 5.10, 5.11, and 5.12 show the corresponding q-q plots for adjusted Western Energy data relative to the experimental data set. The adjusted distribution of Western Energy data aligned closely with the equal values line on the graph. Adjusted Western Energy data were used for all subsequent comparisons of kriging results. Theoretically, adjustments to the Western Energy data should have enhanced the comparison of measured versus predicted values between the two data sets. The adjustments made, however, had the net effect of increasing high values and decreasing low values in all three cases. This effectively reduced the likelihood that kriged estimates would accurately predict measured values since kriging by its very nature creates a smooth surface relative to the original data. In general, extremes of high and low values are poorly predicted by kriging estimates.

5.4.5. Kriging Results - Comparisons to Western Energy Data

Four kriging trials were run on the experimental data for comparison with Western Energy data. Isotropic models were used for kriging runs of subsoil replacement depth, subsoil clay, and subsoil sand. The anisotropic model was used for subsoil clay in a fourth kriging trial. Table 5.3 (p.118) summarizes the models and parameters used for each kriging run. Low sill to nugget ratios characterized all three of the isotropic semivariogram models indicating only weak to

moderate spatial dependence in the sample data. Questions remained about the lack of stationarity in the data even within local estimation neighborhoods.

Figure 5.13 displays the isotropic kriging results for subsoil clay. They contrast sharply with the graphic representation of field means for the same variable (Fig. 5.14). Results from anisotropic kriging of the same variable (Fig. 5.15) show more of an elongated pattern of predicted high and low values, oriented along the north-south axis, parallel to the primary direction of laydown. Regardless of their relative accuracy, each of these patterns represents a different representation of how the underlying spatial data are distributed in space. Field means can be thought of as similar to soil survey map units in this case, by providing a single estimated value within a map unit boundary. Kriging representations of soil properties often appear more realistic but it does not follow that they are necessarily more accurate.

Table 5.4 summarizes results of using kriging estimates and field means to predict subsoil replacement depths, clay, and sand contents relative to the Western Energy data. In all cases, the actual kriging standard deviations (square root of the mean square error) were substantially higher than the average predicted kriging standard deviation for the comparisons made. Differences between actual and predicted standard deviations were on the order of 2 to 1, supporting the notion that kriging assumptions of stationarity were poorly met by the mine soil data.

Table 5.4. Comparison of kriged estimates and field means for predicting Western Energy subsoil data.

Soil Property	Kriging			Field Mean	
	Predicted Std. Dev.	Mean Squared Error (Std. Dev.)	Exceeding Threshold n=38	Mean Squared Error	Exceeding Threshold n=38
Depth (iso)	2.89	22.65 (4.76)	5	22.99	5
Clay (iso)	2.16	21.17 (4.60)	7	20.30	5
Sand (iso)	7.30	183.70 (13.6)	8	194.18	8
Clay (aniso)	2.33	22.81 (4.78)	9	20.30	5

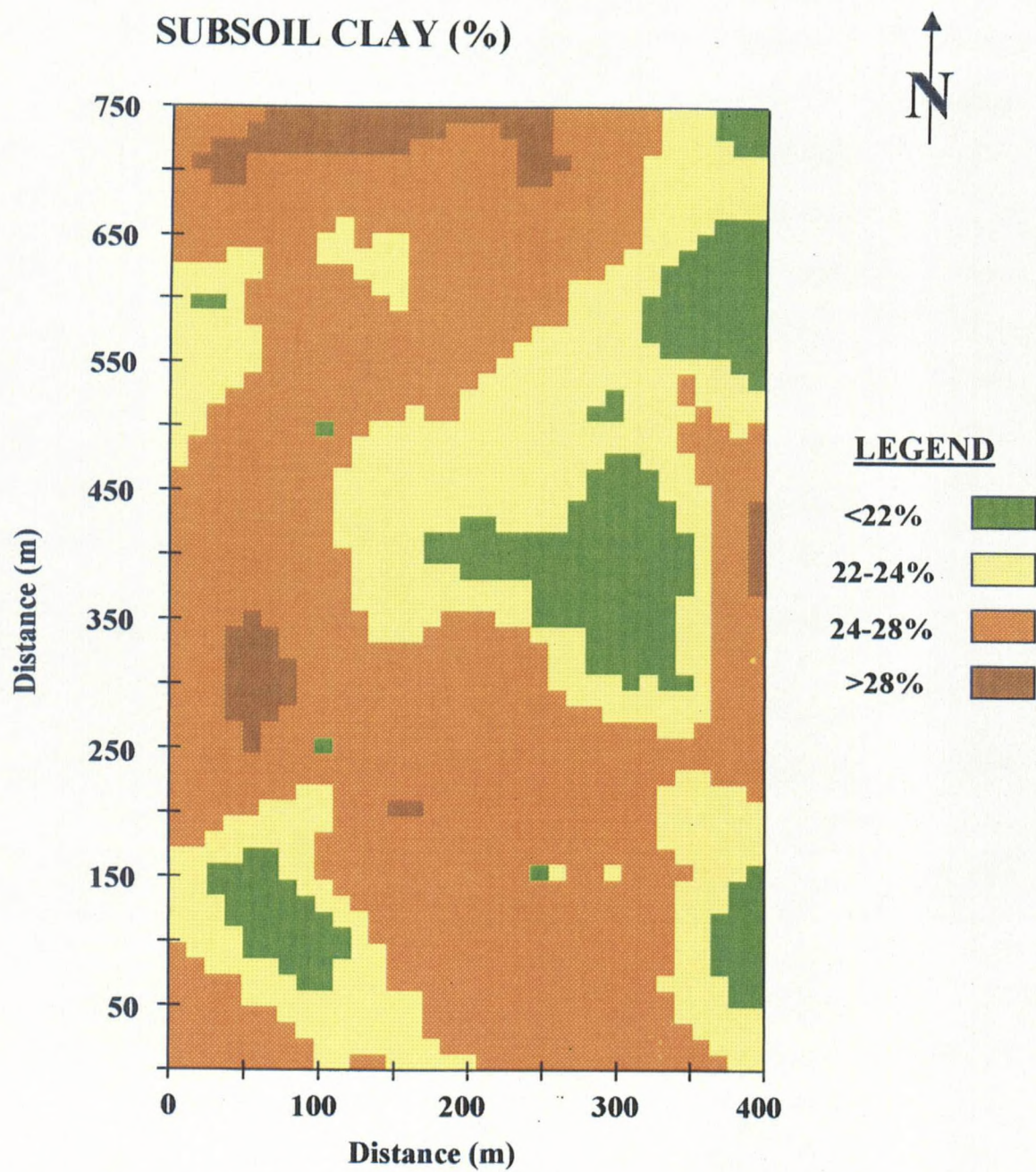


Figure 5.13. Kriging results for subsoil percent clay - isotropic model.

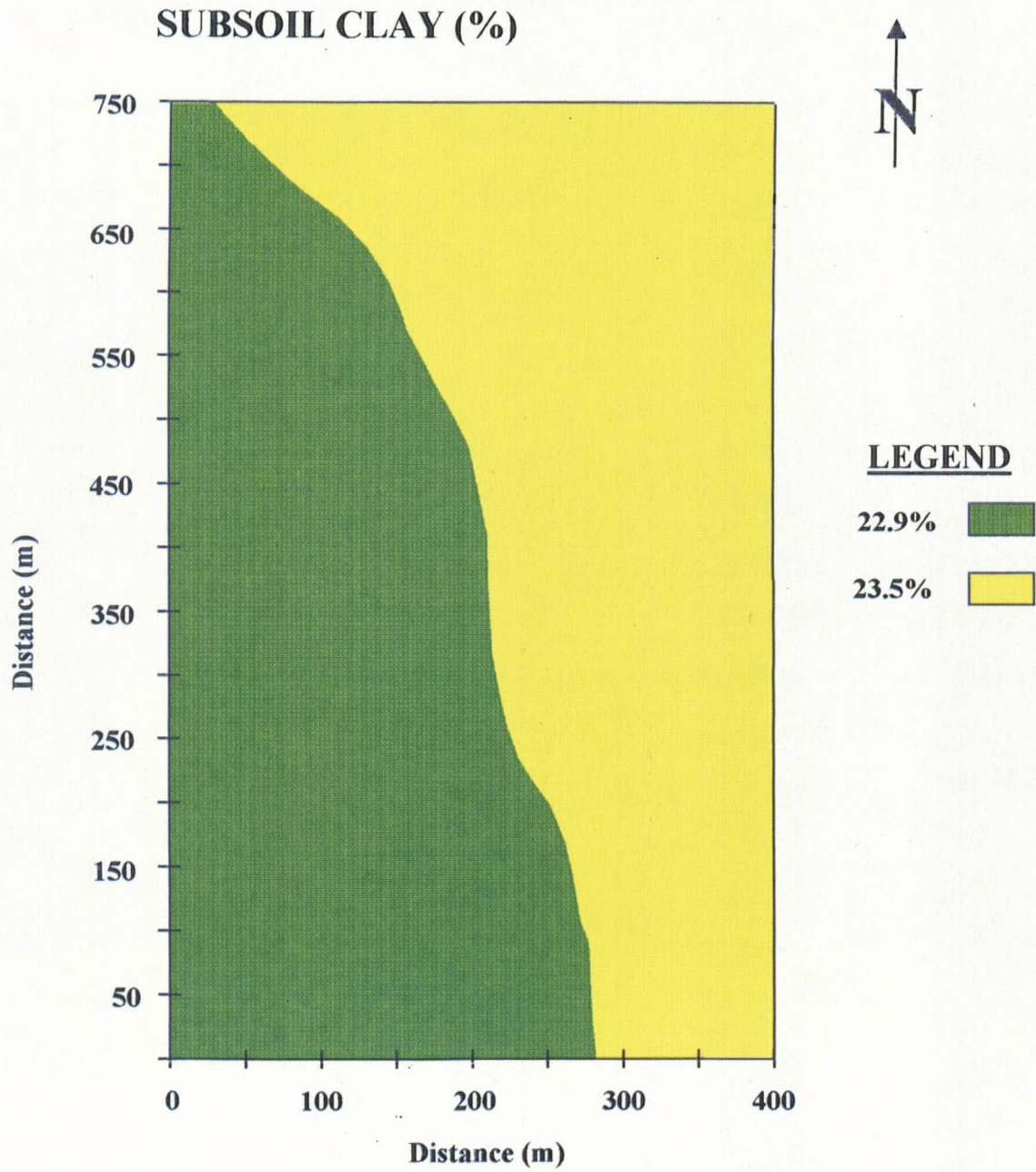


Figure 5.14. Field mean values for subsoil percent clay.

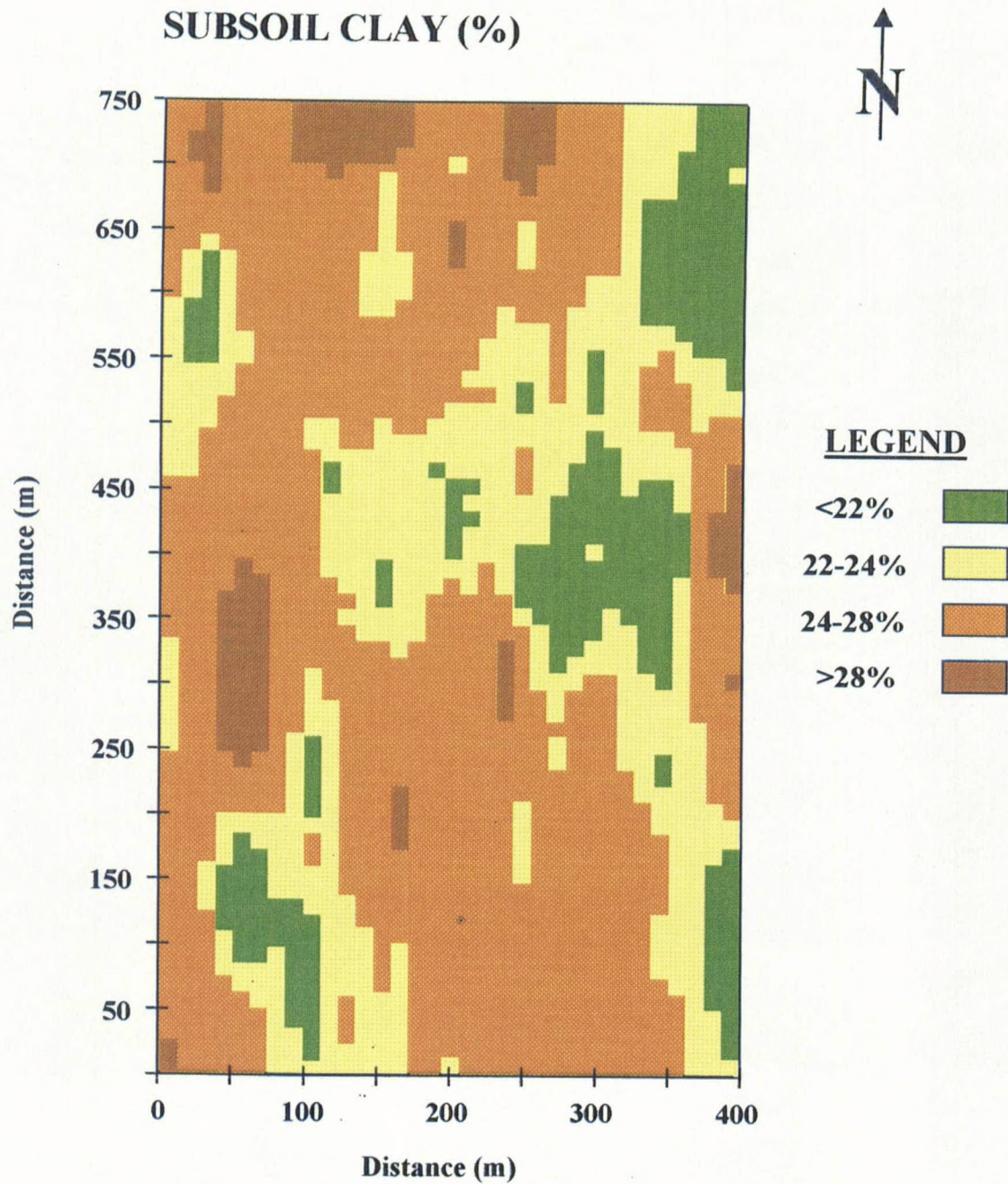


Figure 5.15. Kriging results for subsoil percent clay - anisotropic model.

Only minor differences existed between the mean square error of kriging estimates and those associated with using field means to predict the Western Energy data. A slight improvement of mean square error occurred in kriging the subsoil sand data relative to the field mean values. Semivariograms for subsoil sand showed the greatest amount of spatial dependence (highest sill to nugget ratio) of the three isotropic models. Anisotropic kriging of subsoil clay did not improve results. Mean square error was higher for the anisotropic kriging than for either isotropic kriging or use of field mean values to predict subsoil clay.

More often soil scientists and land managers are interested in a general land management class, such as a soil type, rather than exact values for soil properties. They want to know if a soil is sandy or if it is a loam. Is it shallow or deep, etc.? This coupled with the fact that all estimates have associated error bounds suggests that mean square error alone may not be the best measure of prediction accuracy. Precision in predicting soil properties at unsampled locations can never exceed the precision of field measurements at known locations. For the texture data, the error associated with using hand textures represents an upper limit of precision for all kriging estimates of clay and sand. Mean square error alone overstates the error of predictions to some degree by not accounting for this allowable error.

Exact values of soil properties such as replacement depths or percent clay may have little impact on the potential use and management of the reclaimed soil resource. Reasonably precise and accurate estimates are needed, however, to group soils correctly into management units. Grouping soils into management units, in this instance, may simply mean identifying areas that do not meet suitability criteria. The following thresholds or error bounds appear reasonable for prediction estimates, given the limitations of data accuracy and management considerations: $\pm 6\%$ clay, $\pm 15\%$ sand, and ± 7.5 cm replacement depth.

A second criteria for prediction success would be the number of missed predictions relative to expected error bounds. Field means did as well or better, in this regard, than kriging for all 3 variables. The anisotropic kriging run for subsoil clay gave the worst results with 9 out of 38 or nearly 25% of the predicted clay estimates missing the mark by more than the $\pm 6\%$ clay limit (Table 5.4 - p.129).

Scatter plots, in Figures 5.16 and 5.17, of kriged estimates versus observed values provide some insight into how kriging performed. The cluster of data points near the center of each graph shows where kriging gave the best results which was at the center of the range in measured values. Erratic high and low measured values were consistently under or over-estimated, respectively. These results are not surprising since kriging characteristically has a smoothing effect relative to the input data. The range and variance of kriging estimates are expected to be less than that of the original data. An unexpected result was that in each case, the cloud of data points in comparison graphs was distinctly oriented in a horizontal manner from side to side and not diagonally along the line of equal values between x and y axes. If kriging estimates were more accurately predicting observed values, the orientation of the plotted data would be aligned in a diagonal pattern, parallel to the equal value line on the graph. Lighter lines on either side of the main diagonal indicate the accuracy tolerances for each variable. Data points within these outer bounds were predicted within the accepted tolerance. Data points outside these boundaries missed the mark.

Figures 5.18 through 5.21 provide a more direct comparison of kriged estimates, the field mean, and Western Energy sample values for each of 38 Western Energy sample locations. Comparisons for each variable are split into two graphs, one for each field in the study area. Western Energy samples 1 through 19 were located in field #3903 and samples 21 through 39 were

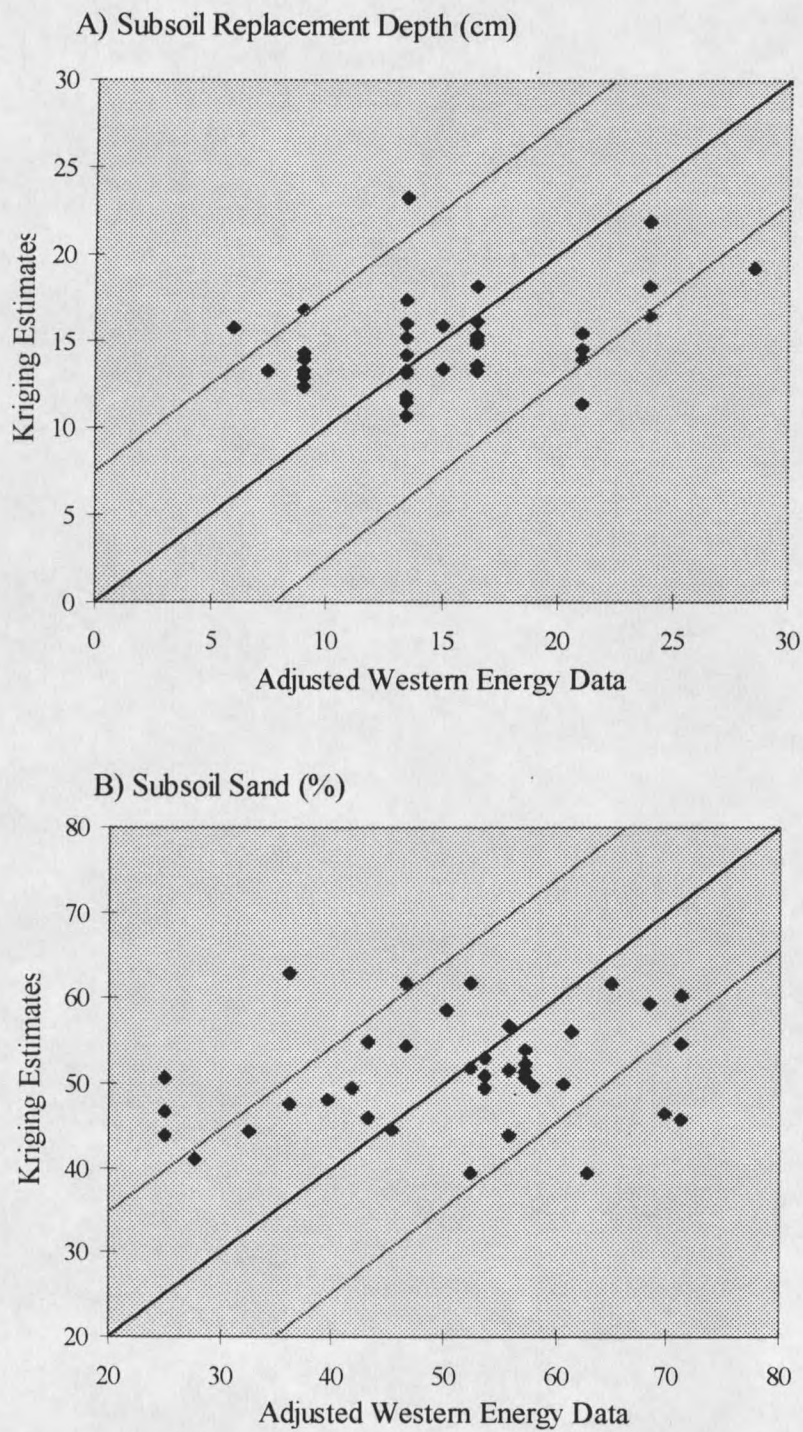


Figure 5.16. Scatter diagrams of kriged estimates versus measured values for: a) subsoil replacement depth, b) subsoil percent sand.

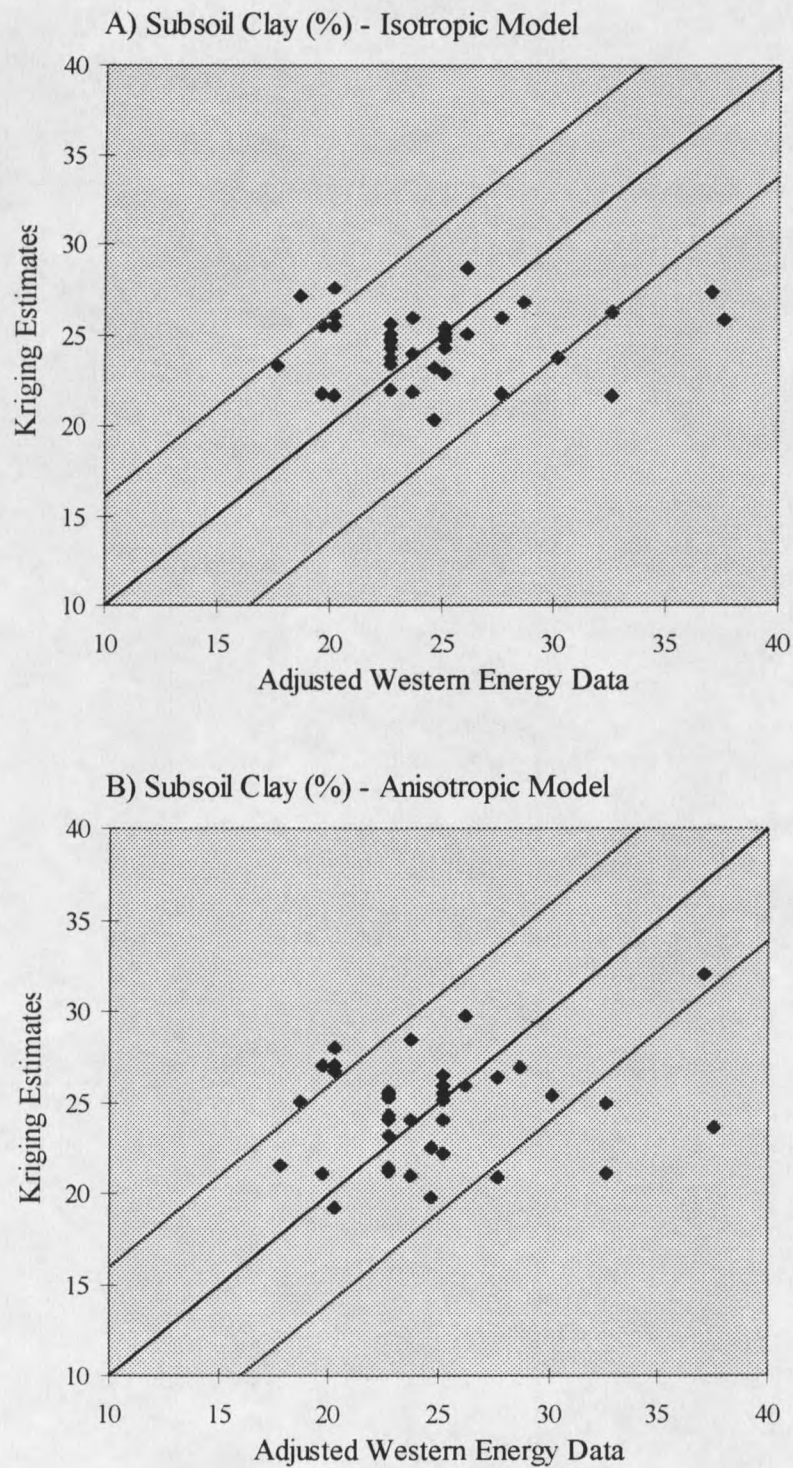


Figure 5.17. Scatter diagrams of kriged estimates versus measured values for subsoil percent clay: a) isotropic kriging and b) anisotropic kriging.

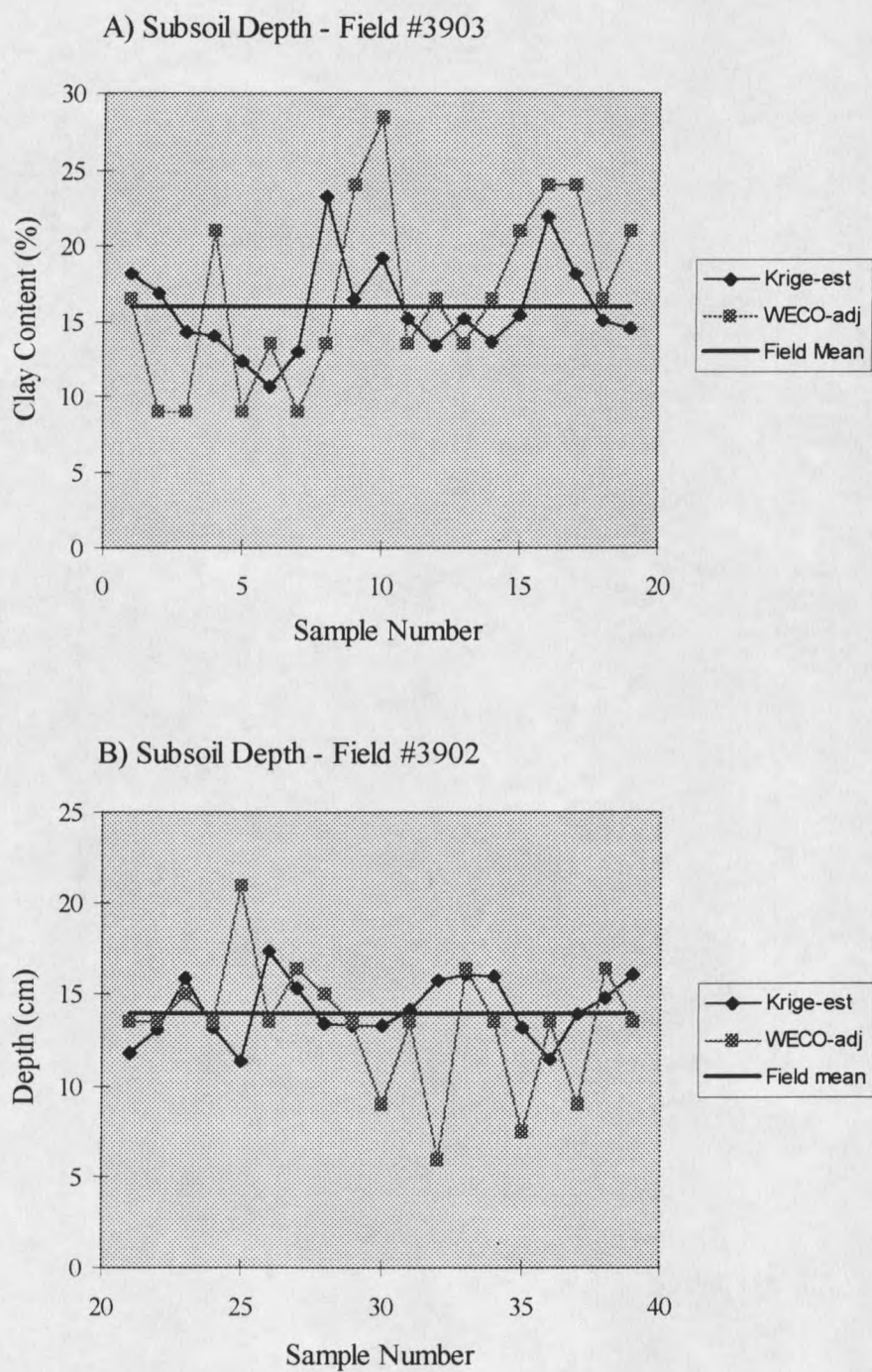
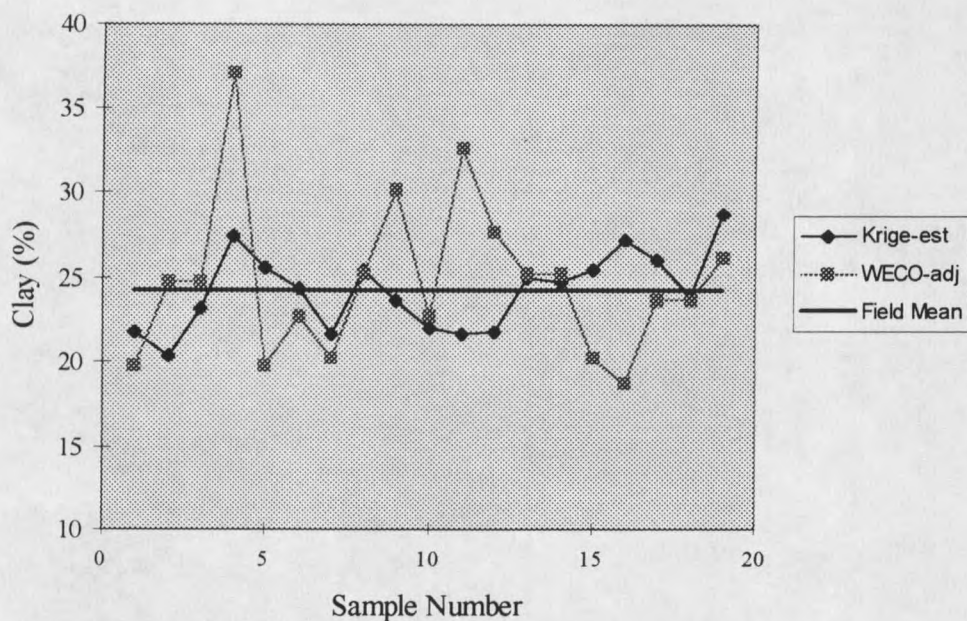


Figure 5.18. Comparisons of measured values, kriging estimates, and field means for subsoil replacement depth: a) field #3903 and b) field #3902.

A) Subsoil Clay Field #3903 Isotropic Model



B) Subsoil Clay - Field #3902 Isotropic Model

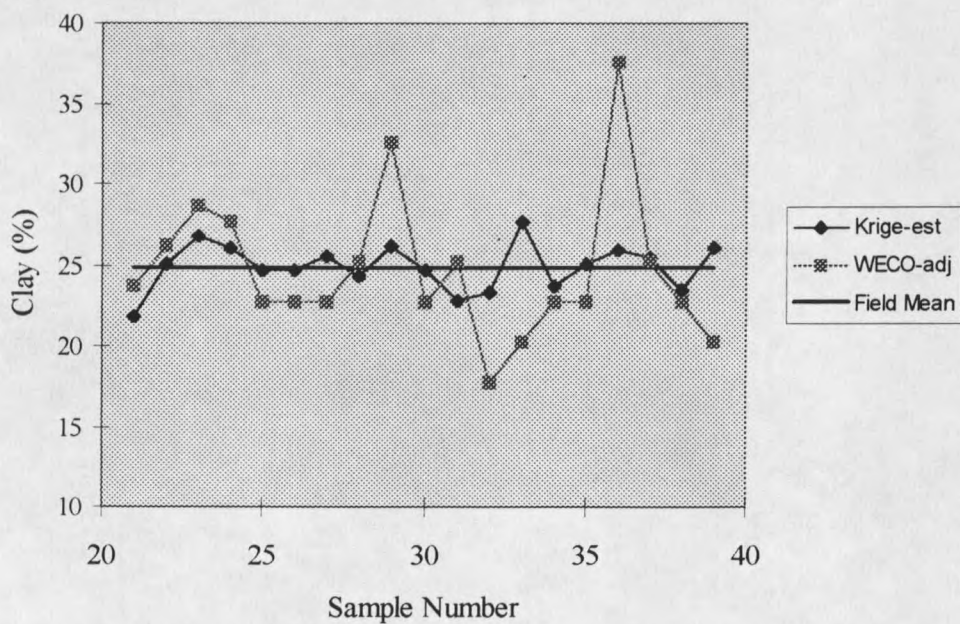
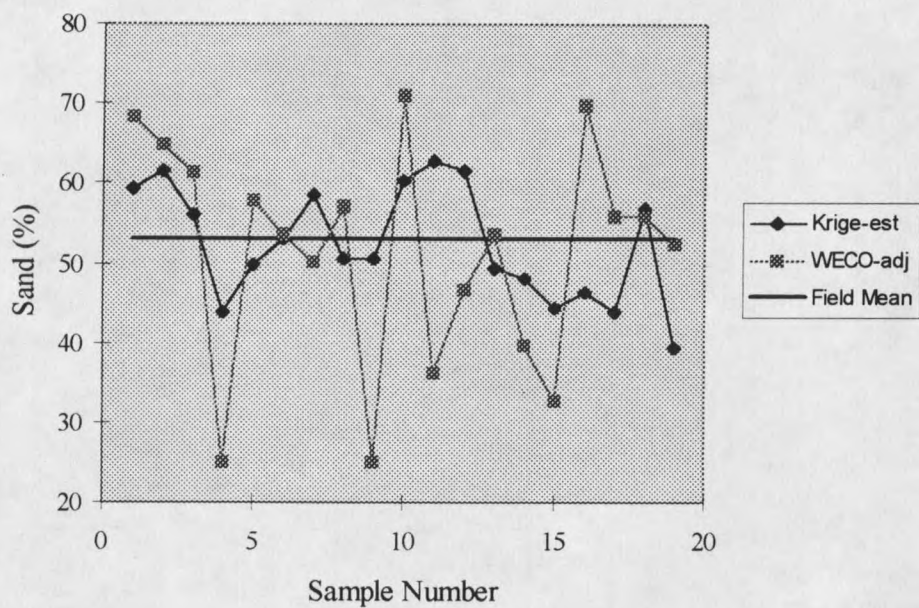


Figure 5.19. Comparison of measured values, isotropic kriging estimates and field means for subsoil percent clay: a) field #3903 and b) field #3902.

A) Subsoil Sand - Field #3903



B) Subsoil Sand - Field #3902

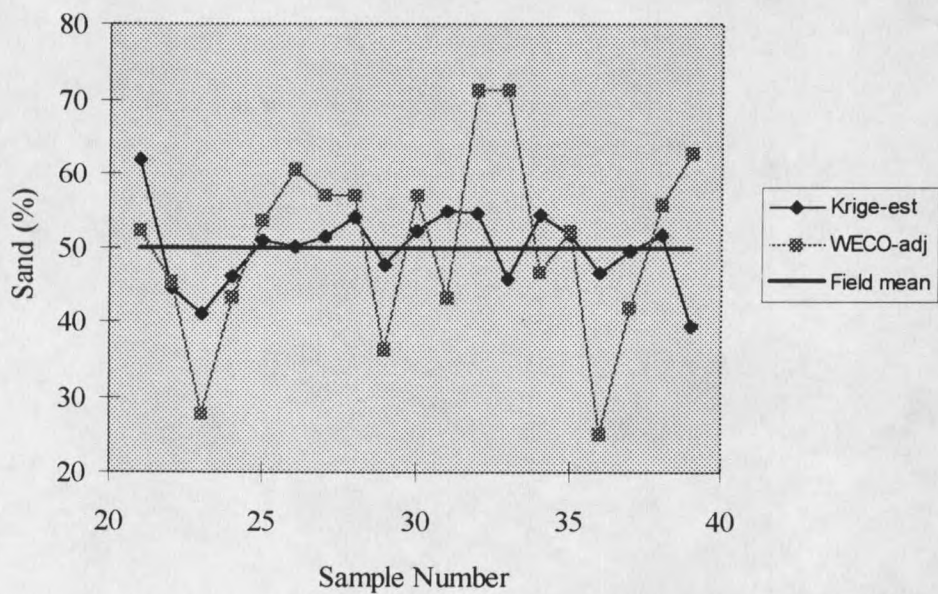
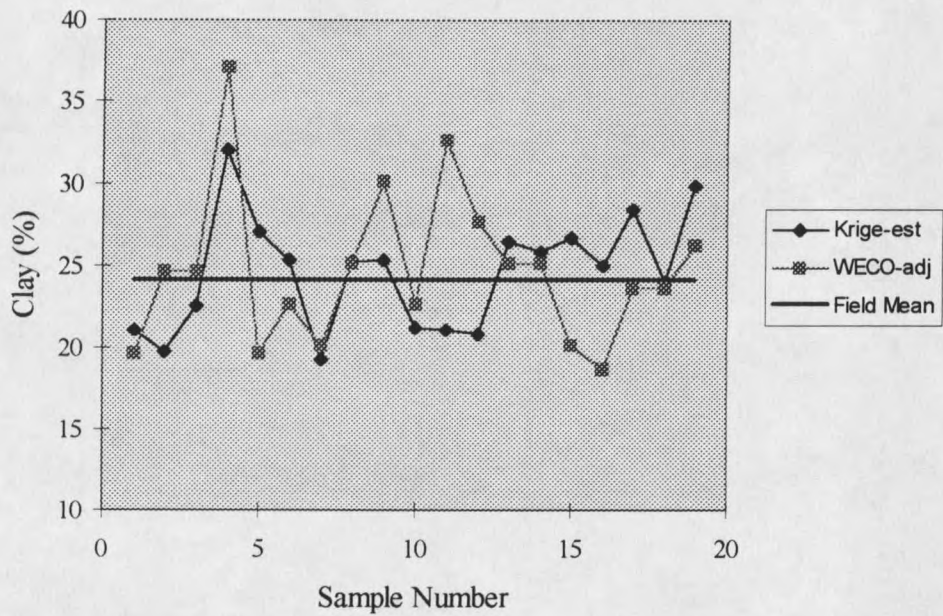


Figure 5.20. Comparisons of measured values, kriging estimates, and field means for subsoil percent sand: a) field #3903 and b) field #3902.

A) Subsoil Clay - Field #3903 Anisotropic Model



B) Subsoil Clay - Field #3902 Anisotropic Model

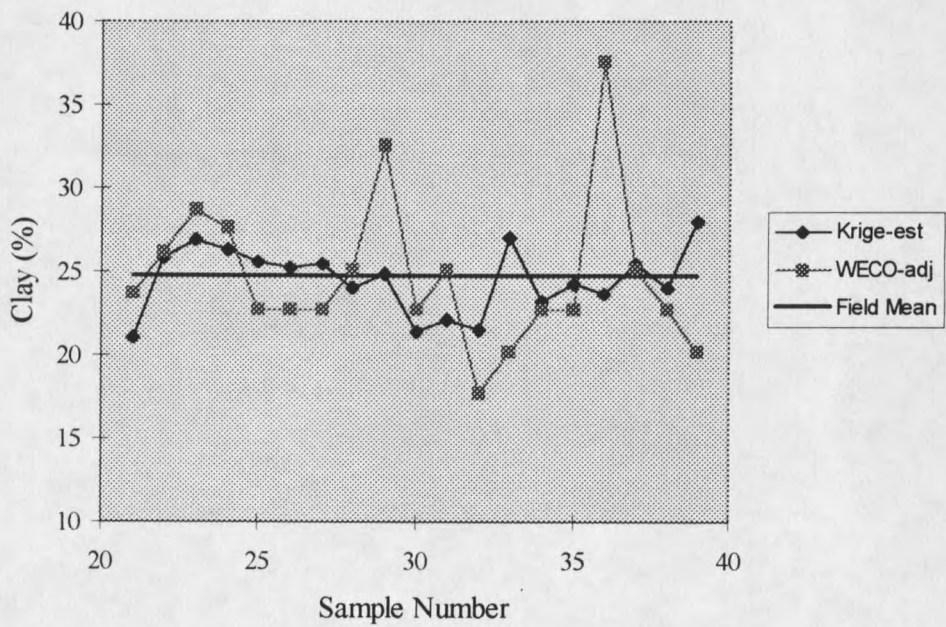


Figure 5.21. Comparisons of measured values, anisotropic kriging estimates, and field means for subsoil percent clay: a) field #3903 and b) field #3902.

located in field #3902. The dark horizontal line on each graph indicates the field mean for the soil property of interest. Dark diamond shaped markers are kriged estimates at each sample point.

Western Energy's data points are indicated by the lighter shaded squares.

The above comparison graphs show some interesting patterns in the data. First, high and low values in the kriged estimates, as expected, were muted relative to the actual data. Adjusting the Western Energy data to more closely fit the distribution of sample data had the effect of increasing high values and decreasing low values in the Western Energy data set. As a result, adjustments made in Western Energy data reduced the overall ability of kriging estimates to predict the adjusted data. There was no substantial net effect, however, since the prediction results of kriged estimates were compared to the use of field means as spatial estimates. Transformations made in the data had the same or an even greater impact in reducing the accuracy of field means to predict the Western Energy data.

In portions of each graph, kriging estimates mirror patterns of measured values in the Western Energy data, albeit in a reduced manner. A good example of this is the left side of the isotropic subsoil clay graph for field #3903 (Fig. 5.19). In other portions of the graphs, kriging estimates appear to be out of phase with the measured values or in places they head off in the opposite direction. An example of the latter is the right hand side of the isotropic subsoil clay graph for field #3903 (Fig. 5.19). Areas where kriged estimates react contrary to measured data account for the majority of prediction errors exceeded threshold values. They also inflate the mean square error associated with kriging estimates relative to the field means so that on the whole the two methods are similar in terms of the mean square error.

Overall, kriging estimates did not perform better than field means in predicting data from the Western Energy data set. These results agree with earlier statements by Keck et al. (1993) that

a constant surface through the overall sample mean provided the best prediction of clay content in reconstructed mine soils. Although some degree of spatial correlation was found in the mine soil data with closer grid sampling, this correlation was not strong enough to improve predictions above those of simply using the field means. Kriging cannot handle the erratic behavior of mine soil data where overall patterns in the data becomes disrupted by pockets of contrasting materials, not predictable from the surrounding data points, at least not at the current sample density.

Assumptions of even local stationarity of the mean do not apply in this case. In many instances, looking at the sample data shows the unlikelihood of predicting erratic high or low values from surrounding data points with any type of smooth, spatial interpolation scheme that uses the surrounding data. Still, it remains disconcerting when kriging estimates follow a pattern opposite to observed results.

Gotway et al. (1996) maintains that any prediction method which cannot outperform the sample mean should not be used since the sample mean provides a much easier and simpler approach. Some credit should be given to the more believable pattern of kriged results relative to mean values. Intuitively they look more correct or more scientific but in this special case, "good looks" do not necessarily translate to improved spatial estimates.

Western Energy's sample data were deliberately spaced at the midpoints in the experimental data grid. Given the 50 meter grid spacing of the main experimental data set, most Western Energy samples were spaced 25-meters away from the closest prediction sample points. The only exceptions to this were Western Energy samples placed in or near the 4 data clusters in the experimental data set. Field mean values would act equally well as a spatial predictor regardless of where surrounding data points were, even at an actual sample location. Theoretically, kriging estimates should become increasingly accurate the closer they are to existing

sample locations. Kriging performed as well as field means at predicting measured values in the worst case scenario from the standpoint of the existing data set. It remains to be seen if kriging would have performed any better with a different configuration of Western Energy sample locations relative to the experimental data set. While theoretically kriging performance should improve with closer proximity to surrounding sample points, nothing in the comparisons made thus far supports that assumption.

5.4.6. Kriging Results - Test Data Set

Analyses comparing Western Energy data to the experimental data set raised several questions about potential biases in the Western Energy data. Although corrections were made to the Western Energy data to account for the bias, questions may still be raised as to whether the adjustments made accurately compensated for all the potential differences between the two independent data sets. A second series of tests were run to check results found in the first comparisons. These additional trials provided an added benefit of testing kriging results for the spoil data, which exhibited the greatest amount of spatial correlation in the initial semivariogram analysis. Previous work by Knutsen (1986) showed spatial correlations for spoil percent clay ranging upward from 2000 to nearly 5000 feet. This previous study and its effects on post-reclamation sampling of spoil materials made the comparisons for spoil clay percent even more interesting. In addition, by generating a test data set, it was possible to test, in at least one instance, the assumption that better kriging predictions would occur for field locations closer to prediction sample points than the Western Energy data.

A test data set of 18 sample points was removed from the experimental data as described in the Methods and Materials section. Ten points were removed from the main data grid or matrix,

while 8 sample points were removed from data clusters. Removing eighteen samples from the experimental data amounts to a modified version of cross-validation. As such, the concerns about the interpolation of cross-validation results expressed by Issaks and Srivastava (1989) pertain to the test data set as well. Kriging performance at predicting removed data points may not truly reflect the overall performance of predictions for unknown sample locations.

Subsoil sand was used in the second set of analyses since it was the only soil property in the initial tests to show some promise of improved performance of kriging estimates over field means. The other variable used was topsoil organic matter. Table 5.5 contains the locations and sample values of the data points removed from the experimental data. Locations of the data points removed, relative to the remaining data points, are illustrated in figure 5.22.

Table 5.5. Data points removed from the experimental data to create a test data set for comparison of predicted versus measured values.

Location	X-axis m	Y-axis m	Spoil Clay %	Topsoil O.M. %	Subsoil Sand %
Line 350	200	350	30	1.2	60
Line 400	250	400	34	1.65	50
Line 450	150	450	30	0.88	40
Line 550	200	550	24	1.24	60
Line 650	200	650	28	1.32	70
Line 700	350	700	10	1.15	30
Line 800	50	800	30	0.60	60
Line 850	300	850	30	1.12	60
Line 900	100	900	26	0.54	60
Line 950	150	950	28	1.28	50
Cluster #1	100	487.5	22	1.28	50
Cluster #1	112.5	500	26	2.06	60
Cluster #2	300	600	22	1.15	50
Cluster #2	312.5	600	22	1.13	40
Cluster #3	150	737.5	26	0.82	50
Cluster #3	150	775	26	1.57	40
Cluster #4	250	975	32	1.24	60
Cluster #4	267.5	1000	34	1.22	70

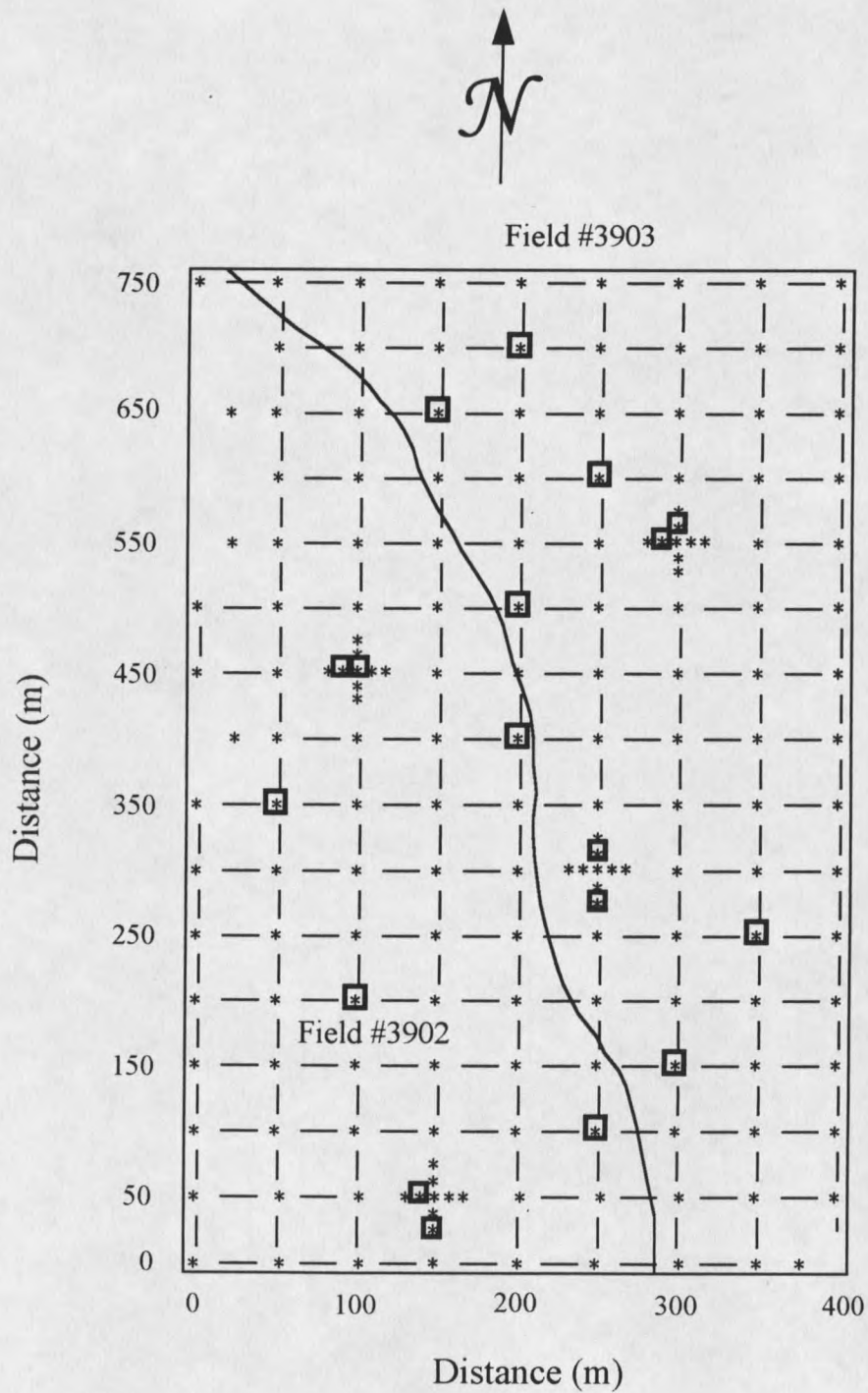


Figure 5.22. Locations of sample points removed (■*) from the experimental data to create a test data set.

The semivariograms for all 3 soil/spoil properties showed a moderate amount of spatial correlation (Fig. 5.23). Spoil clay had the most pronounced spatial correlation at short lag distances but had the shortest range of spatial correlation. Data for topsoil organic matter had the most noise about the semivariogram model line and the lowest sill to nugget ratio yet had the longest range of influence of the three semivariogram models. Properties for the subsoil sand semivariogram were intermediate between the other two. Model parameters and the lag spacings used to generate the experimental semivariograms are listed in table 5.6.

Table 5.6. Isotropic model parameters for semivariogram models fit to the experimental data set after removal of 18 randomly selected data points.

Soil Property	Lag	Type	Nugget	Sill	Range	Sill/Nugget
	m	-	(%) ²	(%) ²	m	-
Spoil Clay	25	exp.	20	60	100	3.0
Topsoil O. M.	25	exp.	.068	.141	300	2.1
Subsoil Sand	30	exp.	60	162	125	2.7

The scatter diagram for spoil percent clay (Fig. 5.24a) showed a distinct orientation of the plotted data in the direction parallel to the diagonal line of equal values between the x and y-axes. This contrasts with previous scatter plots of predicted versus measured values for subsoil replacement depth, subsoil clay, and subsoil sand percentage. Orientation along the diagonal indicates at least some success was obtained in kriging predictions although several erratic data points still exist well outside the desired range of prediction accuracy.

The comparison chart for spoil clay (Fig. 5.24b) shows kriging estimates generally following the direction of the observed sample values. Erratic high and low values in the measured data remained problematic for kriging predictions. The dashed line down the center of the graph separates the main sample grid (matrix) data points on the left side of the graph from the data

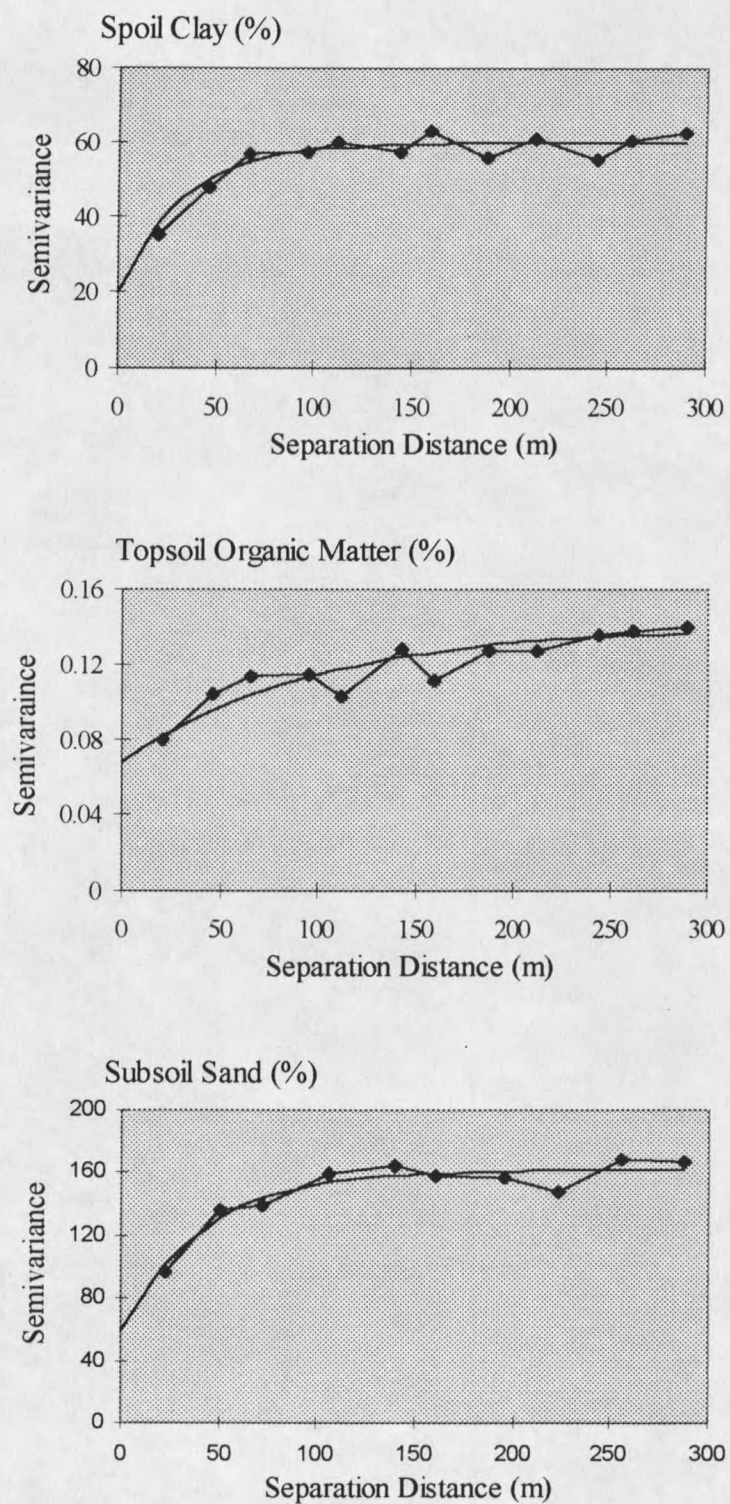


Figure 5.23. Experimental semivariograms and isotropic semivariogram models for: spoil percent clay, topsoil organic matter, and subsoil percent sand.

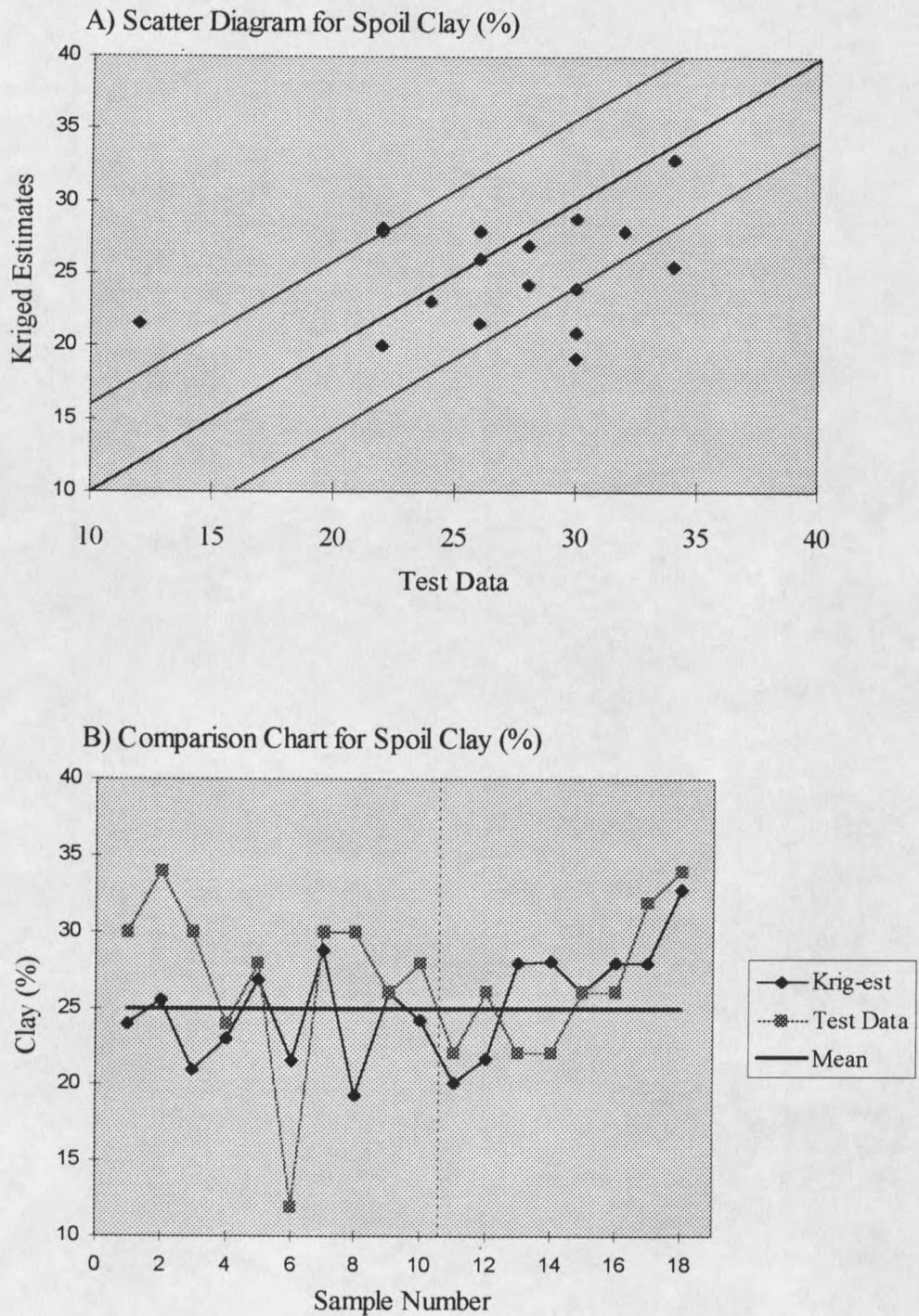


Figure 5.24. Scatter diagram (top) and comparison chart (bottom) for kriging predictions relative to measured values of spoil percent clay.

cluster locations on the right. In general, better agreement existed between kriged estimates and observed values for the more closely spaced cluster samples.

The mean clay content for both fields was 25%. In comparison, kriging estimates ranged from 14.2% to 35.9 percent clay. Still, the mean square error (MSE) associated with kriging estimates for all test data points was essentially equal to that of using the field means; 29.66 versus 29.44 (Table 5.7). Kriging estimates were outside the desired prediction range for 6 out of the 18 data points while estimates based on the field mean missed the mark 4 times. Field means had a slightly lower mean square error relative to kriging estimates for the 10 matrix samples. There was a substantial drop in the mean square error of kriging estimates for cluster samples relative to the main sample grid. Part of this drop can be attributed to luck of the draw in the sample values removed for comparison. A corresponding drop in mean square error associated with using the field mean indicates better predictability in general of the cluster samples, relative to the matrix samples removed, for any data smoothing estimation procedure. The greater relative drop in kriging MSE at this closer grid spacing does suggest a distinct advantage exists in using kriged estimates over the field mean as the distance between prediction locations and sample points was reduced below about 25 meters.

Better agreement, in general, existed between the average, predicted kriging standard deviations and calculated kriging standard deviations for spoil clay than for the other variables tested (Table 5.7). Test data for spoil clay cluster samples gave the best agreement between the two adding to the evidence of good kriging performance at short separation distances.

Histograms of the mean square error associated with kriging estimates and use of the field mean (Figure 5.25) help illustrate the above relationships. Mean square errors associated with both kriging and field mean prediction are substantially lower for cluster samples than for the

matrix samples but the relative drop is greater for the kriging estimates. These findings, while not dramatic, contrast sharply with earlier subsoil comparisons. They do not guarantee success in terms of accurate kriging predictions for the overall population but, at least, they do not raise any red flags about the use of kriging to interpolate spoil clay data, provided adequate sample data exists. Effective spatial correlation distances of approximately 25 meters, where kriging predictions appear to outperform use of the field mean, remain a long way off the 1000 ft. (305 meter) sample spacing recommended by Knutson for sampling spoil materials at the Rosebud Mine (Knutson - unpublished data, 1986).

Table 5.7. Comparison of the accuracy of kriged estimates versus use of field means to predict measured values from the test data set.

	Spoil Clay (%)	Subsoil Sand (%)	Topsoil O. M. (%)
Avg. Pred. Std. Dev.			
Total	4.70	7.21	0.16
Matrix	5.51	8.48	0.19
Cluster	3.68	5.63	0.13
Kriging MSE			
Total	29.66	113.7	0.109
Matrix	41.64	119.5	0.055
Cluster	14.69	106.4	0.175
Actual Krig. Std. Dev.			
Total	5.45	10.7	0.33
Matrix	6.45	10.9	0.24
Cluster	3.83	10.3	0.42
Pred. Outside Range	6 (33%)	2 (11%)	2 (11%)
Field Mean MSE			
Total	29.44	117.2	0.139
Matrix	37.00	127.4	0.118
Cluster	20.00	104.5	0.195
Pred. Outside Range	4 (22%)	3 (17%)	3 (17%)

The scatter plot for subsoil sand (Figure 5.26-top) showed a familiar horizontal orientation to the cloud of data points for predicted versus measured values, indicating kriging did a poor job of predicting the test data. Most of the data points fell within the accepted range for prediction

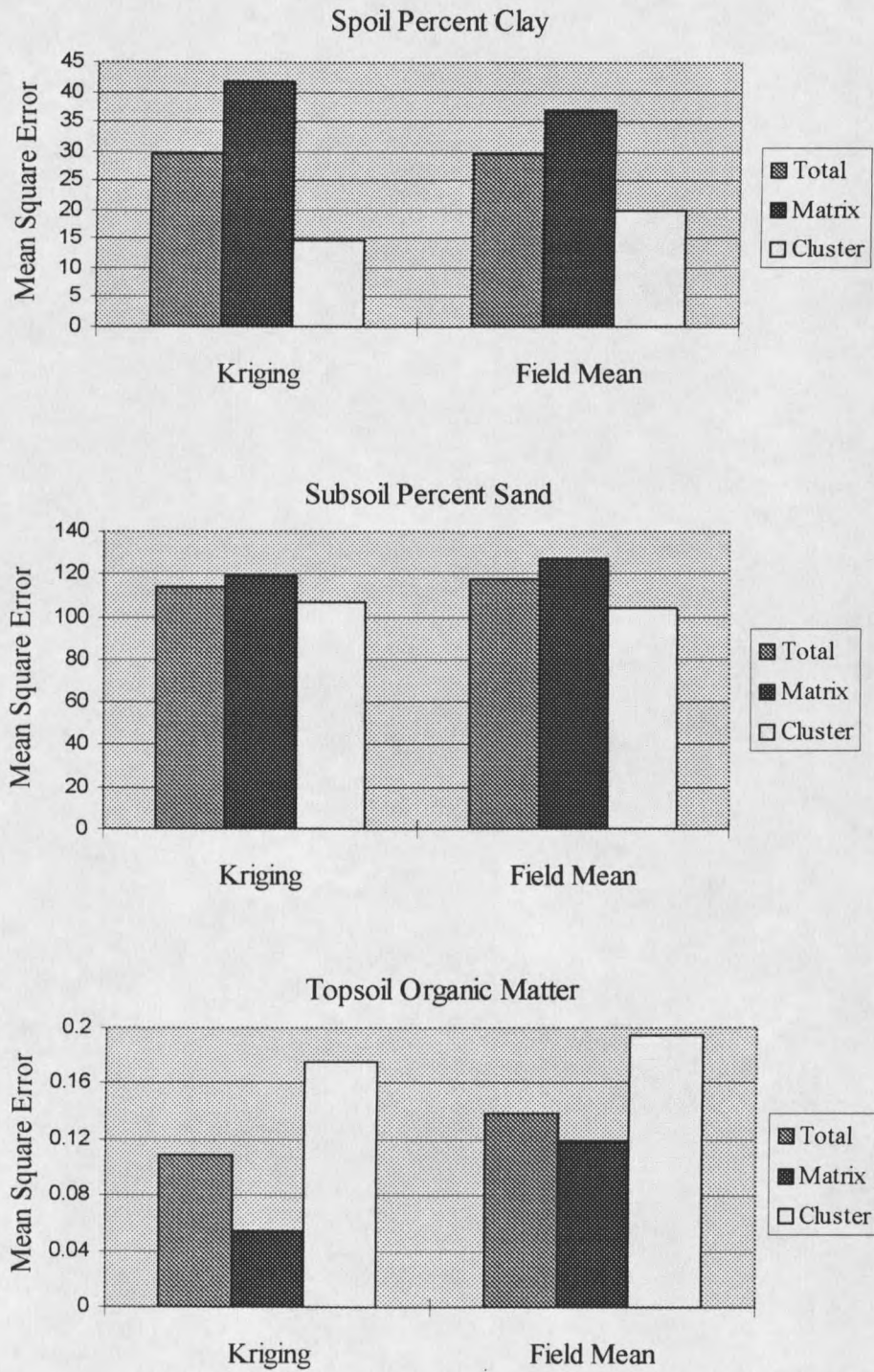


Figure 5.25. Mean square errors for measured versus predicted values, comparing results between kriging estimates and use of the field mean as a spatial estimate.

accuracy. The same can be said for use of field mean values. This reflects more the large acceptable range for sand estimates than any reasonable performance by the estimation procedures.

Erratic high and low measured values in the subsoil sand test data remained problematic for kriging estimates even at the closer sample spacing associated with data clusters (Figure 5.26-bottom). In some sense, the kriging estimates seem to have done a better, although still poor, job of tracking observed values for the more widely spaced matrix samples (left side of graph). Kriging estimates showed no apparent relationship to measured values on the cluster sample side of the graph. Field means in Figure 5.26 (bottom) are represented by the dark circles on the graph. The mean for sand content in field 3902 was 50% while the mean for field 3903 equaled 53% sand. Kriging estimates never varied far beyond the field means in either direction while measured values show substantially more variation.

Kriging estimates provided no real improvement over field means in reducing the MSE of predicted versus measured values for subsoil percent sand (Table 5.7). A slight reduction in the MSE was observed for the cluster samples relative to matrix samples for both kriging estimates and field means. This reflects a slightly lower variance associated with the cluster samples and not any real improved performance by the estimation methods. The above relationships in MSE are summarized in Figure 5.25.

Overall, results from the test data for subsoil sand supported those obtained from predictions relative to the Western Energy data. The soil data behaves in a spatially uncorrelated manner despite empirical evidence from semivariograms indicating the presence of moderate spatial correlation structure. A lack of even local stationarity greatly limited the effectiveness of kriging to make accurate predictions. The earlier suggestion that kriging might have performed better at unsampled locations closer to data points than the Western Energy data has not been

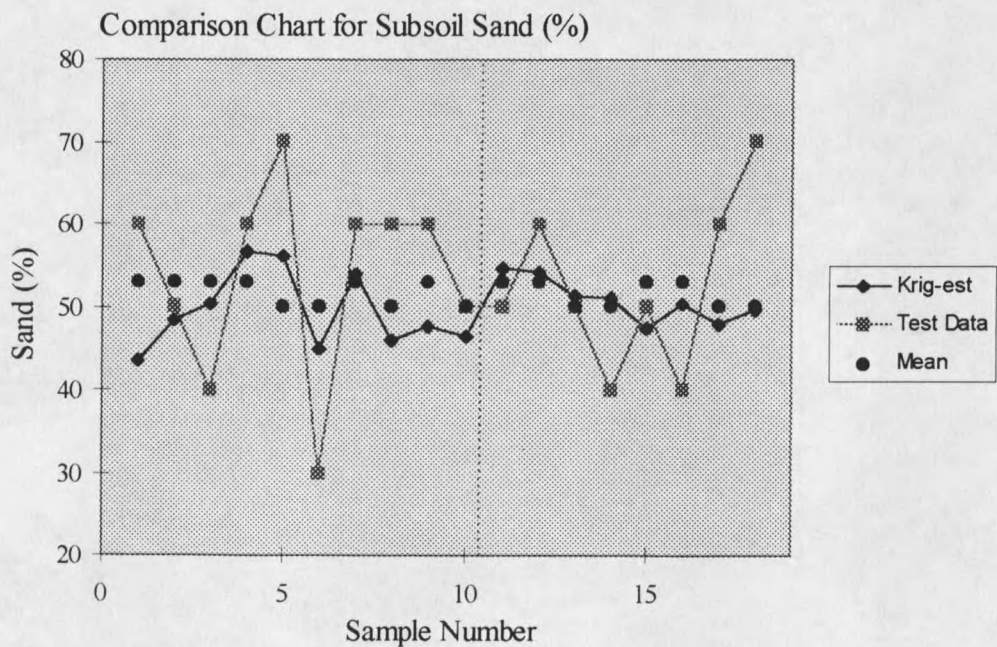
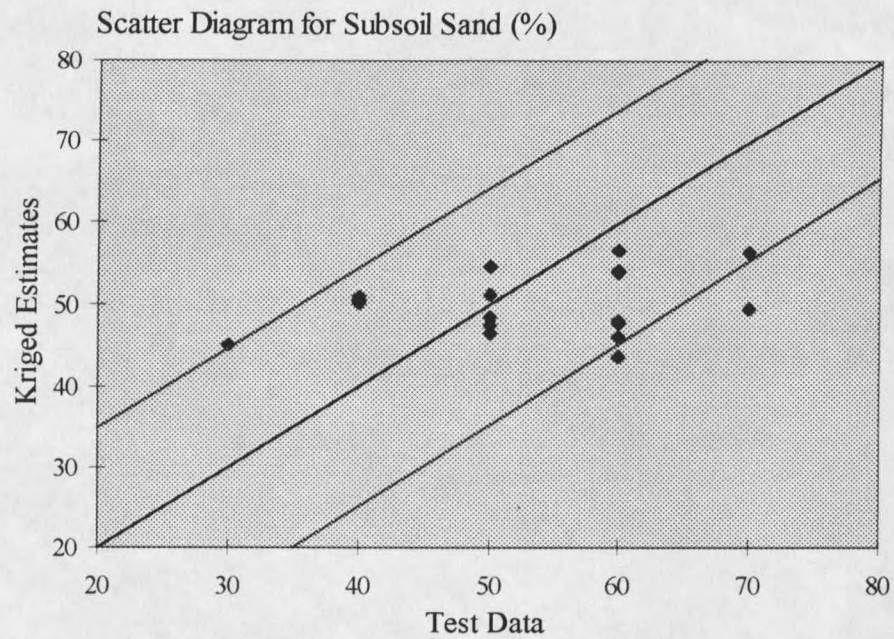


Figure 5.26. Scatter diagram (top) and comparison chart (bottom) of kriging predictions relative to measured values for subsoil percent sand.

borne out by comparisons to the test data set. Kriging estimates were not improved relative to field means for the more closely spaced cluster samples. These results were contrary to what was observed in the predictions for spoil clay percent.

Several noted authors on the application of spatial statistics (Issaks and Srivastava, 1989; Englund and Sparks, 1991; Gotway and Hergert, 1997) have discussed the need to include information about underlying physical or chemical process(es) in decisions about modeling semivariograms and the application of kriging techniques. Models used must make sense in terms of the processes responsible for spatial distributions. Knowledge of the attribute in question, the expectation of how it is spatially distributed, and the processes responsible for that distribution all contribute to informed decisions about model parameters and the appropriateness of kriging techniques. Good agreement between "real world" considerations and kriging assumptions may still not guarantee good results, but failure to meet such criteria will almost certainly ensure poor results.

The process of transporting spoil materials with a dragline retains remnants of the original spatial correlation structure in pre-disturbance geologic materials. In contrast, double lift soil salvaging in areas of mixed sedimentary beds results in a much more diverse mosaic of contrasting materials. Stockpiling soil materials, as was the case in reclamation of the study site, probably acts to mix things up further. The range of soil textures found in overburden and spoil is as large or larger than that found in coversoils (Keck and Wraith, 1996) but the pattern of how these materials are distributed is less complex. When a dragline works through an area of siltstones, materials with a loam to clay loam texture are systematically transported from one side of the mining pit to the other. Sandstone areas result in loamy sand and sandy loam materials which are systematically transported from one side of the pit to the other. Admittedly, some mixing occurs

between contrasting materials that were either vertically or horizontally stratified in the overburden but the systematic manner in which a dragline progresses across the landscape ensures that some spatial correlation will be retained. Thus, understanding of the processes used to move materials and knowledge of the material itself explains spatial correlations in spoil texture data that are not present in coversoils.

The scatter plot for topsoil organic matter (Figure 5.27-top) contained a large cluster of sample points in the center of the graph around 1.2% organic matter. Only one data point fell substantially outside the $\pm 0.5\%$ expected prediction interval. The data exhibited some orientation along the diagonal equal-value line. Kriged data seemed to track measured values better for the matrix than for cluster samples (Figure 5.27-bottom) but in a familiar pattern, difficulties occurred with erratic high test values where there were no surrounding data points with comparable values.

Kriging performed modestly better than field means in reducing the MSE associated with predictions (Table 5.7). Both methods were adversely affected by a single cluster sample with a significantly higher amount of organic matter than surrounding samples. As a result, the MSE's for both methods were substantially higher for cluster samples than matrix samples, illustrating the sensitivity of squared statistical measures to extreme sample values.

Spatial analysis of topsoil organic matter data suffers from the same distribution problem encountered with the soil texture data only erratic high values were less common while low values were more predictable. Most of the topsoil material in the original native soil resource had between 1.0 and 1.5 percent soil organic matter. Positions in the premine landscape that accumulated water and sediments have higher levels of soil organic matter in surface horizons but these are rare in the semi-arid, well drained environment around Colstrip.

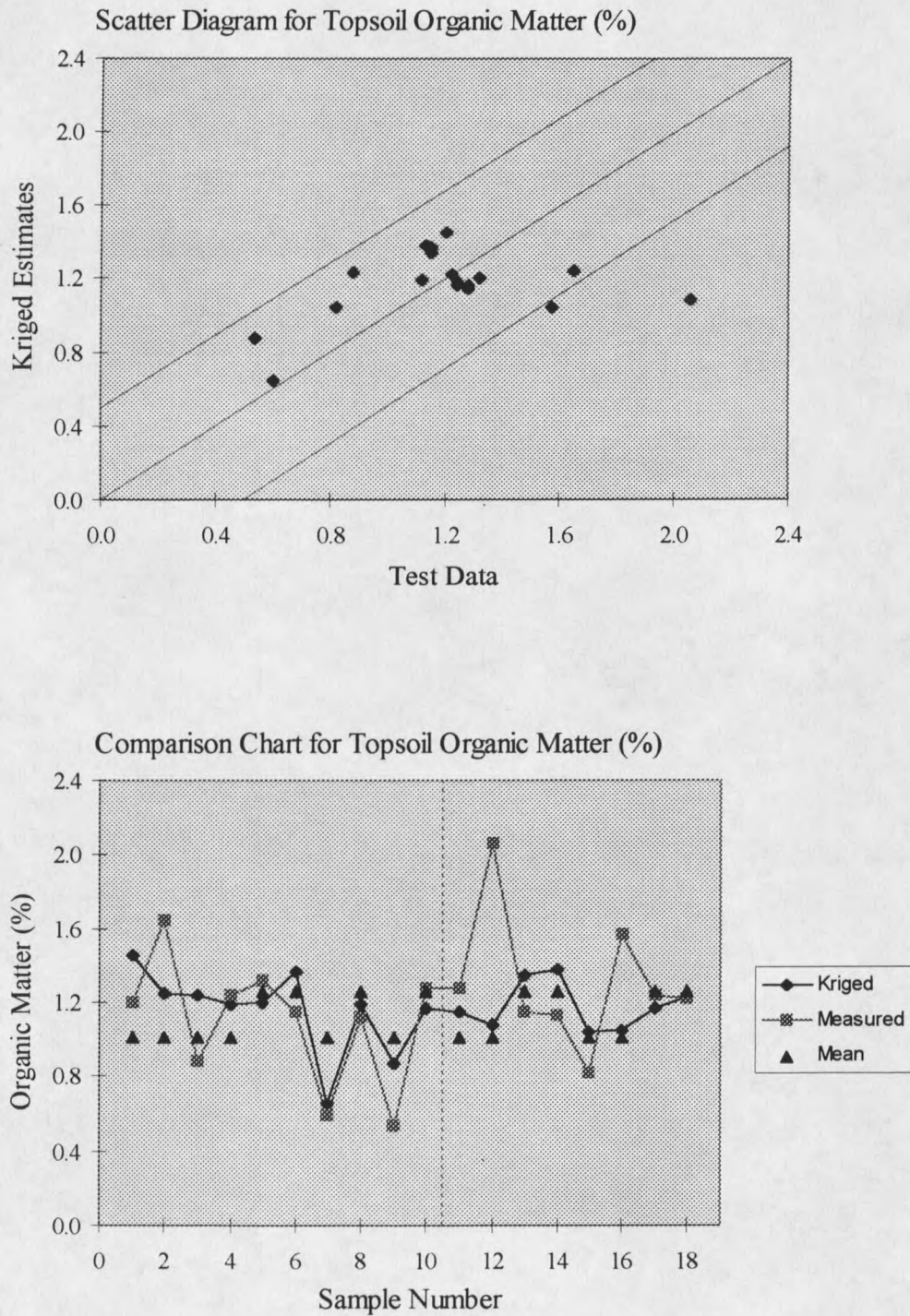


Figure 5.27. Scatter diagram (top) and comparison chart (bottom) of kriging predictions relative to measured values of topsoil organic matter.

The same mixing process occurred with topsoil materials of differing organic matter contents but there were simply fewer high organic matter materials at the start to confound results.

Kriging generally did a good job of predicting low test data values. Topsoil samples with organic matter levels below 0.8% are almost certainly not topsoil. A significantly large area within the study site was apparently not topsoiled. This explains difficulties encountered trying to distinguish between topsoil and subsoil materials in a portion of field 3903. Low soil organic matter values all originate from a single area which was large enough to include surrounding sample points of equally low soil organic matter. For this reason, kriging estimates were able to accurately predict low soil organic matter values in the test data. If you cover the two lowest data points in the soil organic matter scatter diagram (Fig 5.27-top), the graph largely takes on the same horizontal orientation of data points as the other scatter diagrams for coversoil properties.

The same cross-validation test could be re-run numerous times. Over a number of iterations more distinct patterns would likely develop as differences in the variance for cluster and matrix samples from any given test data set would be averaged out. Kriging estimates would outperform use of field means as a spatial predictor for spoil clay percentage and topsoil organic matter.

Better results for spoil would be due to spatial correlations in the data while the better performance of kriging for topsoil organic matter may be largely due to the portion of the study area without topsoil. The spatially uncorrelated nature of subsoil sand data, at the current sampling density, implies that field mean values will likely provide predictions that are equally as good as the kriging estimates.

These results emphasize the need to include expert knowledge about the nature of soil properties and the processes responsible for their distribution when assessing the potential

application of kriging procedures. Such information may be equally important as any empirical evidence found in semivariograms. Many applications of spatial statistics in soil science have ignored this important step. Analysis of semivariograms and kriging techniques are routinely applied without consideration of landscape or soil processes.

5.4.7. Indicator Kriging

Ordinary kriging has often been referred to as the “best linear unbiased estimator” (B.L.U.E.) because it uses a linear combination of surrounding sample values to make estimates at unsampled locations and attempts to minimize both the mean residual error and the variance of errors associated with those estimates. As seen in previous results, the best linear unbiased estimator may still give poor results if necessary spatial correlations are not present in the data. As with any linear estimation technique, kriging produces a smoother prediction surface than the original data and so has a tendency to underestimate extremes of high or low points in the data surface. This smoothing effect can be seen in the plotted results of comparisons between measured values and kriged estimates in Figures 5.18, 5.19, 5.20, 5.24, 5.25, and 5.26. The degree of smoothing depends primarily on the number of sample points available and the smoothness of the underlying data surface.

Perhaps the greatest limitation of ordinary kriging, and most other linear estimation techniques, is that a single predicted value is obtained at each estimation point or block. Spatial estimates made for natural systems are often hampered by erratic data distributions and sparse data points. Estimates of a single value, under these circumstances, greatly overstate the level of knowledge available. Indicator kriging presents an alternative spatial estimation procedure which generates results in terms of probabilities. This approach would appear to be a natural fit for

assessing the suitability of coversoil or spoil materials in reclamation. State regulators and mining company officials are often most interested in whether soil or spoil materials exceed specified minimum or maximum thresholds of suitability standards, e.g.: >10% clay in suitable coversoil materials. Seldom are they interested in the actual values of soil properties at specific locations. Indicator kriging has another potential benefit which may be especially important for mine soil data. Since the data are transformed to indicator variables of 0 and 1 prior to analysis, the method is much less sensitive to the effects of erratic high or low sample values overly influencing results.

Figure 5.28 shows the indicator semivariogram for topsoil organic matter with a cutoff value of 1%. Only weak spatial correlation structure exists in the data, similar to what was found in the standard semivariogram for topsoil organic matter. Lack of spatial correlation in coversoil

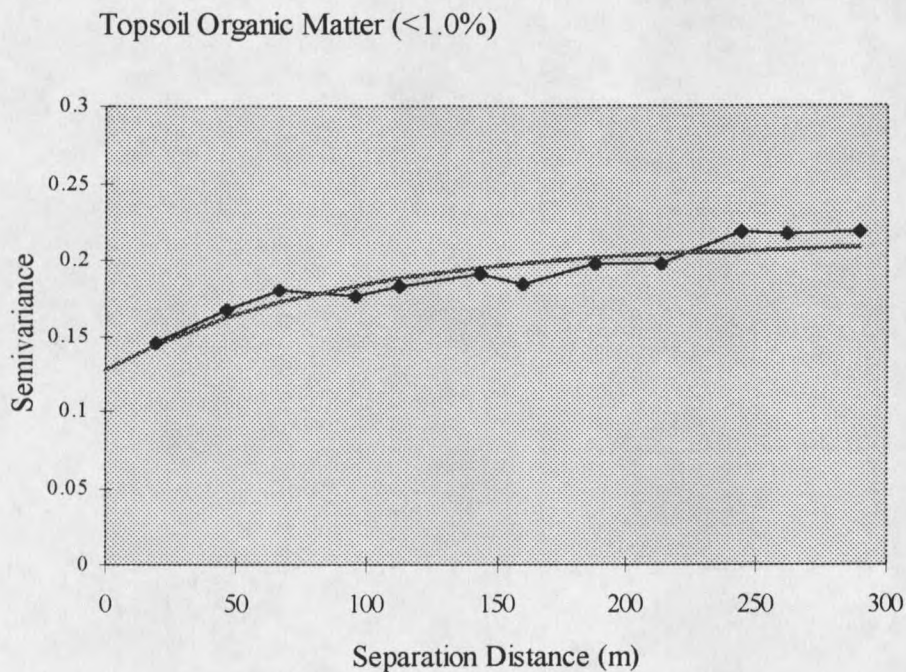


Figure 5.28. Experimental semivariogram and isotropic model for topsoil organic matter, indicator data at a cutoff level of 1% O.M.

data will limit indicator kriging results in much the same manner as it limits ordinary kriging.

Model parameters used to model the semivariogram are listed in Table 5.8.

The <1% cutoff in soil organic matter roughly corresponds to a distinction between topsoil and subsoil organic matter levels in the Colstrip area. Nearly all topsoil horizons in local native landscapes would be expected to have greater than 1% organic matter. Results from applying indicator kriging to the topsoil organic matter data, at the 1% cutoff, are shown in Figure 5.29. A relatively large area in the lower right side of Figure 5.29 identifies surface soils with a high probability of having have less than 1% soil organic matter. This area corresponds to a portion of the study site where no topsoil material was laid down in final reclamation, although the Western Energy replacement depth data did not indicate that such a hole exists in the topsoil coverage. It illustrates in an extreme case of bias in Western Energy data relative to state regulations and also helps explain difficulties encountered in trying to distinguish topsoil and subsoil materials for this portion of the field.

Table 5.8. Parameters used to model the experimental semivariograms for transformed topsoil organic matter (<1%) and spoil clay percent (<12%, <20%, <28%, and <36%) indicator data.

Soil Property	Lag	Type	Nugget	Sill	Range	Sill/Range
	m	-	-	-	m	-
Topsoil O.M.						
<1%	25	exp.	.127	.210	250	1.65
Spoil Clay						
<12%	40	exp.	.005	.041	75	8.20
<20%	25	exp.	.020	.174	75	8.70
<28%	40	exp.	.060	.242	75	4.03
<36%	25	linear	.060	.068	300	1.13

Figure 5.29. Indicator kriging results for topsoil organic matter (%) identifying a lack of topsoil in the southeast portion of the study site.

In the above example, the same approximate area could be outlined by connecting a line around the sample points with low organic matter values. In more complex situations, however, information obtained by indicator kriging would not be so easily observed in the sample data. The topsoil organic matter data provides a simple and verifiable example of how indicator kriging can be used to identify areas in the reclamation that do not meet suitability standards.

Experimental semivariograms were run for a sequence of cutoff values (<12%, <20%, <28%, and <36%) in the spoil percent clay data (Figs. 5.30 and 5.31). Less than 12 percent clay corresponds to the approximate lower limit of clay content for coversoil suitability. The distinction between sandy loams and sandy clay loams relates to the less than 20% cutoff as does the approximate break between fine-loamy and coarse-loamy particle size families. Less than 28% clay is the split between loams and clay loams and the less than 36% clay threshold corresponds to the current upper limit of allowable clay in suitable soil materials for reclamation.

Indicator semivariograms for the spoil clay data behaved in an expected manner (Table 5.8). The sill of successive indicator semivariograms will increase up to a maximum at a cutoff value approximately equal to the median of the experimental data. Beyond that point, the sill will decrease as cutoff values increase beyond the median to the high end of the range (Journel, 1983). The highest sill value for the four trials run was .242 at the <28% clay cutoff whereas the median value for the spoil percent clay data was 26%. Often, indicator semivariograms developed at cutoffs near the center of the range behave better than those for cutoffs near the ends (Issaks and Srivastava, 1989). For this reason, median indicator kriging, using a semivariogram model for a cutoff value near the center of the range to krig at all cutoffs, has gained acceptance as a reasonable approximation to indicator kriging (Kim et al., 1987; Issaks and Srivastava, 1989).

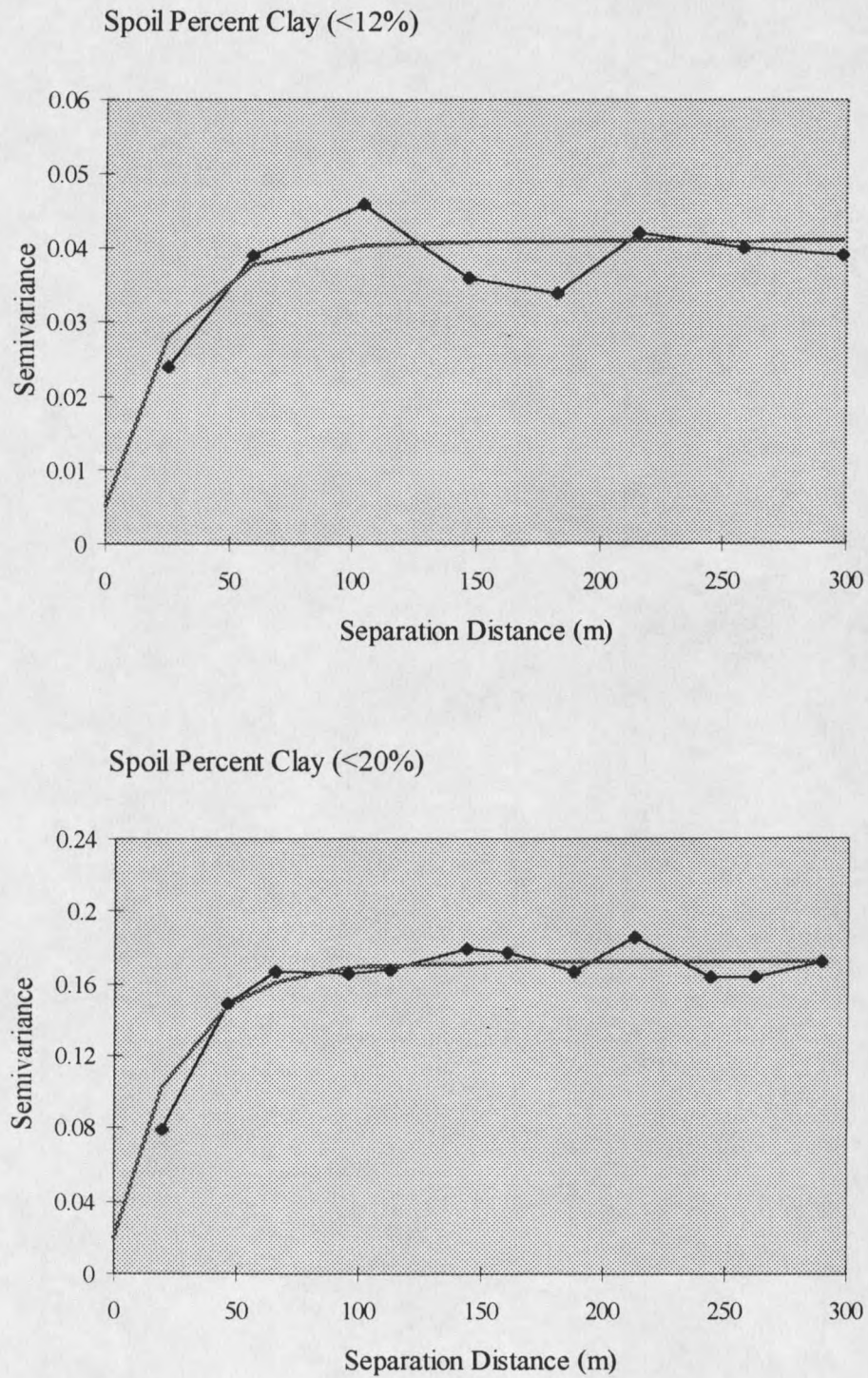


Figure 5.30. Experimental semivariograms and isotropic models for spoil percent clay, indicator data at cutoff levels of 12% clay (top) and 20% clay (bottom).

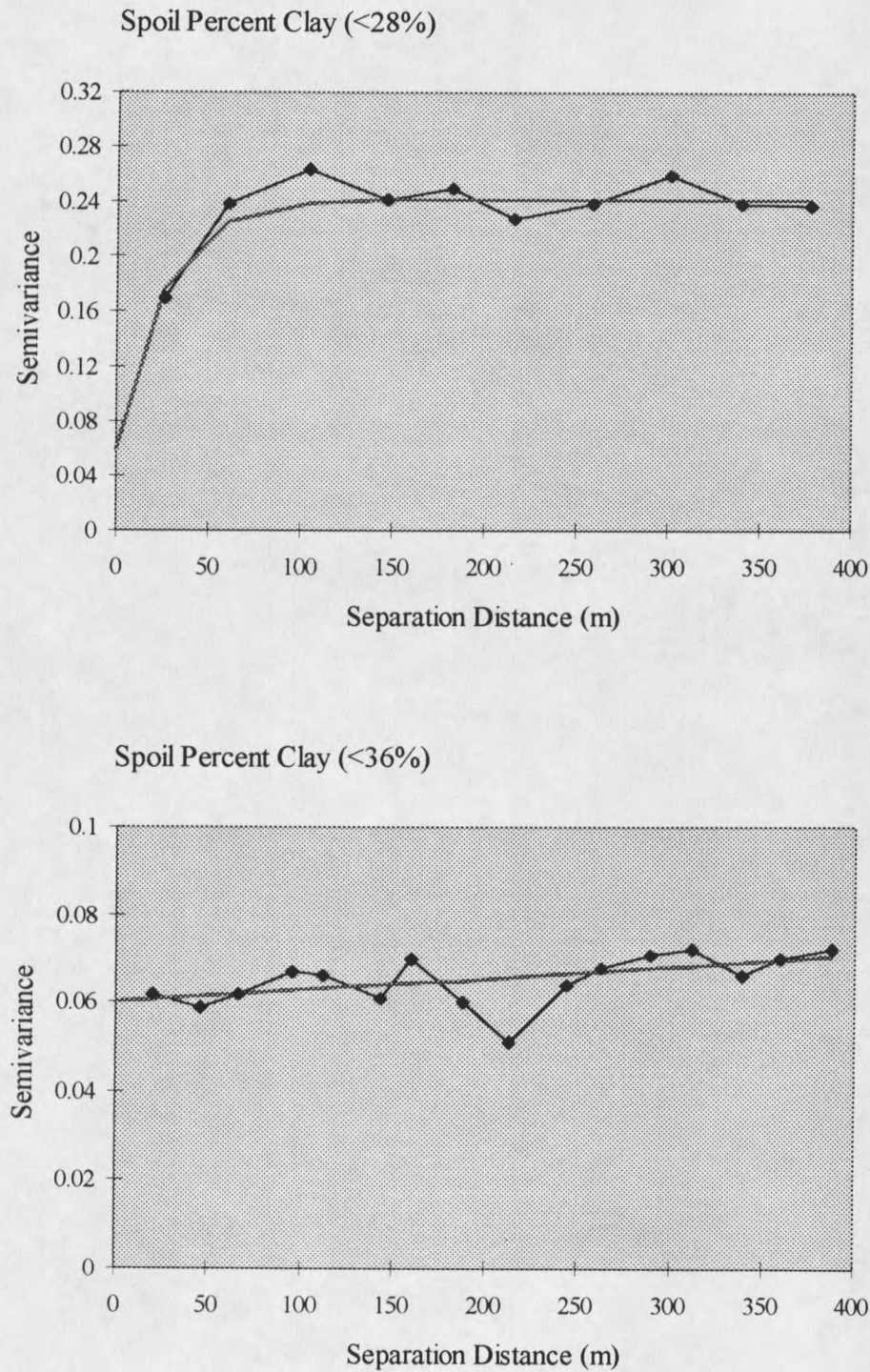


Figure 5.31. Experimental semivariograms and isotropic models for spoil percent clay, indicator data at cutoff levels of <28% clay (top) and an almost pure nugget effect at <36% clay (bottom).

Figures 5.30a and 5.31b show the erratic behavior of semivariograms for the <12% and the <36% cutoffs. An exponential model provided a reasonable fit to the <12% clay indicator data although the experimental semivariogram exhibited a high amount of noise about the model line. The indicator semivariogram for clay <36% exhibited almost a pure nugget effect. Median indicator kriging could have been applied at this cutoff using the semivariogram model for clay <28%. The other two cutoff levels, <20% and <28%, were adequately modeled with exponential models having a short range of 75 meters, and low nugget values relative to their respective sills. Standard indicator kriging was applied to the <12%, <20%, and <28% indicator data.

The sequence of three indicator kriging maps (Figs. 5.32, 5.33, 5.34) presents an interesting picture of how probability patterns change with each successive threshold. If enough cutoffs were selected, they would define a complete, predicted cumulative distribution function for each block, thus potentially providing much more information about a site than the single estimated value of ordinary kriging. More importantly, results from each threshold are reported on the basis of probabilities. The probability of exceeding a given threshold provides a more realistic representation of the available information. The method will not detect every high or low spike in the true data surface but will identify areas with a high probability of exceeding a specified threshold, as well as, providing a more general pattern of soil properties. In the end, however, even probability estimates are subject to the limitations of available data.

5.5. Conclusions

The closer grid spacing incorporated into the experimental data set resulted in semivariograms exhibiting weak to moderate spatial dependence for subsoil properties of percent clay, percent sand, and soil replacement depth. Spatial correlation was largely absent in the initial

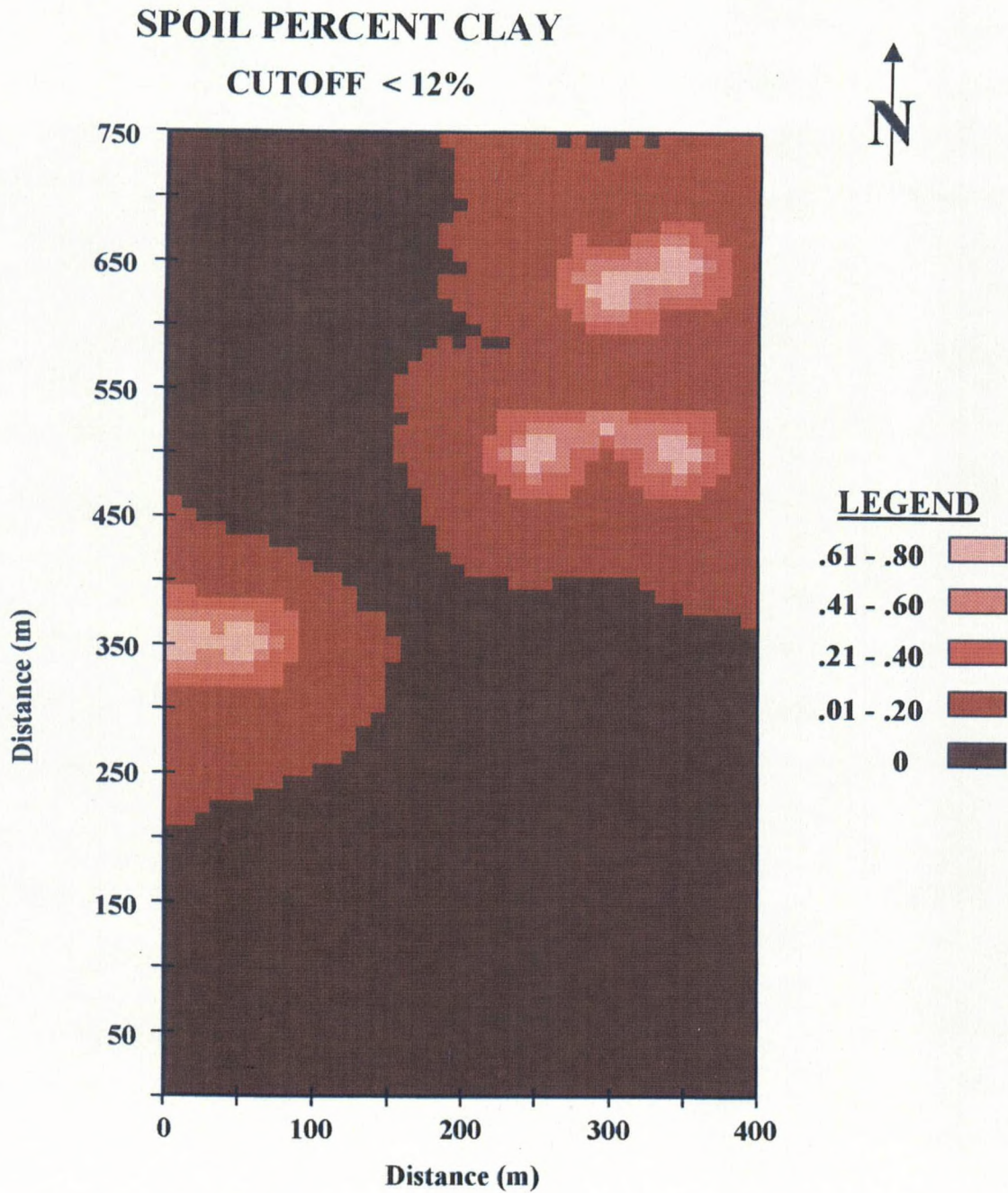


Figure 5.32. Indicator kriging results for spoil percent clay at a cutoff value of <12%.

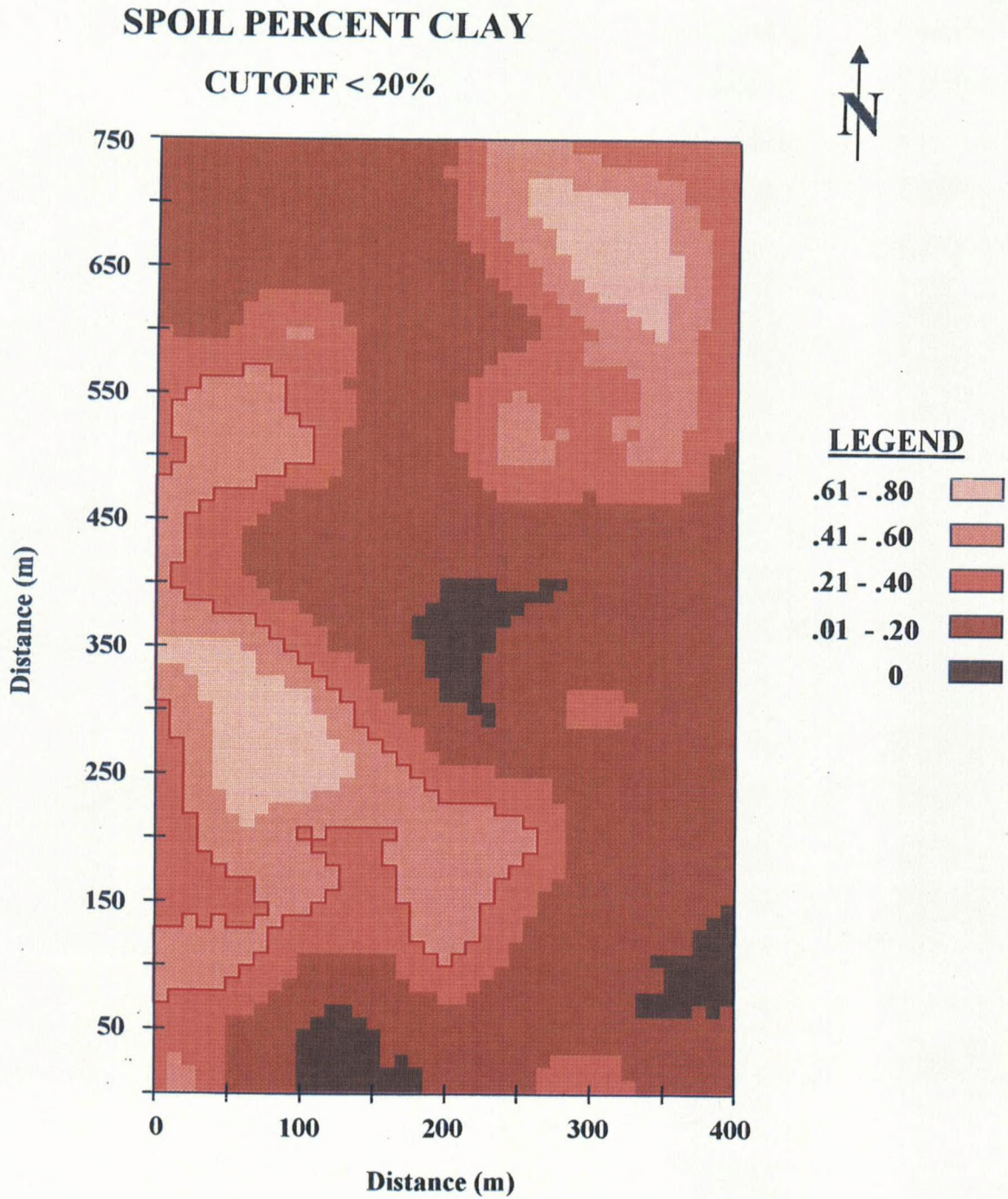


Figure 5.33. Indicator kriging results for spoil percent clay at a cutoff value of <20%.

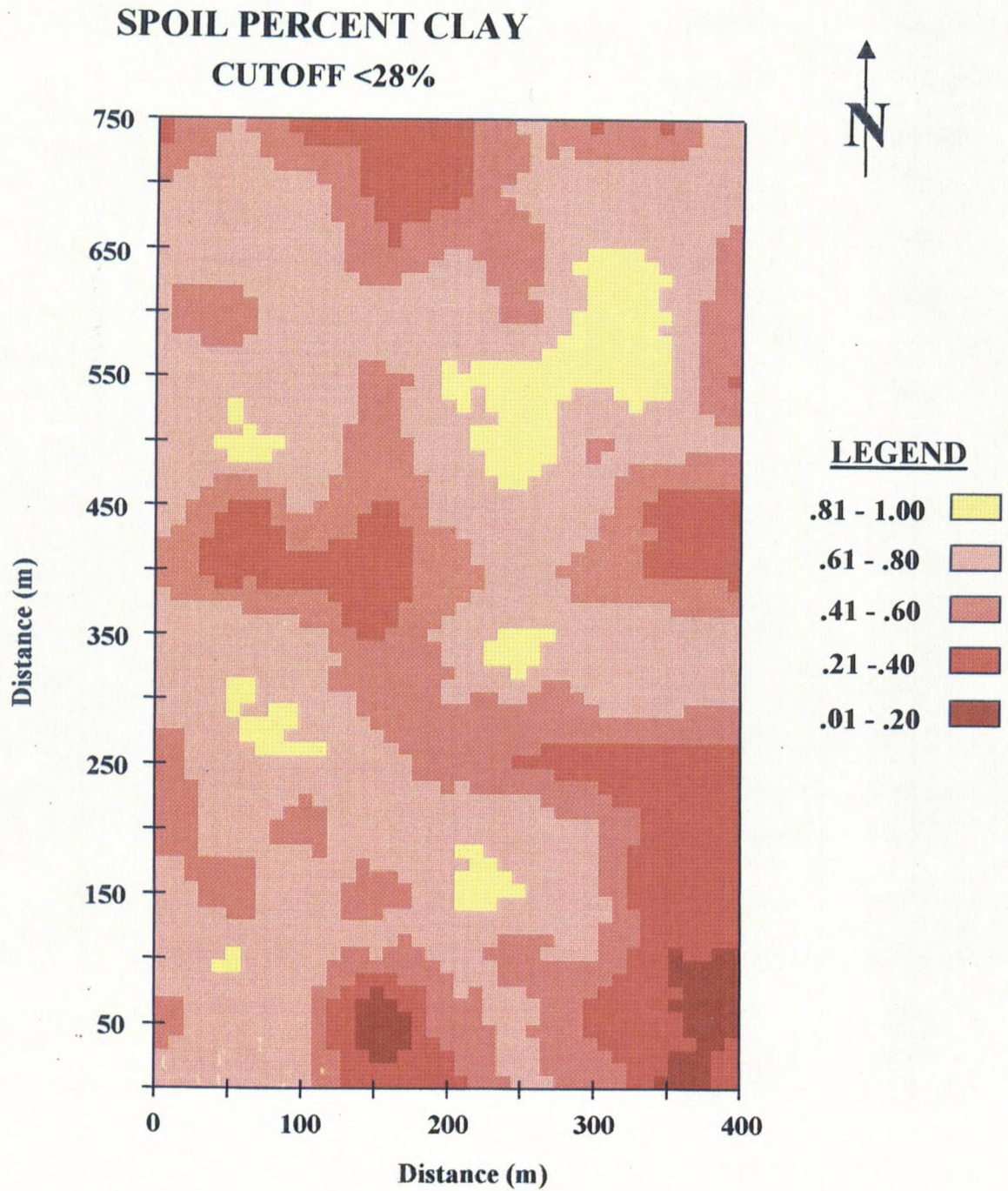


Figure 5.34. Indicator kriging results for spoil percent clay at a cutoff value of <28%.

topsoil data. Despite the empirical evidence of spatial correlations, comparison of kriged estimates of subsoil properties with the independent Western Energy data set showed no apparent improvement of kriged estimates over use of the field means to predict soil properties at unsampled locations. These results agree with earlier conclusions by Keck et al. (1993).

The process of salvaging soils in two lifts from areas of mixed sedimentary beds has resulted in placement of dissimilar coversoil materials side by side or in isolated pockets erratically located throughout the reconstructed landscape. The true data surface for soil texture variables contains spikes of high and low values, resembling more of a chaotic distribution than any smooth, continuous surface. Results are to some degree a function of sample density. Similarly, replacement depths can have abrupt differences along boundaries between adjacent laydown strips or among scraper loads deposited in the same strip. In either case, kriging assumptions of even local stationarity are poorly met by the data. Knowledge about the physical processes controlling spatial distributions of soil attributes appears to be as important in decisions about the appropriateness of applying kriging techniques as any empirical evidence in the experimental semivariograms

Additional comparisons made against the test data set supported the above conclusions. Kriging continued to perform poorly for the subsoil percent sand data. In contrast, comparisons with spoil percent clay data showed some improvement of kriging estimates over use of field means for sample locations within a radius of about 25 meters from known sample points. Processes responsible for the transport and deposition of spoil materials create more of a general pattern of high and low clay areas, retaining at least some of the initial spatial correlations present in the geologic stratigraphy. The resulting distribution of spoil clay data provides a better match to

kriging assumptions. Spatial correlation distances for spoil clay were far less than those used by Knutsen (1986) to justify reduced sampling of spoil materials in the reconstructed landscape.

Topsoil organic matter data suffered from the same general lack of spatial correlation as other coversoil properties. The spatial correlation structure found, as well as the apparent improvement of spatial predictions by kriging relative to field means, relate mostly to an area without topsoil on the east side of the study site.

A limited degree of variability was introduced into the experimental results by using hand texture estimates for determination of sand and clay percents. This variance was small relative to the overall variance in percent sand and percent clay data for the Area-E site. Lack of any significant improvement in kriging performance with the higher sampling density limits any potential benefits of a tradeoff between use of field procedures and incorporating a higher sample density. Results suggest that even greater increases in sample density would provide only marginal benefits of improved kriging estimates of coversoil properties.

Distinct biases in the Western Energy data, relative to suitability standards for coversoil and spoil materials, could be viewed as a need for independent verification of reclamation sampling results. Use of field procedures, such as hand texturing, would increase the potential for biasing results. On the other hand, state regulators most likely have a poor understanding of limitations inherent in the soils data they are requiring mining companies to collect. Lack of significant spatial correlations in the mine soil data greatly restricts the inferences that can be made from the data. Erratic high or low values in the data do not necessarily represent any significant surrounding area of equally high or low values. Similarly, lack of either high or low sample values in the data do not guarantee the absence of nearby soils that have such properties. This raises larger questions about the intended purpose of post-reclamation soil sampling.

Indicator kriging would appear to be a more appropriate approach to the spatial interpolation of coversoil and spoil data. State regulators and mining company officials are most interested in whether significant areas of unsuitable material are present in coversoil or near-surface spoil materials. Indicator kriging provides predictions in terms of probabilities of exceeding specified threshold levels rather than exact predictions. These estimates are more in line with regulatory needs and more accurately reflect the level of information available. For certain soil properties, such as soil texture, even indicator kriging may not be appropriate due to the lack of spatial correlation structure in the data.

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CHAPTER 6

FUTURE EVOLUTION OF RECONSTRUCTED LANDSCAPES AND MINE SOILS AT THE ROSEBUD MINE

6.1. Introduction

Previous chapters have been aimed at describing and mapping properties of reconstructed mine soils at the Rosebud Mine. The emphasis will now switch towards examining changes that will occur over time in both the reconstructed landforms and the reconstructed mine soils that mantle them. Certain soil properties, such as soil texture and pH, will remain essentially constant for many decades to come. These properties were inherited from geologic parent materials in the area. While the distribution of soil textures may be disrupted relative to the original pre-mine landscape, the inherent range of soil textures remains constant. Other attributes of reclaimed landscapes are much more dynamic and will change over the relatively short timespan of human perspective. Portions of the landscape will erode while other portions will accumulate sediment. Soil organic matter will accumulate in surface soil horizons. The leaching of carbonates, the development of soil structure and the transport of soluble salts will all take place within a human lifetime. Processes responsible for these changes do not take place uniformly across the landscape but rather will be spatially variable in both direction and magnitude. The depth to which changes occur in the mine soils will likewise vary depending on position in the landscape and the process involved. Sustainable management of the "fragile" reclaimed landscapes will depend, at least in

part, on our understanding of the inevitable changes that will occur. This final chapter addresses those future changes through the perspective of terrain modeling.

6.2. Background and Literature Review

6.2.1. Soil Formation

Current understanding in pedology relies heavily on the soil formation model of Hans Jenny (1941). This model states that soils develop over time in response to conditions of local climate, parent materials, topographic factors, and the influence of plant and animal communities. Soils are believed to develop progressively towards a common endpoint or until major disturbances, such as glaciation or surface burial, start the process of soil development over again. The idea of soil formation continuously proceeding forward has led many geomorphologists to use the degree of soil formation as a means of determining relative ages in quaternary land surfaces (Harden, 1982, 1990; Birkland, 1984, 1990; Birkland et al., 1991; Markewich et al., 1986, 1987; Holliday, 1988; Kiernan, 1990; Phillips, 1990).

Recent revisions to the soil formation model (Johnson and Watson-Stegner, 1987; Johnson et al., 1990) appear to offer a valid explanation for apparently contradictory field observations of well developed and slightly developed soil profiles occurring side by side in otherwise homogeneous landscapes. These revised ideas maintain that both progressive and regressive processes relative to soil formation occur at the same time. The soil profile then is not the endpoint in a steady progression of soil development but rather a dynamic equilibrium which may go either forward or backward depending on the relative magnitude of progressive versus regressive processes. Phillips (1993) takes this idea one step further by demonstrating that spatially variable initial soil conditions could tip the balance of progressive versus regressive processes leading to a

complex mosaic of soil development stages, which resemble a mathematical characterization of deterministic chaos.

6.2.2. Reclaimed Landscapes

Mapping reclaimed mine soils, whether by soil survey, geostatistical techniques, or both requires mapping areas of different source materials as they have been laid down in the final reclamation. The distribution of those materials results primarily from combined influences of human decisions, with respect to salvage operations and soil replacement depths, and native variability in the original soil resource. Time from the standpoint of soil formation essentially starts over once soil replacement is complete, although the double lift salvage strategy does preserve higher soil organic matter levels in the topsoil lift, simulating an initial level of soil genesis. The local semi-arid climate remains reasonably constant within the confines of the Rosebud Mine. This area receives approximately 13 inches of mean average annual precipitation, has cold winters and hot summers. From a soil classification perspective, this translates to the dry end of an ustic soil moisture regime. The soil temperature regime is frigid. Initially, vegetation differences in the native landscape had variable impacts on the development of soil resources but these effects are minimal in reconstructed mine soils. Grassland vegetation and especially cool season grasses dominate most of the reclaimed landscapes almost regardless of the goals of reclamation staff or state regulators. Difference in geologic parent materials are responsible for the major spatial variations in initial mine soil properties, but their influence remains constant over time. This leaves topography as the major soil forming factor not accounted for in assessing future development of mine soils and reclaimed landscapes.

Topographic relief in reclamation results from a number of factors: state regulations, the mining plan, attempts to minimize earth moving costs, the original lay of the land and the amount of material that needs to be recontoured. None of these factors specifically relate to processes affecting soil erosion or soil formation in the post mining landscape. One exception would be the maximum slope regulations for reclaimed landscapes. Soil properties at the start are completely unrelated to landscape attributes except in special instances where, for example, soils slated for revegetation of ponderosa pine may have been salvaged separately for soil replacement on north aspects. The resulting landforms, however, will have a very definite impact on processes such as erosion, sedimentation, and soil formation that will shape the reclaimed landscapes for years to come.

6.2.3. Landscape Topography and Soil Formation

Relationships between landscape topography and soil formation have been examined by many authors in the soil science literature. These concepts have also been part of the unpublished knowledge base for many past and present soil surveys. Aandahl (1948) provided one of the first studies on the effects of topographic attributes on soil properties. He examined soil nitrogen levels at different locations for a loess dominated landscape in western Iowa and concluded that the A-horizon became thinner as slope gradient increased, and that the direction a slope faced or its aspect was an important determining factor of soil nitrogen content. Some time later, Walker et al. (1968) examined the relationships of A-horizon thickness, subsoil mottle (redoximorphic) features, and calcium carbonate depths with hillslope attributes of slope gradient, slope direction, slope curvature, summit distance, and elevation for selected loess and glacial drift landscapes. Regression results were similar to those reported in subsequent studies. R-squared values for

multiple regressions ranged from approximately 0.4 to 0.7 for most soil properties. Thus, soil properties were definitely related to landscape attributes (no surprise), but much of the variability remained to be accounted for by non-terrain factors. Many other studies have followed. Kleiss (1970) reported differences in particle size distributions, clay content, bulk density, organic matter and cation exchange capacity of soils that occurred on different hillslope positions in northeast Iowa. He attributed these differences to sedimentation processes sorting materials downslope. Carter and Ciolkosz (1991) focused on slope gradient and aspect as being "the most important topographic components affecting soil properties" from B-horizon thickness to Fe and Al indices. Hanna et al. (1982) found aspect to be one of the major factors affecting plant available water throughout the growing season on loess soils in Nebraska. Other studies have focused on slope curvature (Pennock et al., 1987) or wetness index (Gessler, 1995) as the primary determinants of soil properties. Additional studies examining the relationship between topography and soil properties without specific emphasis on terrain modeling include: Furley, 1976; Daniels et al., 1985; Miller et al., 1985; Kreznor et al., 1989; Loague and Gander, 1990; Hairston and Grigal, 1991; Bell et al., 1992, 1994; Stolt, 1993; Brubaker et al., 1994; Cremeens, 1995; and Gile, 1995.

Through these studies and the observations from numerous field soil scientists, general patterns emerge about the overall relationships between topographic attributes, environmental factors and soil properties such as: north aspects are cooler and moister, steep slopes are drier and have less profile development, convex positions tend to have shallow soils, and greater amounts of organic matter accumulate on footslopes and other concave positions. Readers are referred to Boul et al., 1989 for a more comprehensive treatment of the subject.

While general patterns are readily apparent, detailed results tend to be site specific, and anomalies due to unique local conditions are commonplace. For example, Hanna et al. (1982)

reporting the wettest soil conditions occurred on backslope positions under dryland cropping in eastern Nebraska while Carter and Ciolkosz (1991) found the highest levels of soil organic matter on southwest aspects in Pennsylvania. These findings go against commonly observed soil patterns for the northern hemisphere and most likely relate to local site specific conditions such as local geological influences or past vegetation patterns. Researchers of soil-landscape relationships most often attempt to find sites where reasonable homogeneity exists in parent materials. This increases the likelihood of finding significant topographic effects on the distribution of soil properties. Closer examination, however, often indicates unexpected variations in parent materials may have confounded results. For example, Kleiss (1970) reported substantially heavier soil textures on the lowest hillslope positions for a study site in Iowa. Results suggest a possible change in mode of deposition for parent materials on the lowest positions relative to the upper hillslope and not uniform conditions. Similarly, results reported by Wilson et al., (1994) may have been confounded by the occurrence of coarse textured, very gravelly tertiary fill material at relatively shallow depths beneath convex slope positions in an otherwise loess dominated landscape. The single focus on terrain attributes often seems to result in overlooking other factors that may be equally as important to understanding the distribution of soils at a site.

In some instances, terrain attributes play only a minor role in the variation of soil properties. This would most often be the case in older landscapes and regions with hot-moist climates where considerable leaching and soil development have occurred. Stolz et al. (1993) found that less than 8% of the soil variability of Hapludults they studied in Virginia could be attributed to landscape position. Variations due to parent materials and horizon differentiation played a much greater role in explaining the spatial variability of soil properties.

6.2.4. Prediction of Soil Properties with Terrain Models

The advent of digital elevation models (DEM's) or digital terrain models (DTM's) has greatly increased interest in the use of terrain attributes (topography) to predict soil properties. Theobald and Goodchild (1990) define a DEM as "any form of discrete representation of the variation of topographic elevation over an area". They consider DEM and DTM to be synonymous. Terrain modeling has grown out of the tremendous development of geographic information systems in the last 20 years and the ability of modern computers to rapidly analyze large quantities of data. Many of the original applications in terrain modeling were related to hydrology, such as extracting drainage basins and drainage networks from digital elevation data (Puecker and Douglas, 1975; Mark et al., 1982; Mark, 1983; O'Callaghan and Mark, 1984; Jenson, 1985; Band, 1986) or modeling hydrologic functions like throughflow and peak discharge rates (Beven and Kirkby, 1979; Rodriguez-Iturbe and Valdez, 1979; Gupta et al., 1980; Dias-Granados et al., 1984; Moore and Grayson, 1991). Applications in related fields of plant ecology and geomorphology soon followed.

Interest in the use of terrain models to predict soil properties originated, in part, due to the lack of suitable soils data to run terrain based hydrologic models (Moore et al., 1993c). This lack of adequate soils data, especially spatially variable soil transmissivity data, remains one of the greatest shortcomings in the application of physically based hydrologic models. Soil survey data can not be used in physically based hydrologic models because, as noted by Moore et al. (1993c), for most hydraulic soil properties, soil survey data vary by an order of magnitude within a single soil type. As a result, soil transmissivity has most often been treated as a "fudge factor" in the calculation of hydrologic functions. Average values of soil transmissivity are applied to an entire

catchment based on which value results in the best match between calculated flow rates and observed stream flow data.

The development of terrain models and the need to obtain more accurate soils data for hydrologic modeling were soon linked to another need, that of obtaining more accurate and precise soils information for site-specific or precision farming (Moore et al., 1993a; 1993c). Terrain models provide continuous surfaces of derived topographic attributes, the very same attributes that have for years been used by soil scientists to locate map unit boundaries and predict changes in soil properties. They can also provide more complex hydrologic indices, such as a wetness index, stream power index and the sediment transport index, all of which may to some degree be related to the distribution of soil properties on hillslopes. Moore et al. (1993a; 1993c) make the argument that "in many landscapes, catenary soil development occurs in response to the way water moves through a landscape." They hypothesized, therefore, that at a "meso" scale the spatial distribution of terrain attributes determines the way water moves through a landscape and therefore should do a good job of predicting the spatial distribution of soil properties. Assuming a terrain model gave a reasonable representation of the ground surface, it appeared likely that much of the spatial variability of soil properties could then be described and predicted from derived terrain attributes.

A number of recent studies have attempted to test the above hypothesis (Moore et al., 1993a; Wilson et al., 1994; Gessler et al., 1995; Tomer and Anderson, 1995; Gessler, 1996). Most of these studies have relied on multiple linear regression techniques to examine relationships between terrain attributes and various soil properties. Results have been consistent in a number of respects, and not altogether different from results of prior soil-landscape studies. In each case, researchers tried to select sites of uniform parent materials which helps force dependence on terrain variables. Various combinations of terrain attributes have been shown to do a reasonably good job

of predicting selected soil properties. For example, plan curvature and wetness index provided reasonable predictions of A-horizon thickness and solum depth in soils formed from meta-sediments in Australia (Gessler, 1995). Slope steepness and wetness index were similarly used to predict percent silt in the surface 10 centimeters of alluvial/aeolian soils in Colorado (Moore et al., 1993a). Reported r^2 values for "successful" predictions generally range from .40 to .65. Some soil properties, like soil pH, remain more recalcitrant in relation to the ability of derived terrain attributes to predict their variability. Results obtained for "successful" prediction equations are by no means trivial, but often show the limitations of using linear regression techniques to capture soil-landscape relationships as much of the variability remains unaccounted for by the equations. Perhaps more importantly, they also point out that, even in relatively uniform parent materials, other spatially variable factors than terrain attributes can have a significant effect on the distribution of soil properties. Finally, in all cases, the same data set used to develop regression equations was also used to test their validity. This would not be a major concern except that the regression equations are invariably different for each study site. Regressions developed at one study site have very little chance of accurately predicting soil properties at another site; negating much of their value as predictive tools.

There have been a couple of notable exceptions to the above. Moore et al. (1993a) followed their regression analysis with a second approach that used terrain attributes to scale the range of soil properties obtained from soil survey map units. The use of soil survey information represents an attempt to incorporate site specific soils information into prediction equations while utilizing prediction equations that are not specific to the site or a particular data set. This approach appears to have good potential for future applications, especially if needed information about the true range of soil properties in a map unit and the distribution of those properties were

reported in soil surveys. Brubaker et al. (1994) applied a slightly different approach to regression analysis and used landscape position as a filter to create separate regression results for each of five landscape positions. Their approach has many of the same limitations as other regression approaches except one of the independent variables used was observed values at the upper interfluvium, again tying site specific field observations into the relational model. Maintaining such linkages between computer models and site specific observations will be essential if predictive models are to be made transferable from one site to another. In a different study relating soil color to soil organic matter, greatly improved prediction results were obtained by Zelenak (1995) when regression models incorporated site specific data.

Further refinements of the basic regression approach using terrain attributes have been proposed by McSweeney et al. (1994) and at least partially demonstrated by Gessler (1996). They introduce more elaborate methodologies for testing and refining soil-landscape models in an iterative approach that includes other analytical procedures in addition to standard regression techniques. The most promising of these involves the use of a decision tree by Gessler (1996) which could provide the basis for a comprehensive expert systems approach to mapping soil properties. Gessler's work does show improved r^2 values (reported in a non-parametric measure of %RID) for certain soil properties while other soil properties remain intransigent to improved predictions. Overall however, it is this author's opinion that the approach recommended by McSweeney et al. (1994) suffers from many of the same limitations as earlier terrain modeling, regression-based approaches: too much analysis and too little utilization of field expertise.

It does not appear reasonable that terrain models will provide a panacea for predicting all soil properties in all situations. Still, they provide an excellent tool to improve soil resource inventories. Environmental partitions based on terrain attributes offer greater efficiency in soil

survey sampling strategies than standard procedures (See Chapter 2). Scaling observed values across map units can also be accomplished via derived terrain attributes. In reclamation areas, like those at the Rosebud Mine, terrain modeling may provide a unique glimpse of how landscapes and soils will evolve in the years to come. The application of terrain modeling for predicting soil development seems to be ideally suited for reclaimed landscapes because much of the influence of other soil forming factors has been homogenized through the process of mine soil reconstruction.

The objectives of this paper are to examine the impact of model decisions used to create a terrain model for reconstructed landscapes at the Rosebud Mine and then to explore the potential use of terrain models in general to predict changes that will occur in the reconstructed landscapes over time. Based on initial conditions and spatially variable terrain attributes, predictions are made with regard to the future development of drainage networks, soil erosion and deposition, and changes in soil properties due to soil genesis.

6.3. Methods and Materials

6.3.1. Creating Elevation Grids

Topographic lines on ten foot elevation intervals were digitized from 1:4,800 scale planning maps covering a large portion of the reclaimed lands in Area-E of the Rosebud Mine and adjacent native landscape features left undisturbed by mining. This area was chosen because mining was finished and final recontouring of reclaimed land surface was mostly complete for the Area-E mine, providing a large contiguous area of reclamation and adjacent undisturbed landscape features. The original planning map contours were stereocompiled from aerial photographs for Western Energy Company as part the ongoing inventory of mining and reclamation activity. Digitizing of contour lines was accomplished using PC ARC/INFO and a

Calcomp 9100 digitizing table. Section corners on the planning maps were used as registration points and later converted to UTM coordinates.

The digitized topographic vector coverage was cleaned, built, and edited using standard ARC/INFO procedures. This coverage was then converted to a grid based terrain model through a series of steps. The ARC/INFO LINEGRID command was used to convert topographic vectors to a series of points in a grid coverage (Fig. 6.1). LINEGRID essentially places a grid over the vector coverage and evaluates each cell in the grid for the presence or absence of a line segment passing through it. If a line does pass through a cell, then the LINEGRID algorithms code the cell with the ARC ID for that line. Cells without line segments passing through them are coded with zeros.

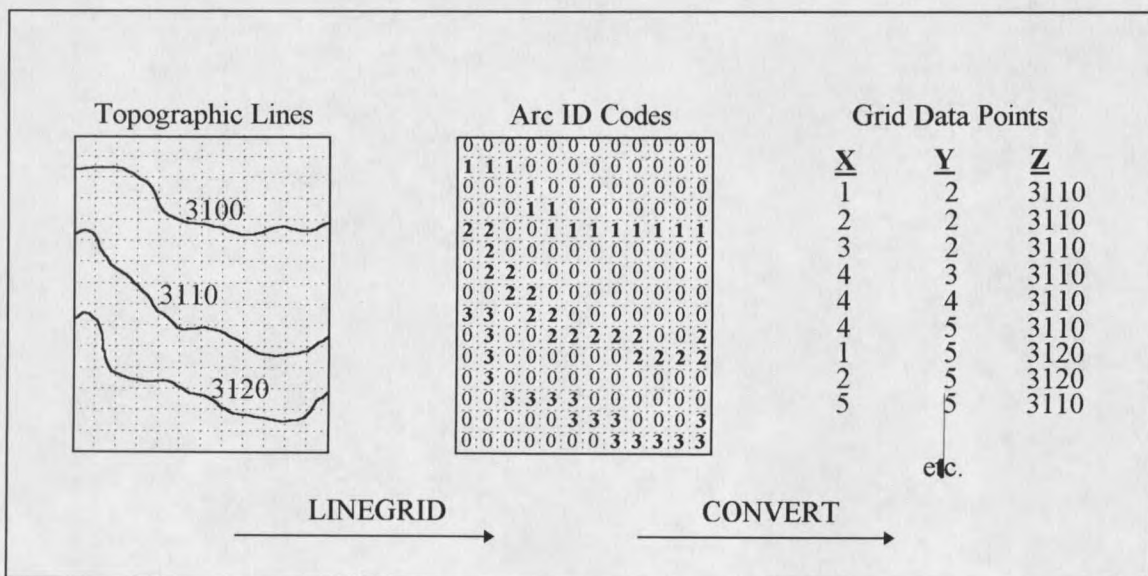


Figure 6.1. Conversion of topographic elevation lines from a vector coverage to an irregularly spaced x,y,z grid.

We next created a separate conversion program, with assistance from Ric Roche of the Montana State Agricultural Statistics Center, to convert the ARC IDS to elevation values in an X,

Y, Z grid. The conversion program contains lookup tables that relate ARC IDS to their actual elevation attributes values. This program systematically scans the data grid created by the LINEGRID and records x,y coordinates along with corresponding look-up table elevations when non-zero values are encountered. Cells containing zeros are ignored. Output from the conversion program is a series of x,y,z triplets that represent an irregular grid of elevation data.

The ANUDEM program developed by M. F. Hutchinsen (1989) converts elevation data from an irregular grid to an evenly spaced, uniform grid with the option to maintain drainage control over the resulting grid if streamline data are available. The version of ANUDEM used in this analysis has since been incorporated into the TOPOGRID command in ARC/INFO version 7.0. TOPOGRID essentially replaces both the conversion and ANUDEM steps completed outside of ARC/INFO with a single ARC/INFO command. The unknown cost is the amount of control users lose over program settings and defaults.

ANUDEM was run without drainage enforcement because established drainages were not as yet present in the newly created reclamation landscape although distinct channel paths have been engineered into reclamation topography. The consistent drop of engineered channel paths would be expected to avoid problems of the terrain model creating sinks along drainage lines, as commonly occurs when grid based digital elevation models are created for natural landscapes. In general, the smooth features of reclaimed landscapes lend themselves well to terrain modeling.

Elevation tolerances used in running the ANUDEM program were 2.5, 10.0, and 50.0 ft. Since no streamline data were used, the third tolerance had no effect. The first tolerance, 2.5 ft., represents the elevation difference that will be considered insignificant by the program. Data points that block drainages by no more than this tolerance are removed. The second tolerance, 10.0 ft., represents the maximum height above a potential sink point in the coverage which can be

considered as a possible exit for drainage out of the sink. Much of the advantage ANUDEM algorithms provide for interpolating elevation data comes from the removal of spurious pits or sink points in the coverage. Removal of these pits allows for more realistic modeling of water movement across the resulting landform.

6.3.2. Terrain Model Outputs

Final output from ANUDEM was in evenly spaced x,y,z triplets on a 50 ft. rectangular grid encompassing the demonstration area. This output is compatible for input into the TAPES-G program, a grid based Terrain Attribute Program for Environmental Sciences (Moore, 1992). Gallant and Wilson (1996) recently published documentation for running the TAPES-G program as well as providing descriptions of the various algorithms available for modeling flow paths.

The 50 foot grid data from ANUDEM were run through TAPE-G using a random - eight node (FRho 8) algorithm to calculate stream directions and a multiple drainage direction (FRho 8) algorithm to calculate flow path lengths. The FRho 8 algorithm allows for flow dispersion in portions of the catchment above a user specified maximum cross grading area for the purpose of calculating upslope contributing areas. The maximum cross grading area used was 200,000 ft². This implies that when there is more than 200,000 ft² of contributing area, non-dispersed channel flow will occur. The value used was a best guess approximation that between 4 to 5 acres of upslope contributing area would be required before channel initiation would occur in reconstructed landscapes (See section on Future Development of Drainage Networks for more details). Once the calculated catchment areas exceeded 200,000 ft² (approximately 80 grid cells), the program switched to a non-dispersive flow direction algorithm.

Terrain model outputs were generated for 6 variables: elevation, slope gradient, slope direction (aspect), profile curvature (slope shape in the downhill direction), tangent curvature (slope shape across the hillside), and upslope contributing area also called the specific catchment area. Specific catchment area is the upslope area per unit cell width that drains to a cell. Terrain attributes were output in ASCII format using the companion TAPESOUT program developed at Montana State University. Terrain ASCII files were then converted to ARC/INFO grid coverages by use of the ASCIIGRID command in ARC.

We contracted Bob Snyder, of the Montana State University Geographic Information and Analysis Center, to create an ARC macro-language program (AML) for rapidly overlaying various terrain coverages on a 3-dimensional plot of elevations. This program, called `drape.aml` and its updated version `drape2.aml`, provided an excellent tool for graphic display of terrain attributes in ARCPLOT. The `drape.aml` programs allow users to set ARC/INFO options for vertical and horizontal viewing angles, the viewing distance, and the degree of vertical exaggeration. Settings used to produce figures 6.2 through 6.7 were: 330 degrees, 2 degrees, 100,000 meters, and 5-times, respectively.

Graphic images of draped terrain attributes were captured from the screen of a SUN workstation using the XV screen capture program and saved as bitmap (.bmp) files. These were transferred to the Microsoft Powerpoint (Microsoft Corporation, 1994) program for creating final figures. Terrain images of the Area-E landscape provide the basis for further discussion of how reclaimed landscapes and reconstructed soils can be expected to evolve over time. From a practical standpoint, the discussion will be limited to approximately the next 100 years, as a reasonable time frame for planning.

6.4. Results and Discussion

Results of any terrain analysis depend on the mechanics of the model used and the quality of input data. Factors such as model type, the density of sample points, the accuracy of input data, and the type of algorithms and tolerances employed in the model can all affect results. For this reason, a discussion of model decisions, used to generate terrain models for the Rosebud Mine, has been included in the Results and Discussion.

6.4.1. Terrain Model Decisions

Digital elevation models are discrete, point representations of land surface elevations in a landscape. As such, all digital elevation models depend on some type of interpolation procedure to connect the dots of known elevations. Subjectivity occurs in creating maps from selected sample points of a surface and there are always systematic errors associated with any interpolation methodology (Fahsi and Chang, 1990). In this sense, DEM's are no different than any other model. They are approximations of the real world. Methods of production can effect the types of artifacts that occur and the accuracy of final results (Issacson and Ripple, 1990).

6.4.1.1. Types of Terrain Models

The first decision that must be made in creating a terrain model involves what type of model to use. Major types include digitized contour lines, grid-based DEM's, and triangular irregular networks (Tin's). Theobald and Goodchild (1990) provide a good discussion of differences between the three types. Often, choices on what type of model depend more on availability of data and programs than decisions about appropriateness. We chose to use a grid-based model due to access to a functional, if undocumented at the time, version of Ian Moore's,

TAPESG or grid-based Terrain Attribute Program for Environmental Sciences. Grid-based DEM's simplify the calculation of terrain attributes at the cost of relatively large data requirements. Inaccuracies in grid-based DEM's are most likely to occur in areas where there are rapid changes in landform elevation and/or direction. This is especially true when grid points do not coincide with local high or low points in the landscape to be modeled. The creation of extraneous pits or depressions in terrain coverages are especially troublesome for modeling hydrologic processes. They create drainage discontinuities and commonly occur in gridded data in or near drainage channels (Theobald and Goodchild, 1990). Hutchinson's (1889) ANUDEM program resolves much of this problem allowing for drainage enforcement in the interpolation of regularly spaced grids where ancillary drainage line elevation data is available. Interpolated elevations are then forced to conform to the existing drainages avoiding the creation of false depressions in the coverage.

Fortunately, from the perspective of modeling terrain, reclaimed landscapes have a distinct absence of abrupt landform changes. Landforms are engineered to continuously smooth surfaces which match well the very assumptions of mathematical interpolation procedures. Drainage enforcement was not deemed necessary for the reclaimed landscapes because incised drainages had not yet developed in the area covered and because the smoothly engineered slopes could be captured without drainage enforcement in the terrain model.

6.4.1.2. Grid Density and Scale

The next important decision in creating a grid-based terrain model is the density of elevation data or grid size. Again this may often be decided by pragmatic considerations, such as data storage capacity and the availability of data. In general, the denser the grid, the more accurate

the results (Isaacson and Ripple, 1990; Fahsi and Chang, 1991; Garbrecht and Martz, 1994; Wolock and McCabe, 1995). Increasing grid density can partially compensate for some of the shortcomings of grid-based models. A tighter grid increases the likelihood that special features, drainages, ridgetops, low and high points, will occur at or near a grid intersection. An important point to consider is how the final data density or grid-size relates to the original source data.

Interpolation procedures can make estimates to an infinitely fine grid subject to the limitations of computer capacity and storage. However, the accuracy of a resulting surface still depends on the measurement accuracy and spacing of the original data.

We interpolated our data to a 50 foot grid. The original source data remains the 10 foot (vertical) interval contour lines on Western Energy's 1: 4,800 foot planning map. The original LINEGRID conversion in ARC/INFO used a 100 x 100 foot grid to convert the equi-elevation line segments to raster points on the grid. This resolution was carried forward through the conversion program which merely discarded zeros associated with non-data points and changed cell attribute values from ARC ID numbers to elevations. As a result, the density of elevation values along a contour in the original grid ranges from 100 feet to 141 feet depending on the direction taken by the elevation lines passing from one cell to the next. Resolution in the downslope direction varies as a function of slope. For a ten percent slope, the resulting sample point density would be approximately 1 per 100 feet. For 5 or 20 percent slopes, the sample point densities would be 1 per 200 or 1 per 50 feet, respectively. An advantage of starting with contour data was that it provides a higher density of data in steeper areas where there is the greatest likelihood of interpolation errors. The contour data also results in fewer data points in flat areas where mathematical interpolation procedures can fit a smooth surface to the data, thus eliminating a

potential problem of grid data where flat surfaces may get broken up by anomalies or inaccuracies in the data (Theobald and Goodchild, 1990).

Increases in grid size affect results by reducing the level of detail that can be captured in the data. Thus, the type of landform to be modeled and the intended use of terrain outputs come in to play on decisions about the density needed for a particular analysis. If the intended purpose requires the model to capture small landscape features or primary drainages then the grid size must be smaller than the feature to be captured (Garbrecht and Martz, 1994).

6.4.1.3. Data Quality

The quality of the source data may be a much more important factor affecting derived terrain attributes than the density of grid points. Fahsi and Chang (1991) compared the elevational accuracy for a number of different grid densities and different qualities of elevation data. Their results showed slight decreases in map quality with reduced DEM resolution (grid density), but a substantial decrease in map quality when lower quality source data were used regardless of DEM resolution. Of noted interest was the poor performance of the USGS 30 meter DEM data relative to the 25 foot stereocompiled DEM data of the original data set. The USGS 30 meter grid data exceeded the US National Map Accuracy Standard of 1/2 the contour interval (>20 feet elevation difference) 30.9 % of the time (Fahsi and Chang, 1991). Apparently, the USGS DEM data were originally stereocompiled on a 90 meter grid and interpolated back to a 30 meter resolution. This makes the USGS DEM data itself interpolated, as opposed to primary or directly measured data. The underlying errors in such interpolated data are very significant considering the USGS data are the most readily available and, therefore, the most readily used source of digital elevation data in the United States.

As stated above, the terrain models developed here started as 1:4800 scale 10 foot contour lines. The map scale is quite large relative to many terrain modeling efforts (i.e. 1:24000 for USGS quads) and the quality of original stereocompiled data is high. Given the variable spatial resolution of the original data, previously described, a 100 ft grid resolution appears to be the most appropriate for final outputs. The 50 foot output grid provides somewhat of a compromise between what is most appropriate and cartographic appearance. The smooth, continuous contours of reclaimed landscapes also help ensure accuracy in the final outputs. The greatest expected errors would occur in the steeper natural landforms present in the background of each terrain figure.

6.4.1.4. Modeling Water Flow

Terrain attributes of elevation, slope gradient, slope direction (aspect) and slope curvatures (profile and tangent) are generated automatically from basic grid data. Different programs use different algorithms for making the calculations. Some are more computationally efficient than others, but the basic approach is straight forward. Calculation of other hydrologic parameters, such as upslope contributing area, involve more complexity, as decisions must be made as to what represents a reasonable approximation of how water moves through landscapes, both laterally through soils and over the land surface. Gallant and Wilson (1996) provide a good discussion of different types of algorithms used to estimate flow direction which in turn affect the calculation of upslope contributing area (specific catchment area). Compound topographic indices described by Moore et al. (1991; 1993a; 1993c) of the wetness index, stream power index and sediment transport capacity index are all derivatives of specific catchment area and slope gradient.

In general, algorithms that model water flow through catchments fall into two classes, those that allow for flow dispersion in upslope areas and those that do not allow for flow dispersion. Most of the literature in this areas seems to agree that algorithms which incorporate flow dispersion provide more realistic distributions of contributing or drainage areas (Quinn et al., 1991; Moore, 1995; Wolock and McCabe, 1995; Wilson and Gallant, 1996). Moore (1995) concluded that algorithms that did not allow for flow dispersion were inferior to those that did for deriving meaningful topographic indices. For some applications, however, hydrologic models do not require the extra precision provided by the dispersed flow approach (Wolock and McCabe, 1995).

Terrain models that attempt to simulate natural drainage systems must be provided with some measure (parameter) that determines the amount of upstream drainage area below which drainage channels become initiated and concentrated flow begins. In many hydrologic models, this parameter is called the critical source area (CSA). In TAPESG, there are two settings that relate to this concept. The first is the critical area-slope, which itself has two parameters; 1) a measure of the upslope contributing area (A) required for a drainage to become established and 2) a weighting factor (r) which varies from 0 to 2 and weights the effect of slope (B) in the following relationship:

$$\text{Critical area-slope} = (A) (\tan B)^r$$

From the standpoint of terrain modeling, the critical area - slope has no effect on final output from the TAPESG program. It does effect an intermediate output where the program draws a diagram of drainage channels in the coverage. A closely related factor, of maximum cross - grading area, determines when flow direction algorithms switch from those that allow for flow dispersion to

those that do not. This threshold generally corresponds to the initiation of channelized flow, once flow becomes concentrated enough, channels are formed. Below that point, water movement in catchments increasingly follows channelized flow paths until the landscape flattens out. Thus identifying the "correct" maximum cross-grading areas remains crucial for a program like TAPESG to accurately model catchment hydrology. Unfortunately, I am aware of no references in the literature that relate the concept of maximum cross-grading or critical source area to site specific factors.

The type and amount of vegetation, permeability of substrates, local climate factors, and the inherent erodibility of surface materials all affect the relationship between catchment area and the initiation of channelized flow in natural watersheds. Drainage densities along with drainage patterns have long been recognized as valuable for identifying different geologic substrates (Lillisand and Kiefer, 1994), yet these relationships have only been examined in a semi-quantitative manner. Understanding the interaction of drainage density/substrate relationships to vegetation, climate, and surface features adds another level of complexity to the discussion. From a predictive standpoint, establishing a realistic threshold between dispersed and concentrated flow appears to be critical, especially given the dependence of wetness index and other compound hydrologic indices on accurate values for specific catchment area. A maximum cross-grading area of 200,000 ft² was used for the Area-E reclaimed landscape. This setting provided a realistic looking image of drainages for the demonstration area and corresponds to a somewhat higher threshold than the minimum 10,000 m² threshold recommended by Moore et al. (1993b) for 20 meter DEM's of natural catchments.

6.4.2. Final Images

Final terrain images are illustrated in Figures 6.2 through 6.7. The same 3-dimensional plot of elevations with a vertical exaggeration of 5 was used in each case. Map scale for final outputs averaged about 1 to 24,000 for these perspective views with a larger (appr. 1:19,000) scale in the foreground and a smaller (appr. 1:28,000) scale at the back of the images. The coverage includes most of the reclaimed Area E portion of the Rosebud Mine. The perimeter of the actual coverage is irregularly shaped. As a result, flat areas in the foreground and upper right corner of these figures are artifacts of plotting to a rectangular grid. Reclamation areas are mostly represented by rolling to hilly landforms, while the two steepest landforms in the background are natural landforms through which mining did not advance. Surface mines generally work around such high points in the landscape as increased depth to the coal seam makes mining uneconomical. In the Colstrip area, high points like these often have a scoria cap which both makes them resistant to erosion and indicate a high probability that the coal seam below them has long since burned out. The presence of such relic areas adjacent to the reclamation provides valuable diversity to the reclaimed landscape on a regional scale.

Figure 6.2 shows the distribution of elevation classes for the reclaimed landscape. Reclaimed areas range from approximately 3,240 feet to 3,460 feet in elevation while the total elevation range, including the relic areas is approximately 3,240 to 3,580 feet. Figure 6.3 shows the distribution of slope classes in the reconstructed landscape. The steepest slopes are associated with the undisturbed hills in the background. Reclaimed slopes are restricted by state regulation to a maximum of 5 to 1 or 20% maximum slope. The terrain model indicates some slopes steeper than 20 percent. Slope classes in the legend represent standard interpretive breaks used for soil

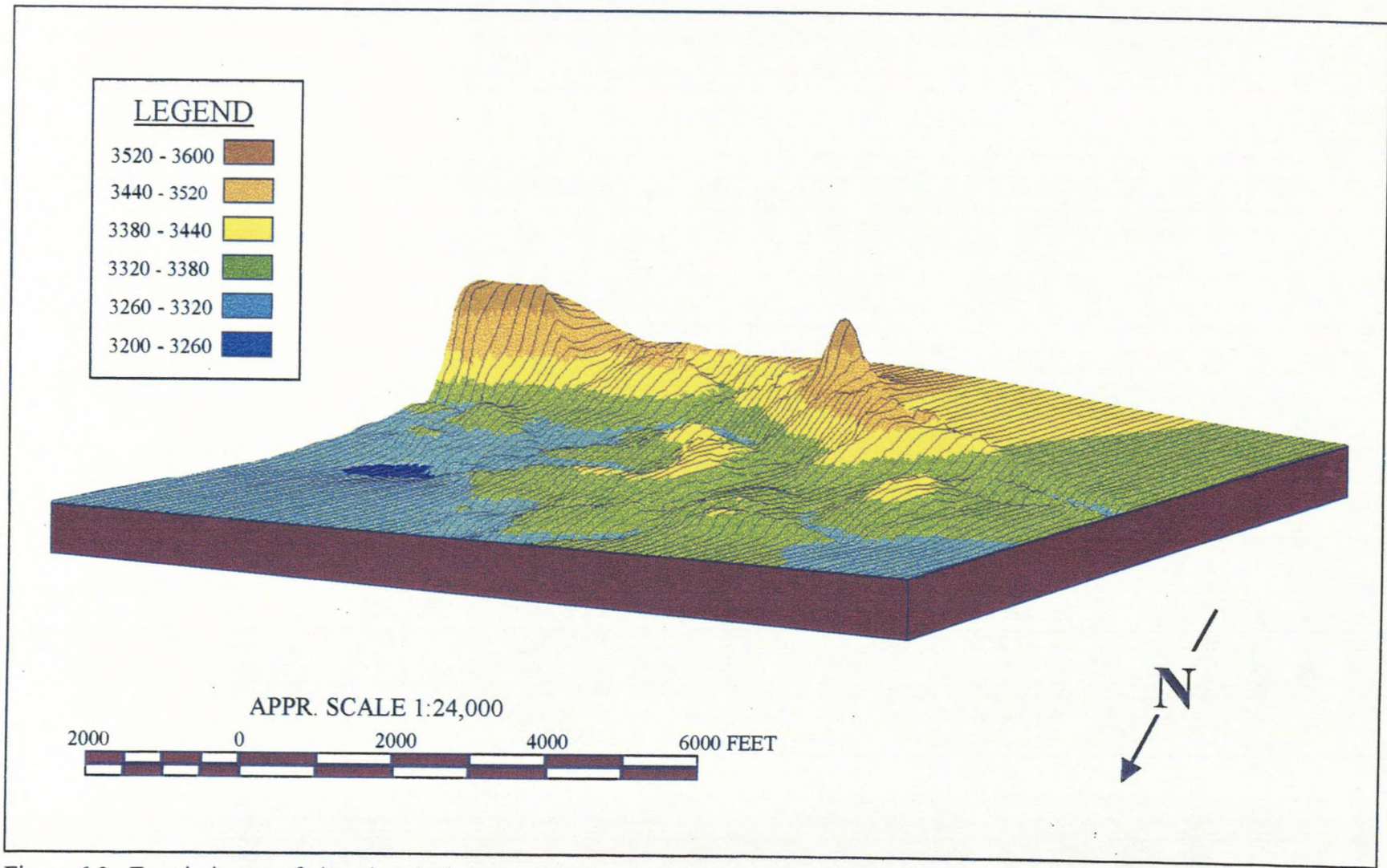


Figure 6.2. Terrain image of elevation, in feet, draped over a 3-dimensional terrain model of reconstructed and native landscapes in Area-E of the Rosebud Mine, Colstrip, MT.

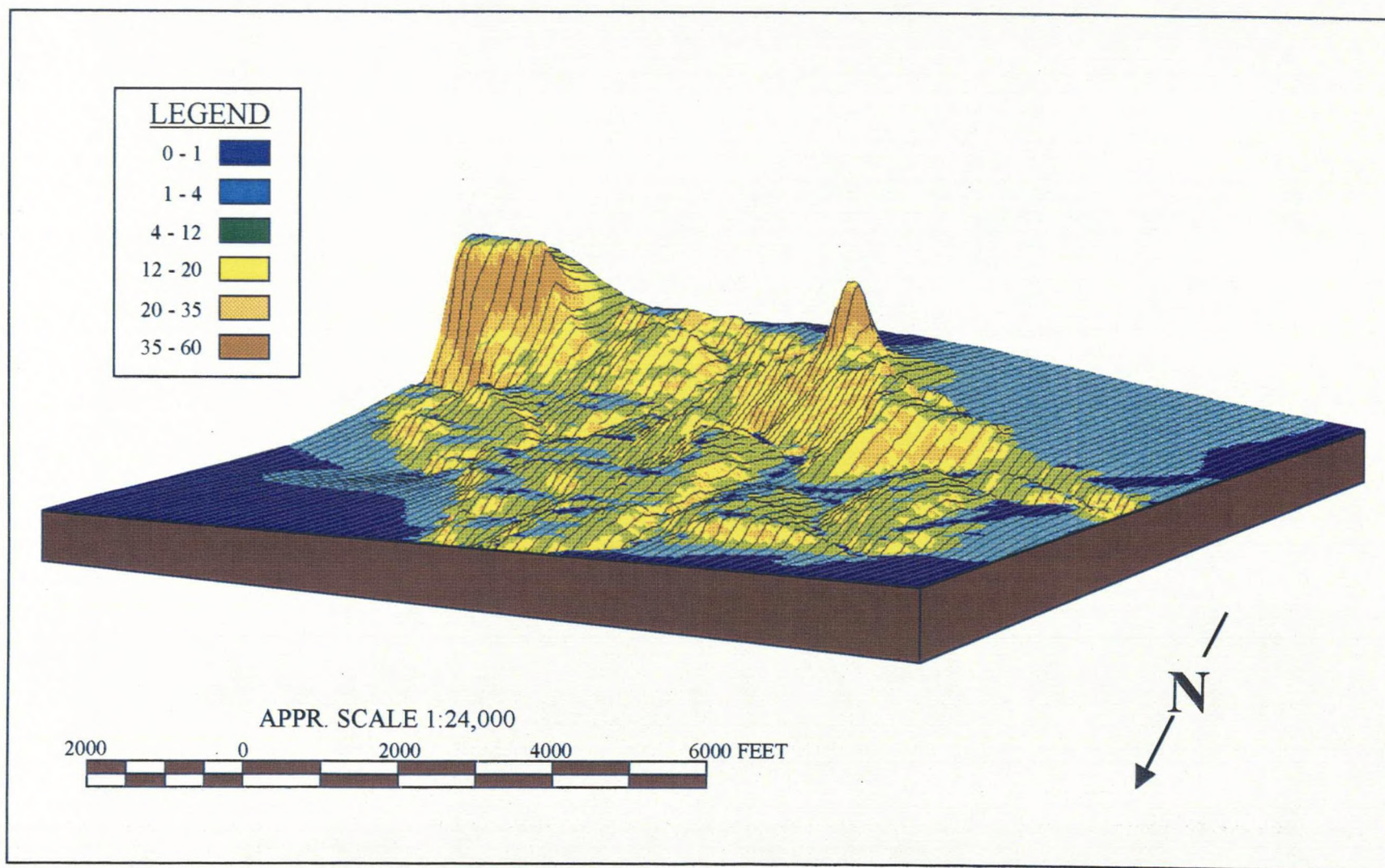


Figure 6.3. Terrain image of slope gradient, in percent, draped over a 3-dimensional terrain model of reconstructed and native landscapes in Area-E of the Rosebud Mine, Colstrip, MT.

surveys in Montana, adjusted to partition the allowable 0 to 20% slope range for reclaimed areas into management units.

Figure 6.4 displays the distribution of slope direction or aspect in the terrain model. The viewing angle for these figures is 330° , thus northerly aspects are primarily in view. Partially for display purposes, south aspects from 90° to 270° have all been lumped into one class. In other applications to soil survey work, similar wide angle classes for south aspects have provided a reasonable partition for predicting the distribution of plant communities in southwestern Montana (unpublished data - Silver Bow County Soil Survey). Northerly aspects were split as follows: Northwest, 270 - 315° ; North 315 - 45° ; Northeast, 45 - 90° .

Terrain models of slope curvature are presented for the downslope direction (Fig. 6.5) or slope profile and for the across slope direction (Fig. 6.6) or slope tangent. Profile curvature indicates the relative degree of convex or concave shape slopes have in the downhill direction. Water and sediment tend to run off convex slope portions and accumulate in concave positions. Tangent curvature, similar to plan curvature, provides a measure of the relative convergence or divergence water flow paths (Moore et al., 1993a; 1993c). Tangential curvature measures the angle of curvature between normal planes in the direction perpendicular to the maximum slope gradient (i.e., tangent to the contour line.). Cutoffs used to delineate significantly convex and concave slopes from those that are linear were $-0.05^{\circ}/\text{ft}$ to $+0.05^{\circ}/\text{ft}$. These thresholds are slightly more conservative, in terms of identifying slope curvatures, than the $\pm 0.1^{\circ}/\text{m}$ curvatures recommended by Young (1972) to delineate moderately concave or convex slopes from those with only slight curvatures. Tangent curvature was used rather than plan curvature for the across slope measure because this standardizes results to the same scale as profile curvature. The same cutoff

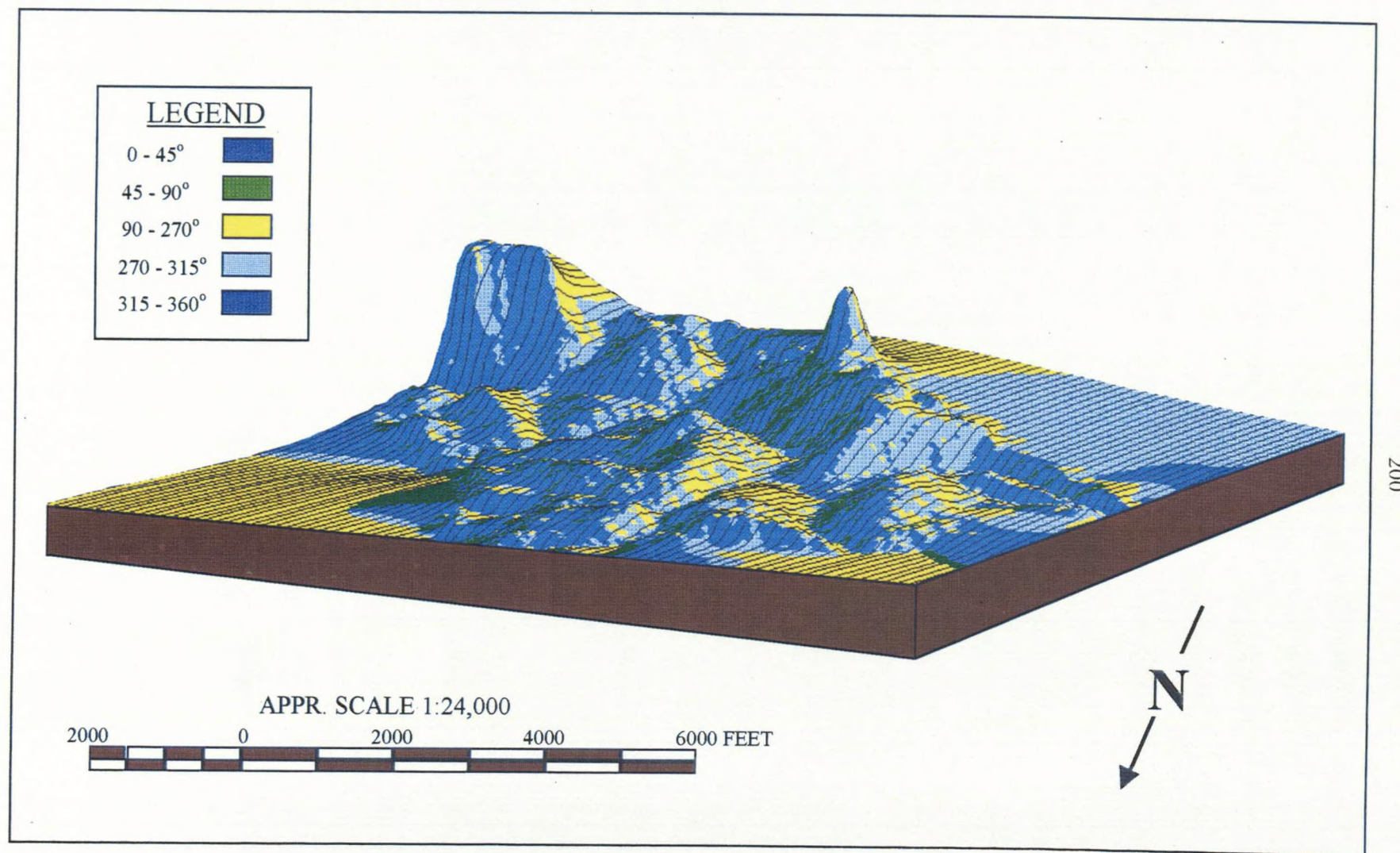


Figure 6.4. Terrain image of slope direction (aspect) draped over a 3-dimensional terrain model of reconstructed and native landscapes in Area-E of the Rosebud Mine, Colstrip, MT.

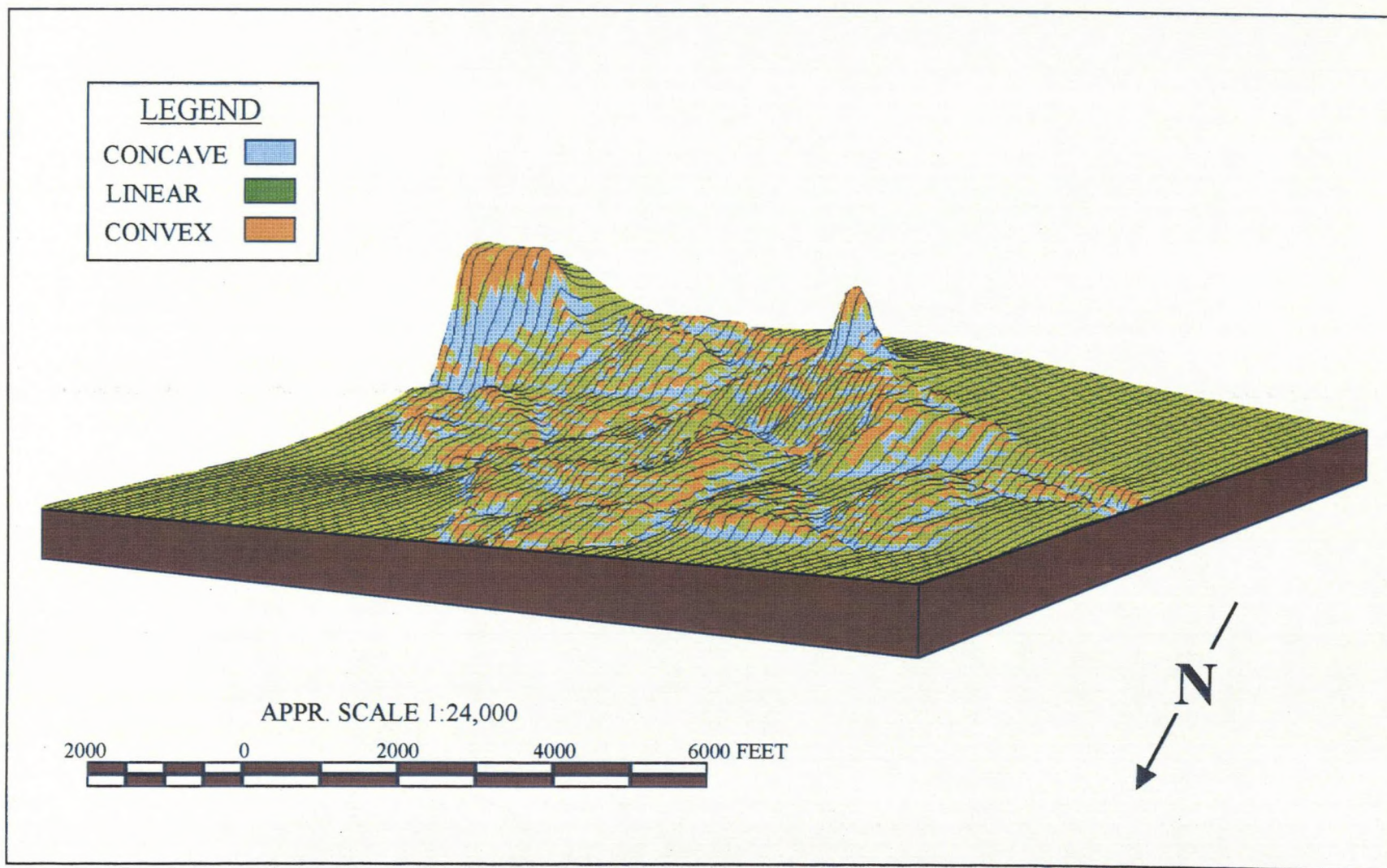


Figure 6.5. Terrain image of profile curvature, slope shape in the downhill direction, draped over a 3-dimensional terrain model of reconstructed and native landscapes in Area-E of the Rosebud Mine, Colstrip, MT.

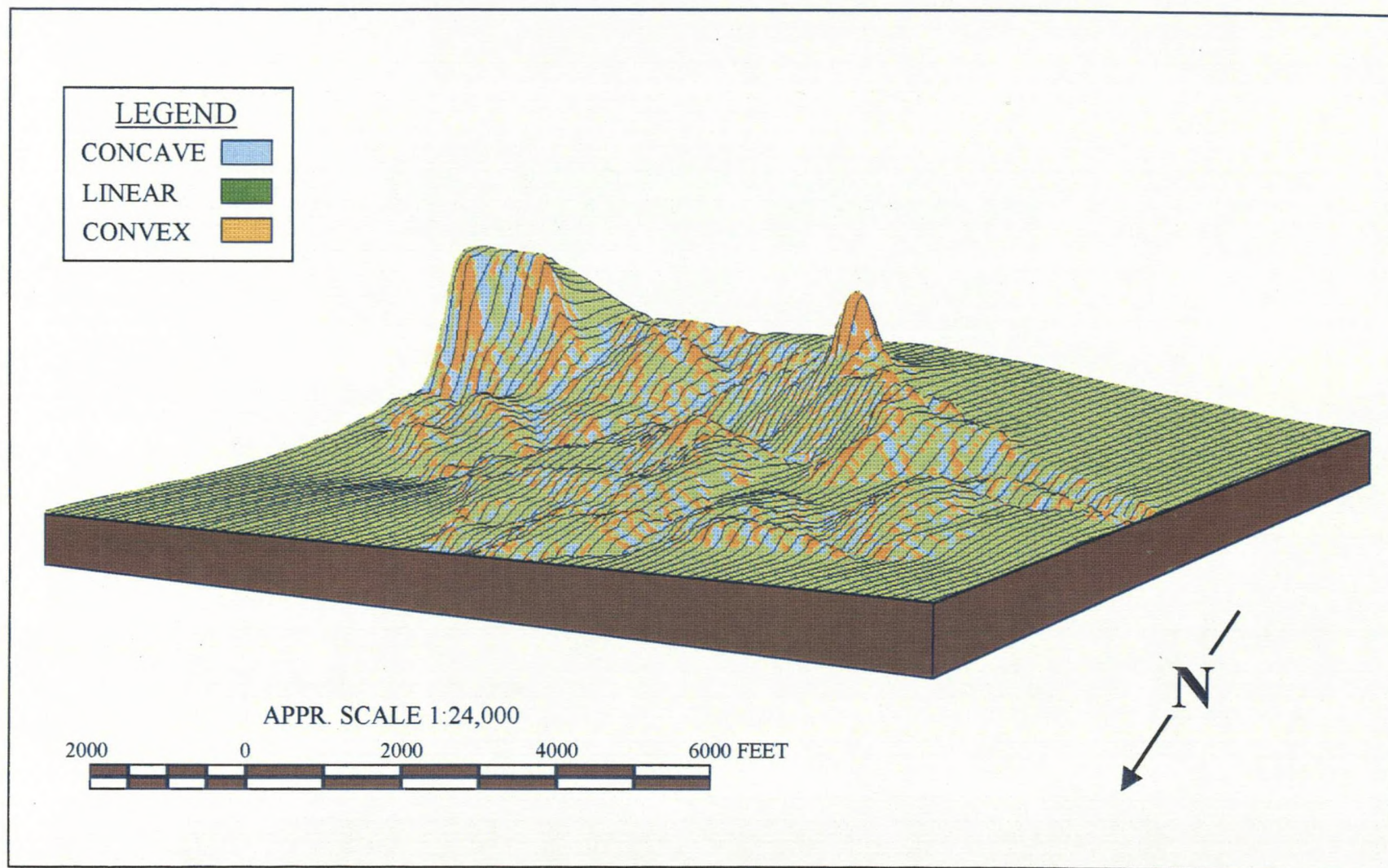


Figure 6.6. Terrain image of tangent curvature, slope shape in the across slope direction, draped over a 3-dimensional terrain model of reconstructed and native landscapes in Area-E of the Rosebud Mine, Colstrip, MT.

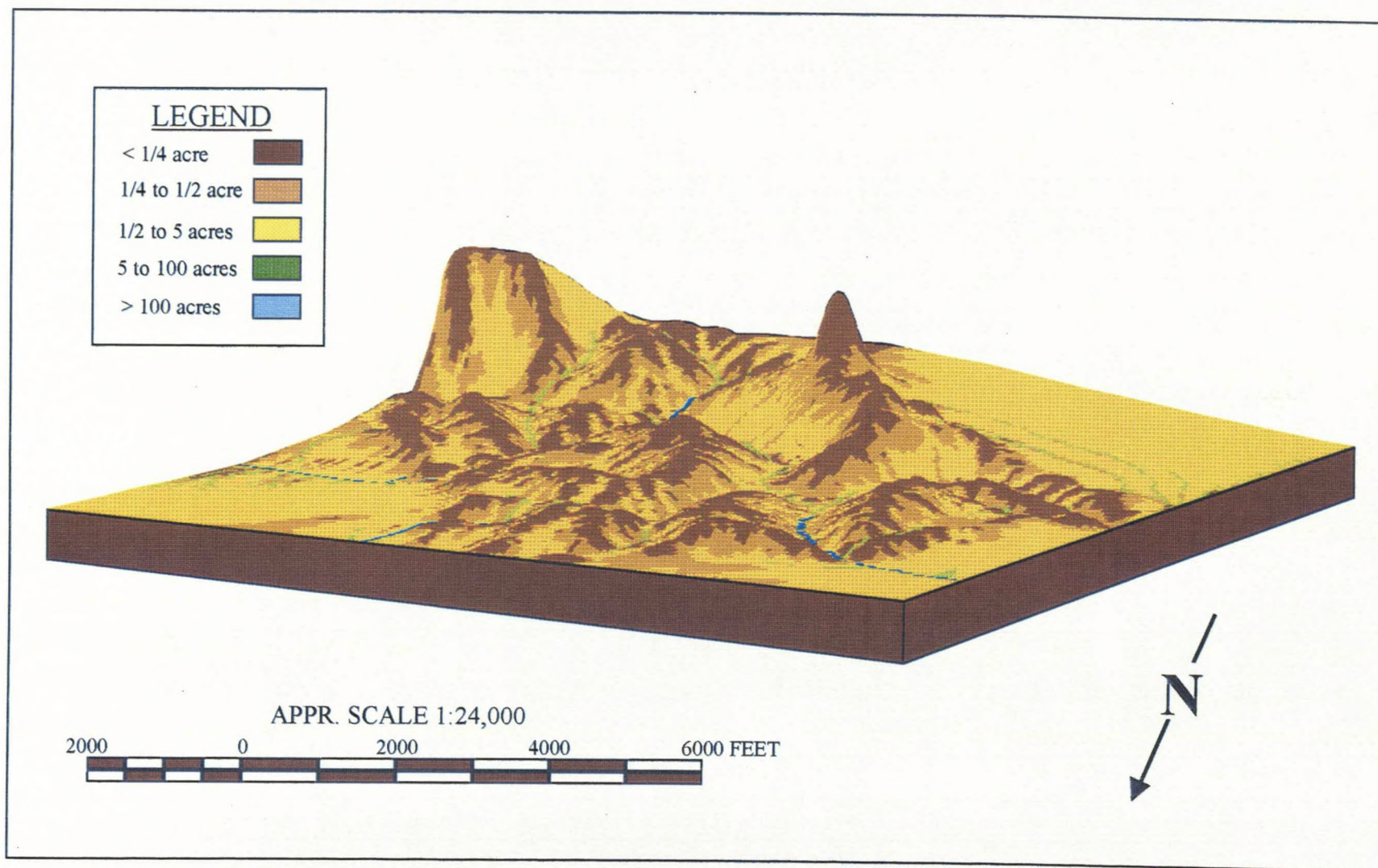


Figure 6.7. Terrain image of upslope contributing area, in acres, draped over a 3-dimensional terrain model of reconstructed and native landscapes in Area-E of the Rosebud Mine, Colstrip, MT.

values were used for both profile and tangent curvature images. Mitasova and Hofierka (1993) recommend tangent curvature be used rather than plan curvature for studying the convergence and divergence of water on landscapes. Slope curvature values are especially sensitive to errors in the original DEM since they are based on second derivatives of the elevation surface (Gallant and Wilson, 1996).

The final Figure (6.7) displays the predicted distribution of a specific catchment area based on flow direction algorithms that allow for flow dispersion up to a maximum cross-grading area of 200,000 ft² and non-dispersed (concentrated flow only) in portions of the landscape with a cross-grading area greater than 200,000 ft². In general, this model predicts channel formation for grid cells with specific catchment area greater than 5 acres.

6.4.3. Future Development of Drainage Networks

Drainages are engineered into reconstructed landscapes of large reclamation projects such as at the Rosebud Mine. Serious efforts are made to ensure that sediment does not leave mining or reclamation areas, since this would result in automatic state violations. Mine company engineers determine where water will leave a reclamation site and calculate the maximum volume that might be expected to drain from a catchment within a specific time period. They can then design necessary sediment traps to keep suspended sediment from leaving the mine above allowable levels. Although plenty of engineering design goes into planning for water drainage, little consideration is given to drainage density relative to natural drainage systems.

6.4.3.1. Drainage Density

Reclaimed landscapes invariably have lower drainage densities than surrounding native landscapes. Initially, this would appear to have serious implications for the long term stability of

reconstructed landscapes as they evolve towards more stable equilibrium conditions. The equilibrium that develops, however, will depend not on the original drainage characteristics of pre-mine landscapes but on a new set of conditions created in the reclamation.

Several factors will ultimately determine the drainage network that develops in new landscapes. These include: local climate, vegetative cover, drainage baselevels, initial topography, slope gradients, erodibility of surface soils, and the permeability of substrates. An additional factor to consider in reclamation areas is the amount of time and money land managers and coal company officials are willing to spend to maintain existing conditions.

Landscape permeability plays a major determining role in how water moves through catchments. Whether water moves downward through the soil and into lower substrate layers or whether it moves laterally at or near the ground surface has a tremendous impact on both soil erosion and the development of drainage channels. Water that penetrates deeply into the ground and intersects a regional water table does not create surface drainage channels. For this reason, highly permeable landscapes, such as karst topography, recent lava flows or aeolian sands, have little or no surface drainage. Water that flows laterally through a catchment, either on or near the surface, creates channels in areas where flows become concentrated enough to erode soil materials. Many other factors come into play, but in general, lower substrate permeability results in higher drainage network density. Landscapes with largely non-permeable substrates, such as shales, will develop much higher drainage densities than more porous sandstone areas.

Natural drainages in the Colstrip area are controlled by local bedrock. Sandstone and scoria ridges as well as siltstone and shale uplands, exert structural control over local drainage patterns and drainage densities. The varying permeability of substrates causes local variations in drainage densities. Portions of the native landscapes underlain by low permeability siltstones and

shales have the highest drainage densities. In contrast, reclaimed landscapes do not have bedrock control. Spoil substrates, while more dense than most native subsoils, do not provide nearly as impervious a barrier to downward water movement as do undisturbed sedimentary beds. As a result, the same drainage densities would not be expected to develop on reclaimed landscapes as are found in local, undisturbed, native landscapes.

Terrain analysis can provide a reliable means of quantitatively assessing the differences in landscape and drainage characteristics between native and reconstructed landscapes. Terrain analysis has also been shown to be useful in identifying areas where channel initiation is likely to occur (Moore et al., 1988a). Terrain analysis alone, however, cannot provide a clear picture of what the ultimate drainage density will be in reclamation. Moreover, results of using terrain models for hydrologic applications often depend on assumptions made about the existing drainage networks. Comparisons with other natural systems are likely to provide the best insight into the future development of the reconstructed landscapes.

6.4.3.2. Comparison to Natural Systems

Because local sedimentary landscapes do not provide a suitable model for comparison, other more comparable native landscapes will be examined. Loess deposits appear to offer the best alternative in this regard. Soils formed in loess provide some of the most fertile farmlands in the world. They have excellent water holding and nutrient holding properties, are free of rocks, and easy to work. Loess deposits are also unconsolidated, much like reconstructed mine soils. The range of slopes found in most loess landscapes is similar to those found in reclamation at the Rosebud Mine. And if stripped of vegetation, loess soils are extremely susceptible to soil erosion by water (Foster et al., 1985); another trait they share with mine soils.

Many of the mine soils at the Rosebud Mine have loamy textures ranging from fine sandy loams to loams, silt loams, and light clay loams. These textures could all be encountered in soils developed from loess. Some reclaimed portions of the Rosebud Mine (although not in Area-E) have sandier textured soils; sandy loams and loamy sands. Hydrologically, the sandy areas would be expected to act more like aeolian sands while more loamy areas would be comparable to loess deposits.

There are several important distinctions between native loess landscapes and reconstructed mine soils, even for the non-sandy areas. The process of wind transport and deposition creates a very effective sorting mechanism relative to soil particle sizes. Loess deposits may vary in texture from fine sandy loam to light clay loam depending on distance from the initial source areas, but within any given area, soils are characteristically quite uniform in texture and have a very narrow range of particle sizes. Some variations in soil texture occur with depth due to pedogenesis. In contrast, most of the reconstructed soils at Colstrip are comprised of three distinct layers, topsoil, subsoil and spoil, often coming from different initial locations in the pre-mine sedimentary landscapes. Reconstructed mine soils, as a result, tend to have distinctly stratified soil textures both laterally across the reconstructed landscape and vertically down through soil profiles. Reconstructed mine soils at the Rosebud Mine also have significantly higher bulk densities (Keck and Wraith, 1996) than native loess soils and correspondingly lower hydraulic conductivities (Hepfner et al., 1996). These differences in soil hydraulic properties tend to decrease the amount of area required to initiate drainage channels in the reclamation relative to loess landscapes, resulting in higher drainage densities. Unfortunately, quantitative treatment of soil/substrate influences on drainage densities have not been documented beyond the general relationship.

Other native landscapes that might provide reasonable surrogates for modeling the hydrologic functioning of reclaimed landscapes include shale uplands and glacial till areas. Shale areas often exhibit the characteristic rolling topography of reclaimed landscapes at the Rosebud Mine. As previously noted, soils in these areas are mostly underlain by nearly impervious shale beds at relatively shallow depths. Correspondingly, higher drainage densities occur in shale uplands than would be expected to develop in reclaimed areas, assuming factors, such as vegetative cover, climate, and drainage gradient are equal. Shale uplands provide a good example, however, of the influence local base level and drainage gradient have on drainage density. Steep drainage gradients in shale areas invariably result in highly dissected landscapes with dense, very fine dendritic drainage patterns due to the combined influences of the impervious substrates and steep gradients. Shale areas, without a locally steep drainage gradient, may not develop near as dense drainage systems and can have drainage densities that actually approach those normally found in loess dominated landscapes. Similarly, drainage densities that develop in reclaimed landscapes will be especially sensitive to the local drainage gradient and local base level.

Soils in glacial till environments characteristically have increased bulk densities and decreased hydraulic conductivities in lower horizons similar to those found in reclaimed mine soils. They do not have stratified textures common in reconstructed mine soils, but generally behave similar to mine soils in how water moves down through the soil profile. Landscapes formed by large continental glaciation, common in northern Montana, North Dakota and elsewhere, also tend to be quite flat. They may have an undulating or rolling nature, but in general, areas of extensive basal till have much less relief than man-made landscapes at the Rosebud Mine. There are areas of significant topographic relief in glacial landscapes, however, which may provide a reasonable model for the hydrologic function of the reclaimed landscapes. These are most often associated

with other glacial features, such as lateral moraines or glacial outwash, which tend to have soils with higher rock fragments contents than the reclaimed landscapes. The presence of significant amounts of rock fragments would reduce susceptibility to soil erosion and so reduce drainage density. Many of the basal till areas also contain perched ground water tables over dense subsurface layers. This situation greatly reduces the local drainage gradient and reduces the drainage density to near zero in much of the pothole region. Although some similarities exist between soils formed in glacial till and those created by reclamation, differences due to other landscape factors appear to limit their applicability as reference areas for assessing hydrologic factors in reclaimed areas.

Overall, the best natural system model for predicting the hydrologic function of reclaimed mine soils at the Rosebud Mine appears to be loess deposits in semi-arid, well drained, grassland environments. This still does not provide an exact picture of how reclaimed landscapes will evolve because many other contributing factors will influence future development. It does provide a valuable reference point. In general, loess deposits have relatively low drainage densities, provided good vegetative cover is maintained and slope gradients are not too steep. The same should hold true for reconstructed landscapes at the Rosebud Mine. The relatively slow subsoil permeability in reconstructed mine soils will tend to increase drainage density compared to loess landscapes. The tendency towards channel initiation in mine soils will also increase in reclamation areas with more clayey substrates.

6.4.3.3. Application of Terrain Models

Terrain models may be used to predict the potential formation of drainage channels. Specific catchment area (Figure 6.7) is a measure of the amount of upslope area draining any point

in the landscape. While we do not know the exact amount of drainage area likely to cause channels to form in reclaimed fields, obviously, the larger an area drained, the more likely a drainage channels will become established, especially in concave areas. Moore et al. (1988a; 1991; 1993a; 1993b) have taken this basic starting point to expound on a series of compound topographic indices which may be helpful in predicting the initiation of drainages. All of these indices, wetness index, stream power index, and the sediment transport index, are based on the calculation of specific catchment area. They differ by having varying influences attributed to slope gradients.

Of the three indices, wetness index (w) has received the greatest attention of late, especially in the prediction of soil properties (Moore et al., 1993a; Wilson et al., 1994; Gessler et al., 1995; Gessler, 1996). The index can be defined as follows:

$$w = \ln (A_s / \epsilon \tan B)$$

The parameter ϵ in the above equation is soil transmissivity which is most often unknown and assumed to be constant throughout a catchment. B equals slope gradient in percent and A_s is the specific catchment area in area-squared per unit width.

Wetness index has been proposed as a measure of the spatial distribution of soil water contents and as an index for potential areas of soil saturation in landscapes (Moore et al., 1988a; 1993a; Moore and Nieber, 1989). It has been found (Moore et al., 1988) to be correlated with the initiation of ephemeral gullies in the upper half of a small catchment in New South Wales. Areas of surface saturation, also correlated to the wetness index, became source areas for overland flow during storm events which in turn lead to the formation of ephemeral gullies. The locations of ephemeral gullies in the lower part of the catchment were related to a measure of stream power ($A \times b$) where "A" equals specific catchment area and "b" equals slope.

Somewhat random variations in soil textures and the lack of impermeable substrates greatly restrict the applicability of using a terrain-based wetness index to predict the initiation of drainage channels in reclaimed landscapes. Assumptions of uniform soil transmissivity and impervious substrates, inherent in the use of the wetness index (O'Loughlin, 1986), certainly do not apply in reclaimed catchments. Locally significant surface saturation zones probably do develop in layered mine soils due to lateral movement of soil water along contrasting soil texture boundaries. This hypothesis is currently being tested in ongoing research by Wraith and Keck. Such effects, if present, are irregularly distributed in the reclamation and could not be predicted from terrain analysis alone. Overall, the best terrain measures for predicting the formation of drainage channels appears to be use of specific catchment area (Fig. 6.7), calculated with algorithms allowing for flow dispersion, or some form of a stream power index (T) which factors in the influence of slope gradient (B):

$$T = A_S * B \quad (\text{Moore et al., 1988a})$$

$$T = A_S * \tan B \quad (\text{Moore and Nieber, 1989})$$

The major value of these predictions would be in identifying sensitive areas in the reconstructed landscape where preventative conservation measures can have the greatest impact.

6.4.4. Soil Erosion

6.4.4.1. Considerations for Modeling Soil Erosion

Much of the concern about future changes in drainage density on reconstructed landscapes stems from the soil erosion that would accompany initiation of new drainage channels. The same bedrock parent material that contributes to the formation of numerous drainage channels in portions of the native landscapes also provides roadblocks to soil erosion. Reclaimed landscapes

do not have bedrock control so in a sense the potential for accelerated water erosion in these landscapes is unlimited. The high susceptibility to water erosion is perhaps the least desirable similarity reconstructed mine soils have with loess soils. The speed and ease with which large gullies can form in the reconstructed hillsides prior to revegetation demonstrates this point.

One soil attribute that nearly all of the native and reclaimed soils in the Colstrip area share is a lack of rock fragments. Significant amounts ($> 35\%$) of rock fragments in surface horizons can greatly reduce soil erosion on even steep reclaimed slopes, especially if most of those fragments are larger than 3 inches (personal communication Mr. Pat Plantenberg - Montana Department of Environmental Quality, Hard Rock Bureau). No such protection exists for reclaimed landscapes in the Colstrip area. Loam surface textures, lack of bedrock control, and few rock fragments combine to make these landscapes very fragile from the standpoint of potential water erosion.

Channel initiation represents just one pathway of soil erosion. Predicting how mine soils and reclaimed landscapes will develop over time requires assessing all the possible pathways of soil erosion and deposition. The Universal Soil Loss Equation (USLE) or more current Revised Universal Soil Loss Equation (RUSLE) has been widely used in North America to predict sheet and rill erosion on croplands. Despite questions about the accuracy of results, USLE has become the accepted erosion prediction method for planning conservation practices and for determining conservation program eligibility, e.g.: Conservation Reserve Program. Moore and Birch in 1986a derived a theoretical terrain model equivalent to the empirical slope length-slope gradient (LS) factor of the USLE from unit stream power theory. Their approach incorporates terrain attributes of specific catchment area and slope gradient to calculate a sediment transport index (T_c). It has since been adapted to grid-based terrain models in the form shown below:

$$LS = (1+n) \ln [A_s/22.13]^n \times (\sin B/0.0896)^m = T_c$$

Erosion prediction results are the same for the two approaches although Moore and Burch (1986) make the argument that a terrain-based approach is more appropriate for complex topography. Exponents in the Sediment Transport equation “n” and “m” equal 0.4 and 1.3, respectively. “A_s” equals the specific catchment area while “B” equals slope steepness. As seen from this equation, increases in either the specific catchment area (slope length for USLE) or slope gradient result in increased erosion estimates. Graphic representations of results from either the USLE or the sediment transport index indicate the highest erosion potential occurs near the bottom of a catchment (Moore and Nieber, 1989; Srivastana and Moore, 1989).

6.4.4.2. Field Observations in Native Landscapes

Field observations of soils in native landscapes can provide valuable insights into the processes that occur on hillsides including soil erosion and deposition. Convex shoulder slopes (Figs. 6.5 and 6.6) characteristically have thinner A-horizons, shallower soil depths, less soil horizon differentiation and, if CaCO₃ is present, shallower depths to CaCO₃ than surrounding soils. Concave footslopes have just the opposite; deeper A-horizons, more horizon differentiation, greater soil depth, and greater depth to CaCO₃. Interpreting these observations in terms of soil erosion is confounded by variable rates of soil formation. Yet, realistically, they are at least partially related to the long term differences in net erosion (deposition) rates between convex shoulder and concave footslope positions. Soil depth, in particular, would likely depend more on relative rates of erosion and deposition than differences in the rate of soil formation.

The above field observations present a paradox to results obtained by either the USLE or its terrain model equivalent for sheet or rill erosion potential. Apparently, water erosion potential,

as determined by standard erosion indices, is not the same as a net erosion index that would account for both erosion and deposition at different locations in a catchment over an extended time period. Soil deposition rarely occurs on steep sideslope or convex shoulder slope positions. Erosion rates on these positions are largely unknown but certainly positive. At footslope or other concave positions, both erosion and deposition rates are unknown yet the accumulation of soil sediment in these positions suggests net deposition occurs over a pedologic time scale. The USLE does not account for soil deposition. This has led some researchers to conclude that USLE should only be applied to portions of the landscape experiencing net erosion (Wilson, 1986). The question remains, on how the landscape should be partitioned into areas of net erosion and net deposition. **Potential** soil erodibility may well be greatest in convergent footslope positions due to greater upslope contributing area, but over the long haul, **net** erosion will be greatest at the top of the catchment.

Many different types of erosion occur on landscapes. Physical weathering has its greatest impact on prominent points in a landscape such as rock outcrops, statues, buildings, etc. Soils on knobs and shoulder slopes are no exception. Physical processes related to gravity have their greatest expression at high points in the landscape where any physical disturbance results in the downslope movement of material, maybe only a millimeter or two, but always downslope. This process becomes accelerated when soils are plowed. Soil may wash downslope during a rainstorm if the soil's infiltration capacity is exceeded or it may creep downslope from raindrop displacement. Prominent points in the landscape are also most prone to net erosion losses from wind erosion.

Often less vegetative growth occurs at convex positions in a landscape. This may be especially true in arid or semi-arid environments where limited water infiltration and shallow soils restrict vegetative growth. Net erosion occurs at convex positions in part because less vegetative

cover results in more exposed ground. In concave positions, additional soil moisture from upslope causes increased vegetative growth which in turn contributes to greater soil development and the capture of additional sediment from upslope, which further increases vegetative growth. The positive feedback mechanism on concave slopes works in reverse on convex slopes. Less soil water restricts vegetative growth resulting in more bare ground and more erosion which limits soil development and soil depth, further restricting vegetative growth, etc.

6.4.4.3. Use of Terrain Attributes

The above empirical discussion, of soil erosion on hillsides, contradicts the images presented by Moore and Neiber (1989) or Srivastana and Moore (1989) of the sediment transport index or point representations of USLE (or RUSLE) that propose to show spatially variable soil loss potential within catchments. Wilson and Gallant (1996) discuss limitations associated with using the Universal Soil Loss Equation or Revised Universal Soil Loss Equation to model erosion in catchments. Limitations include difficulties of scaling up field plot results to landscapes, assumptions about how surface runoff is generated, and practical problems due to the model's inability to distinguish between portions of the landscape experiencing net erosion and those experiencing net deposition. The standard slope-length RUSLE or the sediment transport index version provides valuable information to land managers for the assessment of potential erosion hazards. Spatially distributed terrain models indicating areas of high erosion potential could be used in the same manner as those predicting the initiation of drainage channels, to identify sensitive areas where preventive steps should be taken. Use of the stream power index and the sediment transport index, in this sense, are complementary tools measuring different parts of the same

process. Initiation of sheet and rill erosion in upslope areas, ultimately leads to gully erosion and channel initiation below if left unchecked.

Moore and Burch (1986b) proposed that a change in sediment transport capacity (ΔT_c) may provide a possible measure of net erosion and deposition across a catchment. Accordingly, a positive ΔT_c would relate to net deposition while a negative ΔT_c would indicate net erosion. This empirical relationship seems reasonable. It provides spatially distributed results more in line with field observations but still shows the highest positions on the landscape as having net deposition (Moore et al., 1988b).

Discussion of more elaborate, physically based, soil erosion models such as the WEPP model or the Hairsine-Rose model is beyond the scope of this discussion. Several studies have indicated that different portions of hillslope should be treated separately for predicting the formation of ephemeral gullies (Moore et al., 1988a) and for predicting soil properties (Walker and Protz, 1968; Kleiss, H. J., 1970; and Pennock et al., 1987). It appears reasonable that predicting soil erosion across a catchment would require a similar stratification. Different parts of the catchment react differently and are affected by different soil erosion processes.

6.4.4.4. Net Erosion

The compound topographic indices discussed above will provide a good indication of potential erosion from accumulated flow in the lower portions of reconstructed catchments. A more traditional soil survey model will work better for predicting net erosion in the higher positions of reconstructed catchments. The soil survey model predicts that steeper (Fig. 6.3) and convex (Figs. 6.5 and 6.6) portions of the landscape will experience net erosion. Concave portions with lesser slopes will experience net deposition. The exact rates of these processes and the threshold or crossover values where net erosion vs. net deposition occurs depend mainly on the adequacy of

vegetative ground cover and future management of the site. Over time, aspect differences (Fig. 6.4) may also have significant, if somewhat less pronounced, effects on steeper portions of reconstructed landscapes as cool and moist north aspects favor plant growth that reduces soil erosion. This relationship could be turned around, however, if reclamation strategies are directed towards establishing ponderosa pine with sparse grass cover on steep north aspects. Reconstructed hillsides are highly susceptible to extreme water erosion. Keeping adequate ground cover and maintaining the existing base level for drainages will be essential for protecting the current soil resource from excessive soil erosion.

6.4.5. Soil Properties

Soil development in reconstructed landscapes will follow patterns similar to those of net erosion, in response to differences in terrain attributes. The time frame of interest here will be approximately 100 years. Within that time, organic matter will accumulate, leaching of calcium carbonate may occur, soil structure will develop and soluble salts including sodium will be redistributed in the landscape. Soil texture will remain the same except for areas significantly affected by erosion or deposition.

6.4.5.1. Buildup of Soil Organic Matter

Soil organic matter accumulates rapidly in the surface horizons of mine spoils successfully revegetated to grass (Caspell, 1975; Anderson, 1977; Hallberg et al., 1978; Schafer et al., 1980). Schafer et al. (1980) report $45.4 \text{ g m}^{-2} \text{ year}^{-1}$ for mine soils developing from spoil in the Colstrip area. Organic matter accumulations in lower horizons were much slower. Personal observations indicate the same kind of results for reconstructed mine soils created by the current double lift reclamation strategy. The double lift reclamation results in higher initial organic matter levels in

the topsoil layer than if soils were salvaged in a single lift. Yet, the establishment of vigorous grass stands in reclaimed fields still adds appreciable amounts of soil organic matter to topsoil horizon(s) over a relatively short period of time.

The amount of soil organic matter captured by the soil will depend in part on the texture of surface layers. Clay loam surface soils tend to accumulate more organic matter than sandy loams, yet more darkening of surface layers is likely to occur in the sandier materials. As a result, soils with a sandy loam surface texture are more likely to make color requirements for a mollic surface, in both native and reclaimed areas, even if they have correspondingly less soil organic matter. This is due, in part, to the more rapid leaching of light-colored calcium carbonate from the coarser textured materials and partially due to the tendency for sandy soils to become visibly darker at lower organic matter levels.

Over time, the distribution of soil organic matter in reclaimed landscapes will vary in response to terrain attributes that affect both the net erosion and deposition of soil particles and influence the redistribution of soil water. Areas that received additional water from lateral surface and subsurface drainage along hillslopes will have the greatest potential for grass production in the semi-arid environment. Few inhibitory factors are present in the reconstructed soils to alter this pattern. Increased grass root production results in more soil organic matter. Terrain attributes that correlate to increased run-in of soil water are gentle concave slopes (profile and/or tangent curvature), with high specific catchment area. Figures 6.3, 6.5, 6.6, and 6.7 show the spatial distributions of these factors in the Area-E landscapes. A prediction of high soil organic matter levels in locations of high specific catchment area (Fig. 6.7), assumes that potential channel and gully erosion have been controlled. These general observations agree with findings in native landscapes of Pennock et al. (1987) that the A-horizon thickness was greatest in areas with most

concave plan (tangent) curvature and Tomer and Anderson (1995) who found A-horizon thickness was greatest in low landscape positions. They also agree with the tacit knowledge (Hudson, 1992) of numerous soil mappers.

North aspects (Fig. 6.4) will also tend to accumulate more organic matter due to more moist and cool conditions that favor greater production of organic carbon relative to south aspects (Birkland, 1984). Hotter and drier conditions on south aspects favor increased organic matter decomposition. The influence of aspect increases as slopes become steeper. Again relying on tacit information, significant differences due to aspect are rarely found until slopes exceed 8 to 15 percent. Other interactions between slope and aspect occur as well. Carter and Ciolkosz (1991) found the organic carbon contents in B-horizons were affected by slope steepness on southwest aspects but not on northwest aspects.

In an older study, Walker and Protz (1968) reported increasing A-horizon thickness on east aspects relative to west aspects for glacial drift hillsides in Iowa. They attributed these differences to the prevailing westerly winds. This points out another factor affecting the redistribution of organic matter on landscapes; the erosion and deposition of topsoil. The same terrain characteristics, using a soil survey model, that help indicate where sediment accumulates in a landscape also identify where organic matter accumulates since most of the surface transported material is topsoil.

To summarize, soil organic matter will accumulate most rapidly in areas that have a high specific catchment area and slopes that are moderately to strongly concave, with north and east aspects (away from the prevailing wind). Steep south and west aspects and the tops of ridges with convex slope curvatures will over time accumulate much less soil organic matter. This pattern will develop superimposed over variable soil textures and discrete reclamation unit boundaries. Soil

texture will effect both the amount of soil organic matter that accumulates in surface horizons and the visible effect that organic matter has on soil color.

6.4.5.2. Leaching of Carbonates

One of the first changes in the genesis of reconstructed mine soils should be leaching of calcium carbonate (lime) downward in the profile. High levels of calcium carbonate in soils limit the development of subsoil structure and restrict the leaching of clay particles. Development of clay-enriched B-horizons remains slow so long as high lime levels persist in upper soil horizons. The calcium carbonate also acts as a strong pH buffer, maintaining soil pH around 8.2 to 8.4. This, in turn, affects the nutrient status of the soil, especially availability of phosphorus and micronutrients.

Nearly all of the parent materials at the Rosebud Mine are highly calcareous (i.e.: they contain high amounts of CaCO_3). Calcareous parent materials combined with a semi-arid climate have limited soil development even on native soils in the area. Ustochrepts, Haploborolls, and Ustorthents are the predominant soil great groups in the native soils, all of which have minimal soil profile development. Depths to secondary lime are shallow in nearly all of the native soils.

The double lift reclamation strategy at the Rosebud Mine tends to stratify CaCO_3 concentrations in the reclaimed profiles in a manner similar to that found in native soils (Keck and Wraith, 1996). All but the most sandy soil surfaces, however, are strongly calcareous. Even in some reclaimed soils where the top lift has salvaged relatively carbonate free material, fugitive dust from adjacent active mining has added a thin calcareous layer at the surface.

Soil texture plays a major role in the rate at which carbonates may be leached from soils. Gile (1995), working in calcareous soil parent materials in an arid region of New Mexico, reported

the depth to stage II calcium carbonate accumulations ranged from 10 to 42 cm in fine-loamy soils, whereas they were at 55 to 90 cm in sandy loam soils and were not present at all in sandy material. At the same landscape position, a difference in soil texture from sandy loam to sand resulted in nearly a threefold decrease in the total amount of carbonate found in the soil.

Soil development, in terms of the leaching of carbonates, will occur very slowly at the Rosebud Mine, in part, due to the continued additions of high lime dust at the surface. The movement of surface and subsurface water plays an important role in the distribution of carbonates in native landscapes (Miller et al., 1985). The same locations in reconstructed landscapes that favor the accumulation of soil organic matter will tend to have the highest leaching potential for calcium carbonate; high specific catchment area, gently sloping, concave positions and north aspects. Figures 6.3 through 6.7 show the spatial distributions of these factors for reclamation in Area-E. In this instance, the accumulation of sediment from upslope will provide additional calcareous material at the surface, masking the effects of leaching and reducing differences between slope positions.

Variable soil textures will play a dominant role over terrain attributes in affecting the removal of carbonates from surface soils in reclamation. Sandy loams will tend to lose carbonates while loam, clay loam and sandy clay loam soils will retain high concentrations of calcium carbonate throughout the soil profile. Removal of carbonates from reconstructed mine soils in all instances will be a slow process. Schafer et al. (1980) reported that in a loamy mine soil developing in spoil, calcium carbonate had leached out of only the top one centimeter in 50 years. They estimate at this rate it would take 6,000 to 30,000 years for the carbonate distribution in mine soils to approach that of native soils. The translocation of clay minerals will take even longer, since significant clay illuviation generally does not occur until after leaching has removed most of

the calcium carbonate from a horizon. Birkland (1984) estimates, that under normal conditions, it takes between 1,000 to 10,000 years for clay accumulation to form a weak argillic horizon.

6.4.5.3. Soil Structure

The process of salvaging and constructing mine soils with huge scrapers has essentially destroyed native soil structure in reconstructed mine soils. Surface structure may develop relatively quickly due to frequent freezing and thawing, wetting and drying, and the addition of organic matter. The development of subsoil structure will take much longer. Birkland (1984) suggests as a general guideline 500 to 5,000 years are needed to develop sufficient subsoil structure to meet the requirements of a cambic horizon (diagnostic subsurface horizon of minimal soil development). Bilzi and Ciokosz (1977) reported finding cambic horizons in 40 year old mine soils in Pennsylvania under much higher rainfall conditions than the Colstrip area. As a general rule, native soils in the Colstrip area seldom have any appreciable structure development in horizons with high calcium carbonate content.

Like the leaching of carbonates, development of subsoil structure will proceed slowly in the reclaimed landscape. Areas of lesser slopes (Fig. 6.3) favor the development of soil structure while steeper slopes and north aspects (Fig. 6.4) tend to have less soil structure development. The increased frequency of wetting and drying and freezing and thawing cycles on south aspects often results in more distinct subsoil structure development in these areas. Convex portions of the landscape (Figs. 6.5 and 6.6) will have the least development of soil structure while concave and linear portions will experience more structural development. Gently sloping, concave sites with high contributing area (Fig. 6.7), if they are wet enough, may develop more of a granular-type,

surface structure to greater depths, which would commonly be associated with high organic matter soils that are somewhat poorly to moderately well drained.

Differences in soil texture effect both the degree to which soil structure becomes expressed in the soil and the size of structural units. Sandy textures tend to have larger structural units than finer textured loams and clay loams, i.e.: coarse vs. fine or medium structure. Sandy textures also tend to have less expression of soil structure and less need for structural development to improve water relations. In either case, loamy or sandy soils, the development of subsurface soil structure will proceed slowly. Subsoil and spoil layers in the reclamation will retain their massive (structureless) condition and high bulk densities (Keck, 1993; Keck and Wraith, 1996) for a long time. Eventually, patterns of soil structural development will occur in response to environmental gradients created by variations in the reclamation topography. The patterns of soil formation will be superimposed on and affected by more random texture variations across the reclaimed landscape.

6.4.5.4. Accumulation of Soluble Salts and Exchangeable Sodium

Soluble salts may be readily leached through soils by the movement of soil water, provided there is good drainage and no sodic problems. They are more transient than the slightly soluble calcium carbonate. On level ground with no barriers to the downward flow of water and semi-arid conditions, soluble salts accumulate at greater depths in the soil profile than calcium carbonate. Sloping ground and relatively impermeable layers in a soil can result in appreciable lateral transport of soluble salts along a slope gradient, possibly creating saline seep conditions at the base of the slope. Terrain variables that influence the movement of water within a catchment, especially

when coupled with impermeable layers in the soil, largely determine the redistribution of soluble salts and exchangeable sodium in landscapes.

Natural levels of salinity and sodium are quite low in the parent materials and hence soil and spoil materials at the Rosebud Mine (Keck and Wraith, 1996). Some isolated hot spots with regard to high exchangeable sodium levels in overburden have been encountered in pre-disturbance surveys (personal communication - Greg Milhollin, Reclamation Soil Specialist, Western Energy Company) associated with areas of shale. Overall, high concentrations of soluble salts and exchangeable sodium are not a concern in soils and overburden at the Rosebud Mine. Despite the low soluble salt levels, some accumulation of soluble salts in level or concave areas at the base of reclaimed slopes will be inevitable. Producers and Keck (1996) argue that isolated areas of relatively high soil salinity present an opportunity to increase vegetative diversity in the reclamation area. Areas of high specific catchment area and low slope (high wetness index) would be especially susceptible to some salinization (Figs. 6.3 and 6.7). These sites could follow 2 or 3 very divergent paths. They might accumulate soluble salts in the soil which could reduce vegetative growth of planted species leading to more salinization. They might accumulate organic matter which would improve both vegetative growth and soil hydraulic properties, limiting salinization. In the third option, if poorly protected, these areas could develop deep gullies with the potential for massive soil erosion.

Once again variations in soil textures across the reconstructed landscape will affect results. Areas of sandy subsoil and spoil materials will act like sinks where excess water moves downward through the soil profile, taking soluble salts with it. Areas with clay loam subsoils or spoils, especially below sandy loam overlying materials, will facilitate the lateral movement of water and

soluble salts downslope. Overall, the low levels of salinity and sodicity in reclamation materials provides a significant plus for the long term success of reclamation at the Rosebud Mine.

6.4.5.5. Interactions with Spatially Variable Soil Texture

In every instance, the spatially variable development of soil properties will be influenced by terrain attributes. Changes in soil properties will be greatly dependent on interactions with soil texture. The amount and depth of organic matter incorporation in the soil, the depth to which carbonates are leached and the likelihood that soluble salts accumulate at different sites in the reclamation are all examples of how the interaction of terrain attributes with soil textures will affect future development of reconstructed mine soils. The type and degree of potential erosion and the redistribution of soil moisture also depend on the interaction of systematically variable terrain attributes and the more randomly distributed variations in soil texture.

Phillips (1993) describes deterministic chaos as characterized by sensitive dependence on initial conditions. "Even minute differences at the beginning of a system's evolution lead to large and increasing differences as the system evolves." Deterministic chaos results in apparently random patterns evolving from the interaction of largely deterministic processes. Reconstructed landscapes at the Rosebud Mine appear to provide a large scale field demonstration of deterministic chaos at work. While the above statement is based primarily on theory, the potential implications for future vegetative diversity on reclamation may be very significant.

Establishing vegetative diversity on the reconstructed mine soils has become an increasingly important issue as more and more reclaimed land reaches the end of a ten year waiting period to be eligible for final bond release. Final bond release for open pit coal mines requires that reclaimed areas be restored to a condition as productive or more productive than the original

resource and that diverse, native plant communities are well established on the land.

Unfortunately, vegetative diversity can be an elusive target which may be defined several different ways and may mean different things to different people. See Producers and Keck (1996) for a thorough review of diversity concepts and how they apply to reclamation.

Reconstructed mine soils created by a double lift reclamation strategy at Colstrip are quite homogeneous in a number of respects; due in part to the processes that created them. They are uniformly deep, highly calcareous, have high soil pH (8.0 - 8.4) and provide a nearly structureless, rock free soil environment well suited for the establishment of highly competitive, stress adapted, cool season grasses. Levels of soluble salts and exchangeable sodium, are quite uniformly low. No other toxic or inhibitory substances are present to restrict vegetative growth. The one soil factor varying in a nearly random manner across the reconstructed landscapes is soil texture; the result of applying a double lift strategy in areas of mixed sedimentary parent materials.

Producers and Keck (1996) discuss several different reclamation strategies aimed at increasing vegetative diversity at the Rosebud Mine. The basic tenant is establishing patches of non-uniform soil substrates, as a pre-requisite to establishing diverse vegetative communities. Strategies to accomplish this all run the risk of creating fragile patches in the reconstructed landscape, prone to soil erosion. The goal is to reduce the relative advantage of stress tolerant competitors, i.e.: cool seasons grasses, in the patches. In the end, trade-offs must be made between vegetative diversity and landscape stability.

Chaos theory suggests that there may be another alternative. The trade-off in this case is time. The diverse pattern of differences in soil texture present uniquely variable initial conditions. Superimposed on those initial conditions will be a whole range of largely deterministic processes of erosion, deposition, and soil formation. Chaos theory would predict that the initial variability will

result in increasing differences in the edaphic environment as the system evolves. These soil differences will inevitably create increasingly diverse habitats for vegetative diversity over time.

The remaining question is, how long we are willing to wait?

6.5. Conclusions

Reclaimed hillslopes at the Rosebud Mine have a high potential for new drainage channels to become established, especially in areas with poor vegetative cover. Drainage densities are significantly lower in reclaimed landscapes than local native sites, but comparisons of this type should be made with comparable landscapes instead of local sedimentary landscapes. Semi-arid, grassland areas with loess parent materials appear to provide the best surrogate model for predicting the future development of drainage networks in reconstructed landscapes.

Use of a wetness index to predict channel initiation, based on assumptions of lateral water flow, would not be appropriate for reconstructed landscapes. Specific catchment area or the stream power index provide more reasonable measures for identifying critical areas where conservation practices could be applied to prevent future problems.

Channel initiation is a major concern in reclaimed areas because of the substantial amount of water erosion that would result. Reconstructed mine soils at the Rosebud Mine have an extremely high potential for water erosion because they are unconsolidated, lack underlying bedrock, do not contain appreciable rock fragments, and have primarily loamy textures. Establishing good ground cover remains essential to avoid substantial water erosion problems on reclaimed landscapes. The sediment transport index provides a terrain-based equivalent to the Universal Soil Loss Equation for predicting areas in the landscape of high susceptibility to sheet and rill erosion. Results from this index are not altogether different from those derived from the

stream power index for potential channel initiation. In both instances, the best use of these terrain-based tools is in the identification of critical areas before problems occur.

Water erosion **potential**, as determined by standard erosion indices, is not the same as a **net** erosion index that would account for both erosion and deposition over an extended time period. Areas in the reconstructed landscape with steep slopes, convex slope curvatures, and south aspects are likely to experience the greatest net soil erosion over time. Gentle, concave slopes will result in areas of net soil deposition, provided excessive gully erosion is controlled.

The same terrain factors that will influence net erosion across reclaimed landscapes affect soil development. Convex, steep slopes result in limited soil organic matter accumulation, reduced soil structure development, and very little leaching of soil carbonates. Gentle, concave slopes and high specific catchment areas favor increased soil organic matter accumulation, greater soil structure development, and increased leaching of calcium carbonates. Results for carbonates may be confounded by continued additions of calcareous sediment from upslope areas. Terrain models present a spatial representation of systematic differences in the intensity of soil forming processes across the reconstructed landscape.

The influence of terrain attributes on soil formation will be partially controlled by near-random variations in soil textures. Chaos theory suggests that spatially variable initial conditions in soil textures will result in increasingly divergent soil formation over time. Resulting diversity in edaphic factors could have significant implications for the future development of diverse plant communities. These developments should be monitored with keen interest as reclaimed areas provide a unique outdoor laboratory for scientists to study the complex interactions among plants, soils, and other living organisms in semi-arid, grassland environments.

6.6. Literature Cited

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CHAPTER 7

FINAL SUMMARY AND CONCLUSIONS

Mine soils at the Rosebud Mine have been used to explore several methods of modeling the spatial distribution of soils on landscapes: soil survey, spatial statistics, and use of terrain models. Each has its own strengths and weaknesses. Clearly, any comprehensive analysis of soils and their relationship to landscapes will require a combination of techniques. The best approaches will incorporate strengths of all three.

The soil survey perspective provides expert knowledge often absent from purely quantitative attempts to map soil resources. Native landscapes have a greater degree of spatial correlation among soil properties and between soil and landscape attributes than mine soils. Yet, even in natural landscapes, spatial correlations are generally not strong enough nor the density of sample points high enough to accurately model soil attributes by purely quantitative methods, except for limited, site specific applications. There needs to be some means of distributing limited point sample information over larger areas. Standard soil surveys utilize ad hoc procedures to accomplish this but the solution is often part of a larger problem of individual and systematic biases in final results.

One approach to enhancing quantitative methods would be to generate a continuous variable for the area of interest which contains spatial information about a particular soil attribute at all locations. Terrain models, remote sensing products, and many possible combinations of the two can be used to produce the spatial variable. Better analytical tools can then be developed to

combine point samples and expert knowledge with the spatial data. It appears unlikely that simple linear relationships will adequately describe relationships between soil properties and spatial variables in most cases, since natural systems seldom function in such a linear fashion.

An essential first step in any soil/landscape modeling project will involve site specific observations and field measurements from soil profiles. The number of profiles sampled may actually be less than most soil mappers are accustomed to in the production of standard soil survey maps, but obtaining an adequate number of high quality field measurements is the minimum requirement for any soil modeling exercise. Soil models can not be expected to achieve sufficient accuracy without site specific observation. The second step in this approach is then to scale field measurements across the landscape through their relationships to the spatially distributed variable.

Generating the spatial variable will in many instances involve a series of "if/then" statements that encodes knowledge about the relationships of soils to landscape, imagery and possibly vegetation characteristics of the site. Relationships on north slopes may be quite different from those on south slopes. Color patterns on the imagery may have a different interpretation on one landscape position than on another. These are examples of the type of information needed. Through a series of "if/then" statements this "expert" knowledge of field soil scientists can be captured and converted to a non-linear combination of spatial data layers, thus creating a separate predictive spatial variable for the soil property of interest. The soil survey type of understanding about soils, and their relationships to landscapes, vegetation, imagery characteristics, and other site factors becomes crucial in generating the predictive variable and in obtaining the site specific data. Where do you sample? What are the relationships among landscape components? What are the relationships between soil properties and imagery characteristics or between soil properties and landscape attributes? What are the conditional responses of soil properties to changes in landscape

or imagery attributes? How do soil properties change between sample points? What is the primary sampling unit, i.e.: where do observed relationships remain reasonably stable? These are just a few of the questions to be answered. They include many concepts routinely considered by good field soil scientists in the production of soil maps although seldom thought of in quite this manner.

Each sampling unit, especially in complex landscapes, will likely be unique. For this reason, no cookbook formulas exist on how to model the spatial distribution of soils in every situation. Spatial information and point samples alone, will not be enough without the site specific "expert" knowledge to interpret results. There will always be a need for site specific data and a need for expert knowledge to interpret results. Additional site adaptive, quantitative tools may still need to be developed further to adequately scale the available information across landscapes.

Many advantages exist in modeling soils on native landscapes that are not present in reconstructed landscapes. Spatial correlations found in native landscape are mostly lost during salvage and reclamation activities. It is possible to construct an accurate spatial inventory of mine soil properties, but different approaches will need to be used. Before proceeding, however, there needs to be a clearly defined goal for the work. What is the reason why post-reclamation soils are sampled? Decisions on how to proceed with an inventory of post-reclamation mine soils depends on this critical question.

Coal mining permits, in compliance with state and federal regulations, generally require post-reclamation sampling of mine soils to ensure the suitability of soil materials used. The goal, based on this scenario, is to ensure the suitability of soil materials. Assuming that is the only goal, legitimate questions need to be asked about the requirement for post-reclamation soil sampling at all. Soil materials that were judged to be suitable in the pre-mine soil survey will still be suitable after soil replacement, provided an adequate job was done in the pre-mine soil survey. Soil pH, the

level of soluble salts, and soil texture will not be changed in soil materials at the Rosebud Mine by transporting them from one location to another. No appreciable acid-forming materials are present in native soils of the Colstrip area which could alter soil pH. To the contrary, nearly all soil materials are highly calcareous with soil pH's largely controlled by the presence of lime in the soil. The biggest variation in the Western Energy pH data results from their improperly calibrating the pH meter for certain sets of samples. Toxic substances are not present in native soils of the Colstrip area and inhibitory substances, such as soluble salts and exchangeable sodium, are found in relatively low amounts. These substances could be more readily identified in the pre-mine soil survey in any event. On the other hand, it does make sense to sample the spoil materials for pH, EC, and texture because, even though spoil material for the local Ft. Union stratigraphy is generally of good quality for reclamation, a certain level of uncertainty exists with regard to materials brought to the surface that were previously buried and unsampled. There does not appear to be reasonable justification, however, to resample soil properties that were sampled in a pre-mine survey, assuming the goal of sampling is solely to identify unsuitable materials.

Further support for not resampling soil properties comes from the lack of spatial correlations in existing mine soil data. Lack of spatial correlation means that isolated high values for soil pH, EC, clay, or sand content do not necessarily represent any significant surrounding area of equally high values. Similarly, lack of high values in an area do not ensure that such pockets of "unsuitable" materials do not exist. Thus, the lack of spatial correlation greatly restricts inferences that can be made from point data. Reducing post-reclamation soil sampling can be justified on the basis of knowledge about the resource and adequate pre-mine soil surveys. The presence of spatial correlations in the mine soil data, initially hoped for by Western Energy, are just not part of the justification.

Replacement depth data for the Area-E study site presents the extreme case of bias in Western Energy data, since the lack of topsoil on a significant portion of the Area E reclamation was not reported in Company sampling results. In this author's opinion, the lack of topsoil will likely have little influence on the vegetative potential of the site in question. It does provide an opportunity for someone to test one of the underlying assumptions of the double lift reclamation strategy. Company personnel undoubtedly took a similar position, that the missing topsoil would not be missed from the standpoint of successfully establishing seeded species. Whatever the reason, the shortage was not reported. This raises the same question as above, about the purpose of post-reclamation soil sampling. If post reclamation soil sampling is important, then there needs to be adequate oversight and independent verification of results. Reclamation on the Butte Hill, in Silver Bow County, MT, presents a prime example of what happens without sufficient oversight. If the post-reclamation soil sampling is not important, for whatever reason, then resources should not be wasted on extra sampling. Soil replacement depths, because they cannot be determined from the pre-mine soil inventories, are perhaps the most important soil property sampled in the post-reclamation soils inventory.

There are a number of valid reasons why more accurate information about the distribution of soil properties across reconstructed landscapes might be desired. Predictions about potentially unstable areas in reclamation due to lateral water flow through layered mine soils and identifying other erosion prone sites would be especially valuable if they lead to effective preventive measures that avoid soil erosion problems. A similar argument could be made for the use of accurate soil/landscape information to address vegetation diversity concerns, identifying microsites where different plant community types could become established. Identifying revegetation success and

response to different management practices, fertilizer applications, and/or seed mixes, would also require fairly detailed information about soil-site conditions.

Decisions about the need for accurate soils information on reconstructed landscapes are beyond the scope of this project. They are made at state or corporate levels. If such detailed soil information is warranted, it does not appear reasonable to use point samples and spatial statistics alone to obtain the necessary information. Such an approach would require a prohibitive amount of point sampling given limited spatial correlation distances. Scanning techniques, such as using an EM38 to screen for soluble salts or possibly spectral reflectance techniques to estimate soil textures, may offer some promise.

A more straight forward approach would be to track different materials from salvage to replacement sites. Areas in the pre-mine survey can be classified as sandy in sandstone areas, loamy in siltstone and alluvial areas, and clayey in shale and gumbo knob areas. Within each class there would be a greatly reduced range of associated soil properties, like soil texture or soluble salt content, relative to the entire range of soil properties at the mine. Once good quality, pre-mining soil maps are prepared, GIS and GPS technologies, available today, could be used to track materials from source to final destination with each scraper load. The resulting post-reclamation soils maps would far exceed the accuracy of maps generated from point samples in reclaimed areas although soil replacement depths would still have to be monitored on a field by field basis.

Of the geostatistical tools used, indicator kriging appears to offer the best promise for use in assessing soil suitability in reconstructed landscapes. Indicator kriging results, in terms of the probability of exceeding a specified threshold, are more in line with the actual level of information available at unsampled locations. Questions remain, however, about the accuracy of even indicator kriging results for mine soils, given the generally uncorrelated spatial structure of the data and lack

of agreement between kriging assumptions and the spatial distribution of mine soil properties.

Reasonable spatial correlations exist in the spoil data at relatively short separation distances. Any further studies with this data set should examine the accuracy of indicator kriging estimates against known sample values for both mine soil and spoil properties.

The distribution of soils present on reconstructed landscapes today will not be the same as those in the future. Spatially variable processes of erosion, deposition, water movement, and soil formation will reshape the soil resource over time. Interactions between these processes and variable initial conditions of soil texture will tend to create increasingly diverse soil conditions. Vegetation will respond to these changes as niche differentiating species begin to occupy the new microsites created. Thus, some of the present concerns about vegetative diversity on reclamation may be ill-founded. Establishment of certain species, like ponderosa pine, which are adapted to bedrock substrates in local semi-arid environments, will remain problematic in the uniformly deep mine soils.

Reconstructed mine soils at the Rosebud Mine represent a potentially valuable land resource, that if managed correctly will support wildlife and domestic livestock for many years to come. The reconstructed landscapes also provide a large outdoor laboratory for future research in such diverse fields of study as plant ecology, insect ecology, soil genesis, landscape hydrology, and many other disciplines interested in the functioning of semiarid grassland environments. The uncontrolled experiments have already begun. Hopefully, researchers will be there to take advantage of the opportunities presented.

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