UNIVERSITY OF ALBERTA

THE USE OF DIGITAL ELEVATION MODELS FOR SOIL TYPE INTERPRETATION

by

Craig A. Coburn ©

A Thesis
Submitted to the faculty of Graduate Studies and Research
in partial fulfillment of the requirements
for the degree of

MASTER OF SCIENCE

Department of Geography
Edmonton, Alberta
Fall, 1996

ISBN 0-612-18246-0

UNIVERSITY OF ALBERTA

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NAME OF AUTHOR: Craig A. Coburn

TITLE OF THESIS: The Use of Digital Elevation Models for Soil Type Interpretation

DEGREE: Master of Science

YEAR THIS DEGREE GRANTED: 1996

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Abstract

The objective of this study was to map the relationship between soil and landform at a scale and resolution suitable for environmental modelling and site-specific farming. The current approach to high-resolution soil mapping is airphoto interpretation in combination with a grid survey. The result of this thesis is an automated mapping technique that allows for the accurate characterization of the soil landscape based on the relationship between soil type and landform.

The study was conducted in east-central Alberta, Canada, south-east of the city of Edmonton, at 53° 33" north latitude and 113° 28" west longitude. The DEM used in this research was surfaced from contour lines extracted from a 1:5000 orthophoto with 1 metre contour lines, available to the public from the City of Edmonton, Alberta. Analytical surfacing techniques were used to generate a DEM of the study area. Using the results of the geostatistical analysis, a spatial resolution of four metres was selected to produce a DEM with sufficient spatial resolution to capture the variability of the landscape.

In this study, geomorphometric measures derived from DEMs were used to classify and map landforms. Traditional methods of landform classification are based on the field experience of the researcher doing the classification (Dalrymple *et al.*, 1968; Young, 1972; Pennock *et al.*, 1987; Pennock and DeJong, 1987, 1990; Martz and DeJong., 1987, 1991; Martz, 1992). The method used to classify landform in this study was based on the concept of the geometric signature developed by Pike and Rozema (1975). Pike and Rozema (1975) conceptualized the geometric signature as a set of measurements that abstracts the essential shape of each type of topographic surface and distinguishes it uniquely from other surfaces.

Measures of classification accuracy based solely on the training field data are usually calculated at the time of the classification procedure and many observers report this measure as a means of assessing map accuracy. What this statistic measures is the accuracy of the classification and has little to do with the accuracy of the map. In this study the overall correct classification was 99.3%. This statistic measures the degree of statistical separability in the data. Therefore, the landform classes were statistically well defined.

The most often overlooked measure in studies of this type is map accuracy. In this study, map accuracy was assessed using the soil type data surveyed using differentially corrected GPS locations. These points were then overlayed on the landform classification map. The landform class information was then added to the table of soil attributes. The relationship between these data was then analysed using a combination of Chi-square to test for a significant relationship at the 0.001 significance level and Spearman rank correlation to test the strength of the relationship. The Chi-square test showed a significant relationship between soil type and landform. The result of the correlation analysis was an r value of 0.87009 which indicates that the relationship between soil type and landform is strong and positive and landform explains 75.7% of the total variance (r^2) in the soil type classes.

The results of this study indicate that there is a strong correlation between the landform units that were derived from the classification procedure and the soil types that were surveyed in the field. This technique should prove useful in soil mapping and other forms of mapping that require some form of landform analysis. This procedure is an improvement over the traditional methods as it provides an unbiased and replicable technique for mapping landforms.

Acknowledgements

The process of completing a Master's research project is never a singular effort. I began this research under the supervision of J. Ronald Eyton and, therefore, would like to thank him for his support and guidance. I would like to thank Ed Jackson, my administrative supervisor, for taking on the task of helping me through the latter parts of this research and providing guidance and encouragement when necessary. I would also like to thank the members of my supervisory committee, Bruce Rains and Art Peterson for their suggestions and comments. I am indebted to all of the students in the department of Earth and Atmospheric Sciences. I would like to thank (in no particular order): Bill Ranford, Scott Robertson, Vince Miller, Dave and Caroline Burgess, Darren and Elizabeth Sjogren, Rod and Sandra Smith, Dan Hemenway, Mark Skidmore, and Doug Mair. There is no possible way to express adequately my gratitude to my parents, all four of them, for their support through the years.

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CHAPTER 1

INTRODUCTION

Soil, next only to water, is our most important resource. A soil is a natural part of the surface of the earth, characterized by layers or horizons parallel to the surface resulting from the modification of parent materials by physical, chemical and biological processes operating under varying conditions during varying periods of time (Thornbury, 1969, p. 68). Standard soil surveys are not designed to provide the high resolution soil information required in environmental modelling and site-specific farm management (Petersen, 1991). Conventional approaches to soil mapping produce maps that delineate neither the inherent variability of the soil nor the variation of the attributes mapped. These approaches to mapping the spatial variability of this fundamental resource have proven expensive and often unreliable (Moore *et al.*, 1993). There is, therefore, a need for the development of accurate and inexpensive methods of mapping the spatial variability of the soil system.

In the last 30 years, agriculture has undergone several revolutionary changes, the latest being the ever increasing use of personal computers to help in the management and planning of farm practices. This increase in personal computer use and the associated Geographic Information Systems (GIS) for farm based planning requires high resolution soil base maps containing useful information about the nature of the soil (Arnold, 1987). Developments in the field of precision farming make it possible to vary the rates of fertilizer and herbicide application based on the ability of a soil to use these inputs at maximum efficiency (Moore *et al.*, 1993). In order to achieve this level of precision and accuracy, high resolution soil maps and reliable application methods are necessary.

Soil surveys undertaken for large scale mapping, using grid survey methods, are a labour-intensive and cost-prohibitive process (Beckett and Burrough 1971a, 1971b). Traditionally, soil surveys at the soil association level are conducted over large areas for regional planning purposes. Soil mapping at this resolution is often conducted using air photo interpretation and sparse field observations. This coarse resolution of soil information is not adequate for modern farm management and planning.

The current approach to high resolution soil mapping is airphoto interpretation in combination with a grid survey. Using this technique, the sampling effort of the area surveyed determines the precision of soil maps. Beckett and Burrough (1971) have noted that "if the purpose of a soil map is to equip its user to make more precise statements about soils than he could have done without it, then the success of a given survey may be assessed on the extent to which the variability of the soil properties within mapped units is less than their variability in the landscape" (Beckett and Burrough, 1971a, p.468).

For local areas in environments similar to those found in the Canadian prairies, where moisture is the limiting environmental factor, the strongest factor controlling soil development is topography (Milne, 1935; Jenny, 1941; Furley, 1968; Huggett, 1975, 1982; Birkeland, 1984; Miller *et al.*, 1985; Gerrard, 1992). Topography has the effect of altering the local distribution of moisture. Topographic form is also a strong controlling factor on the spatial distribution of erosional and depositional environments. Topographic control of these two factors results in different soil types developing in different topographic areas. For example, in topographic depressions the relative increase in soil moisture and an accumulation of eroded material may lead to the formation of gleyed soil types.

Studies attempting to quantify and map the relationship between soil type and landform using digital methods have had limited success (Pennock *et al.*, 1987; Lee *et al.*, 1988; Swanson, 1990a). The primary difficulty encountered in these studies was the site-specific nature of the soil-landform relationship. Soils form in response to similar environmental conditions, but due to different farm practices and levels of conservation, different soil types may be expressed. Studies conducted in the three major agricultural soil zones in the Canadian prairies have demonstrated that there is a significant amount of variation in the topographic variables which control soil development within a single soil zone (Pennock *et al.*, 1987).

The objective of this study was to map the relationship between soil and topography at a scale and resolution suitable for environmental modelling and site-specific farming (1:10,000). This study is different from other published studies in the soil distribution field because it seeks to develop a methodological approach to modelling landform in an unbiased and reproducible manner that allows for the characterization of the soil *landscape* in local area as a function of topographic form.

CHAPTER 2

LITERATURE REVIEW

Introduction

This thesis deals with concepts and techniques developed in three separate bodies of knowledge: soil science, remote sensing, and geomorphology. From the field of soil science and geomorphology the concept of the relationship between soil type and topographic position was used. Remote sensing studies contributed to the definition of the relationship between soil and topography in large scale soil distribution studies. Terrain classification was the fundamental technique used for landform analysis in this thesis and was developed in the field of geomophometry, a sub-discipline of geomorphology. It is, therefore, necessary to review the pertinent literature in these areas.

The founding principle upon which the conceptual framework for this thesis was developed comes from the catena concept developed by Milne in 1935. Milne visualized soil distribution as a system of soils developing in the same sequence as a response to topography. Following Milne's work, Speight (1974) developed the concept of the toposequence, the landform analogue of a soil catena, as a method of classifying landform. Several early studies developed two-dimensional landform classifications (Milne, 1935; Wooldridge, 1950; Ruhe, 1956; Acton, 1965; Dalrymple *et al.*, 1968). One of the difficulties encountered with two-dimensional classifications is they are unable to adequately characterize many landforms due to their simplicity (Evans, 1972).

The development of fast and efficient computers made research into three-dimensional landform classifications using digital elevation models possible (Evans, 1972; Pike *et al.*, 1975; Pennock *et al.*, 1987; Pennock and DeJong, 1987, 1990; Pike 1988; Martz and DeJong, 1987, 1991; Martz, 1992). Recent research into the relationship between three-dimensional landform classifications and soil type has shown that landform classification can be a useful tool in mapping soil types (Huggett, 1975, 1982; Pennock *et al.*, 1987; Lee *et al.*, 1988, Swanson, 1990a, 1990b; Moore *et al.*, 1993). More recent work on the automation of landform classification, based on frequency-based contextual measures (Schmid-McGibbon, 1993), has shown that the use of frequency-based contextual classifiers can discriminate between subtly-differing landform types.

Topography Soil Relationship

In 1935, Milne introduced the concept of the soil catena. Since the development of this concept the relationship between soil distribution and topography has been studied extensively. According to Milne a catena is a grouping of soils that are different in a morphological sense but occur in the same sequence under similar topographic conditions (Milne, 1935). This concept has led to many two-dimensional models of the soil-topography relationship (Milne, 1935; Jenny, 1941; Wooldridge, 1960; King *et al.*, 1983). More recent works conceptualize soil as a spatial system (Speight, 1974, 1976; Huggett, 1975, 1982; Pennock *et al.*, 1987; Lee *et al.*, 1988; Swanson, 1990a).

Soils form in response to a variety of environmental factors. One of the first efforts to conceptualize this relationship was proposed by Jenny (1941). Jenny proposed a series of soil-forming factors in the form of the fundamental equation of soil-forming factors; $S = f(cl,o,r,p,t)$. In this equation, soil (S) is a function of climate (cl), organisms (o), topographic relief (r), parent material (p), and time (t). Several authors (Jenny, 1941, Gerrard, 1992) noted that, because many of the variables have a great deal of inherent complexity, and no absolute values, attempting to find a solution to the equation is meaningless. Therefore, it is more useful to see the equation presented by Jenny as a conceptual framework for the study of soils (Gerrard, 1992).

Speight (1974, 1976) introduced the concept of the toposequence. Speight defined a toposequence as the topographic sequence of elements passed over by a conceptual particle moving down-slope under the influence of gravity. This concept is a continuation of the catena concept proposed by Milne (1935), differing in that it contains no specific soil information. Speight thought that as landform elements are better defined in a numerical classification, the predictive power of the toposequence in the determination of soils will increase and, in so doing, the toposequence and catena concepts will converge (Speight, 1974).

In a later paper, Speight (1976) specified that the position of a landform element in a fully specified toposequence implies a number of contextual attributes of the element, such as soil type, or slope stability. Speight also proposed that an empirical landform element classification is more realistic because the landform elements arise as a product of local characteristics. This approach to landform classification in local areas may show more subtle distinctions than in broader indices, such as the nine-unit landscape model presented by Dalrymple *et al.* (1968).

King *et al.* (1983) conducted a regional study of the relationship between soil type and topography. In this study, they surveyed slope profiles and evaluated detailed soil properties. While considering the two-dimensional effects of slope curvature on the development of soil they found that there was a relationship between: 1. upper convex slopes and regosolic soil series, 2. mid-slope positions and orthic soil series, and 3. concave lower slopes and gleysolic soil series.

Gregorich and Anderson (1985) studied the effect of cultivation on the distribution of various soil properties. They found that erosional processes were strongest at upper slope positions. The upper slope areas showed weakly developed A-horizons that eroded to lower slope positions. The study was conducted in native prairie and cultivated land and showed that cultivated land showed a greater degree of erosion and depletion in various chemical constituents of the soil over time.

Moore *et al.* (1993) conducted a study that showing that terrain attributes can be used to characterize soil types at a scale of 1:6000. This research used heuristic methods to class various terrain measures. The terrain measures were then used to model soil attributes. The resultant soil map explained 41 to 64% of the variability of measured soil attributes.

Remote Sensing Use In Large Scale Soil Distribution Studies

Air photo interpretation and remotely sensed images are used widely in the study of soil distribution (Acton, 1965; Crown *et al.*, 1971; Harrison *et al.*, 1987). The current technique for mapping soil distributions is to delineate soil boundaries manually on aerial photographs (Acton, 1965). Other studies have used video scanning of aerial photographs and digital methods to manually delineate soil boundaries based on image tonal variations (Crown *et al.*, 1971; Harrison *et al.*, 1987). These interpretative approaches to soil mapping rely on the investigator's tacit knowledge to determine soil boundaries. Tacit knowledge is acquired through practice and experience. This type of knowledge is not easily defined because interpretative decisions are based on rules of thumb (Hudson, 1992).

Acton (1965) mapped the relationships between soil colour and soil type from large-scale aerial photographs. Acton demonstrated that using traditional, although subjective, interpretation methods reliable large scale soil maps can be made. This research also shows that there is an association between soil type and gradient, although it does not present any means for quantifying this relationship. Shields *et al.* (1968) studied the relationship between soil colour, soil moisture, and organic matter. This study found that soil colour differs between soils that are air-dry and soils that are at field capacity. As the soil moisture content increases from air-dry to field capacity the colour darkens.

Crown and Pawluk (1971) quantitatively measured the tonal variation of soil types within fields from colour infrared and panchromatic photography south east of Edmonton. They observed that the variation in tone was a result of different surface colour, organic matter and moisture content. This study also found significant differences between the spectral responses of various soil types that would help with soil classification at the soil type level.

More recent research has attempted to converge LANDSAT thematic mapper (TM) data (30 metre resolution) with DEM data to determine soil characteristics (Lee *et al.*, 1988). In this study, a spectral classification from the TM data was added to slope measures from the DEM. A classification was then developed using unsupervised training field data. The resultant map had a 72% agreement between the soil map and the classification.

Agbu and Nizeyimana (1991) used SPOT data to classify soil map units based on image texture analysis. This study was conducted to assess the usefulness of SPOT MLA (20 metre resolution) data for mapping the variability of soil properties. Classification results showed percent overall agreement of discriminate map units from soil properties to be 61 percent. This level of accuracy is inappropriate for this level of soil mapping, although it was similar in accuracy to the field soil map tested. The data demonstrates that image analysis can be used for initial reconnaissance phases of soil surveys (Agbu and Nizeyimana, 1991).

Terrain Classification

Traditionally, terrain classification was performed by manual and visual interpretation and measurements of maps and airphotos (Strahler, 1956; Evans, 1972; Speight, 1976). Strahler (1956) was one of the first researchers to quantitatively compare landforms. Strahler (1956) compared areas of different terrain using the distributions of terrain derivatives (slope, across-slope curvature and down-slope curvature). In this paper, Strahler suggested that altitude matrices (DEMs) may provide a useful means of terrain evaluation. Until relatively recently, the classification of terrain based on measures derived from a DEM was a theoretically possible but seldom implemented technique.

Evans (1972) proposed a systematic methodology for the description of landform based on measurements derived from DEMs. In this system Evans described two levels of mapping landforms: general geomorphometry and specific geomorphometry. General geomorphometry is the measurement and analysis of the characteristics of landform which are applicable to any continuous rough surface. The basic measures used for general geomorphometry are altitude, gradient, curvature, distance, area, and hypsometry. Specific geomorphometry is the measurement and analysis of specific landforms. The measurement of specific landforms implies that there are clear criteria of delimitation that set certain landforms apart from others *a priori* (Evans, 1972).

The fundamental difference between general and specific geomorphometry is that specific geomorphometry involves more arbitrary decisions and leaves more room for subjectivity than does general geomorphometry. General geomorphometry provides a basis for the quantitative comparison of qualitatively different landscapes. The advantage of specific geomorphometry over general geomophometry is that specific geomorphometry allows the researcher to tailor the variables used to processes (Evans, 1972).

Pike and Rozema (1975) developed an approach to the analysis of landforms based on the geometric signature of the landform. The goal of this approach is to develop a comprehensive description of landforms from which various topographic types can be compared. They conceptualized the geometric signature as a set of measurements that abstracts the essential shape of each type of topographic surface and distinguishes it uniquely from other surfaces. Towards this end, there is no single "magic number", such as average slope or relative relief, that adequately expresses landform for taxonomic purposes (Pike and Rozema, 1975).

In a later paper, Pike (1988) expanded his original conceptualization of the geometric signature to include the geomorphic signature. A geomorphic signature is a broader and largely undeveloped concept that includes much more than topography. A geomorphic signature can characterize the entire physical landscape, including soils. Pike mentions that the position of a landform element in a fully specified toposequence implies a number of contextual attributes of the element that are likely to be of geomorphic significance.

Geomorphometric measures derived from DEMs are at the foundation of the automated classification of geomorphic surfaces. The process most commonly used for the extraction of these variables is neighbourhood processing. Neighbourhood processing involves the roving of an odd-numbered window through a matrix of elevations. As the window is moved to each successive position, the result of the computation is assigned to the centre cell position of the window in a new convolved data set.

Evans (1972) was the first author to propose that parameters derived from altitude matrices (DEMs) showed potential as significant parameters in the measure of geomorphic processes. The parameters measured by Speight (1974) provide a rigorous method of terrain classification and terrain mapping in land evaluation surveys. To this end, Speight proposed two broad categories: *landform elements* and *landform patterns*. Landform elements are areas of land that can be distinguished on the basis of the measurement of surface geometry, for example, slope, aspect, curvature and derived context. Landform elements are conceptually similar to Evan's (1972) measure of general geomorphometry. Landform patterns, on the other hand, are more complex areas of land composed of many landform elements arranged in toposequences. Speight also notes that the use of such rigorous measures enhances the predictability of soil from landform elements.

Several researchers in the fields of soil science and hillslope geomorphology have developed landform classifications from DEM derivatives (Pennock *et al.*, 1987; Pennock and DeJong, 1987, 1990, Martz and DeJong, 1987, 1991, Martz, 1992). The primary focus of this research was to identify erosional and depositional elements of the landscape with respect to topographic position. Results indicate that there is an association between depositional elements of the landscape and depressional landforms and between upper slopes and erosional elements.

A few studies specifically focused on the relationship between soil distribution and topography in a three-dimensional system. Pennock *et al.* (1987) developed a quantitative land form classification based on the relationship between landform and soil distribution. This study found a significant relationship between landform elements and soil distribution.

Weibel and DeLotto (1988) proposed a methodology for the classification of terrain based on measures derived from DEMs using multivariate statistical methods commonly implemented in the field of remote sensing. One difference in the methodology proposed is that the variables used are the derivatives of elevation, rather than the record of spectral reflectance or emittance. The authors note that the variables used in the classification procedure should reflect the known properties of the phenomena in question. The variables selected should also be tested for independence because, if the variables selected are highly inter-correlated then these variables may not be measuring different terrain parameters.

Schmid-McGibbon (1993) demonstrated that frequency-based contextual classifiers are an effective method for automating the process of landform mapping. Frequency-based contextual classifiers use frequency counts of classed morphometric descriptors calculated from neighbourhoods. These counts are then used in a discriminant analysis to classify landforms (Schmid-McGibbon, 1993). This method provides a objective method for the classification of landform.

Summary

From the early work by Milne (1935), and other later researchers (Jenny, 1941; Wooldridge, 1960; Speight, 1974, 1976; Huggett, 1975, 1982; King *et al.*, 1983; Pennock *et al.*, 1987; Lee *et al.*, 1988), it is evident that there is an association between soil properties and landform elements. The field of remote sensing provides two significant contributions to this study. First, the advanced classification techniques developed in remote sensing makes it possible to classify landform in an objective, replicable manner (Weibel and DeLotto, 1988). Studies using air photographs and remotely sensed images show that different soils have unique spectral signatures and that these soils occur in definable landscape positions (Acton, 1965; Crown *et al.*, 1971; Harrison *et al.*, 1987). Using DEMs, it is possible to compute, in an unbiased fashion, the necessary variables to classify landform as a geomorphic signature (Evans, 1972; Pike and Rozema, 1975; Pike, 1988).

CHAPTER 3

STUDY AREA AND DATA COLLECTION

The purpose of this chapter is to describe the nature of the study area, define data requirements, and outline the methods used for the collection of the data. This study focuses on the automated mapping of landform and the association between soil type and landform. A detailed DEM of the study area was the basis for the differential landform measures. The second type of data required was information on various soil properties. These data was collected from the study area and spatially registered to the DEM with the use a of Global Positioning System (GPS).

Description of Study Area

The study area is located in east-central Alberta. Canada, south-east of the city of Edmonton, at 53° 33" north latitude and 113° 28" west longitude (Figure 3.1). Figure 3.2 is a subset of the soil map for the Edmonton map sheet 83-H, located between 53° and 54° north latitude and 112° and 114° west longitude showing the range of soil associations in the Edmonton area. The study area is located in township 51, range 23, on six quarter sections located on sections 19, 20, 29, 30 (Figure 3.3). The soils in this area formed on the Cooking Lake moraine deposit. The area is described as "undulating to hilly, primarily of the knob and kettle variety" (Bowser *et al*, 1962, p.11).

The climate of the Edmonton area is continental with warm summers and cold winters. The average frost-free period is 100 days. The mean annual precipitation is between 40 and 45 centimetres with, on average, half of the precipitation falling during the summer months of June, July, and August (Bowser *et al*, 1962). In general, the

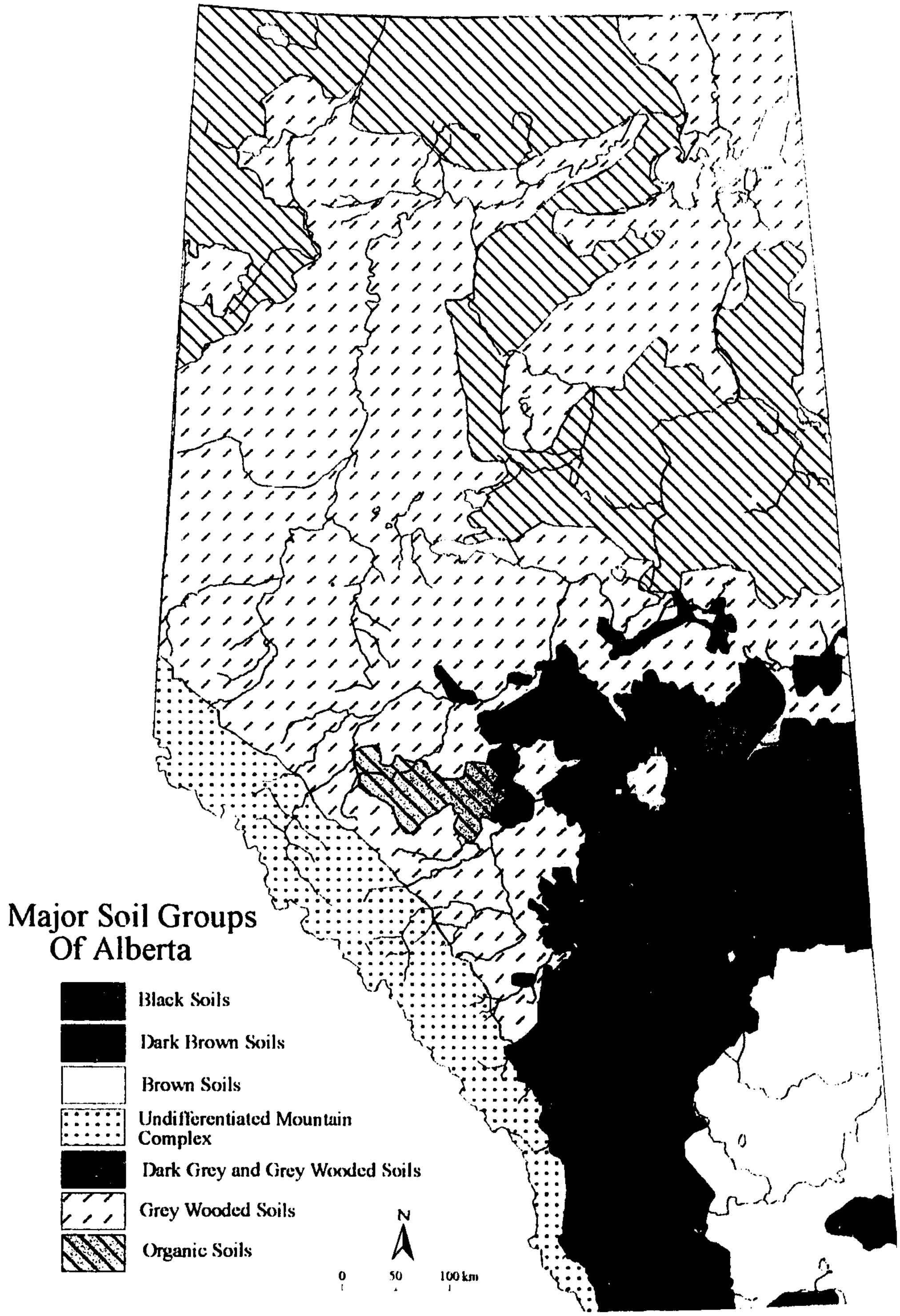


Figure 3.1. Study Site Location Map With Soil Zones.

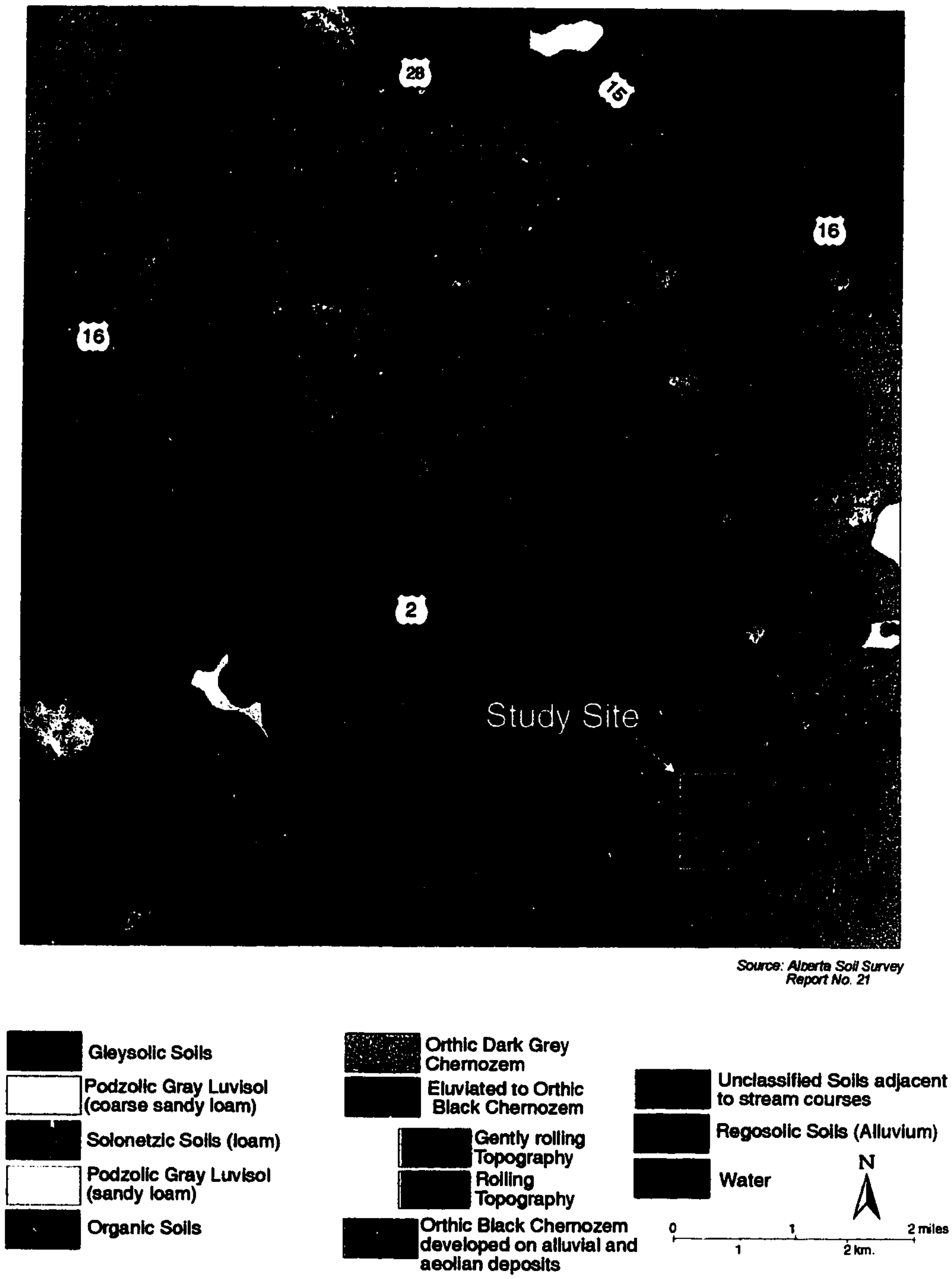


Figure 3.2. Study Site Location Map With Regional Soil Associations.

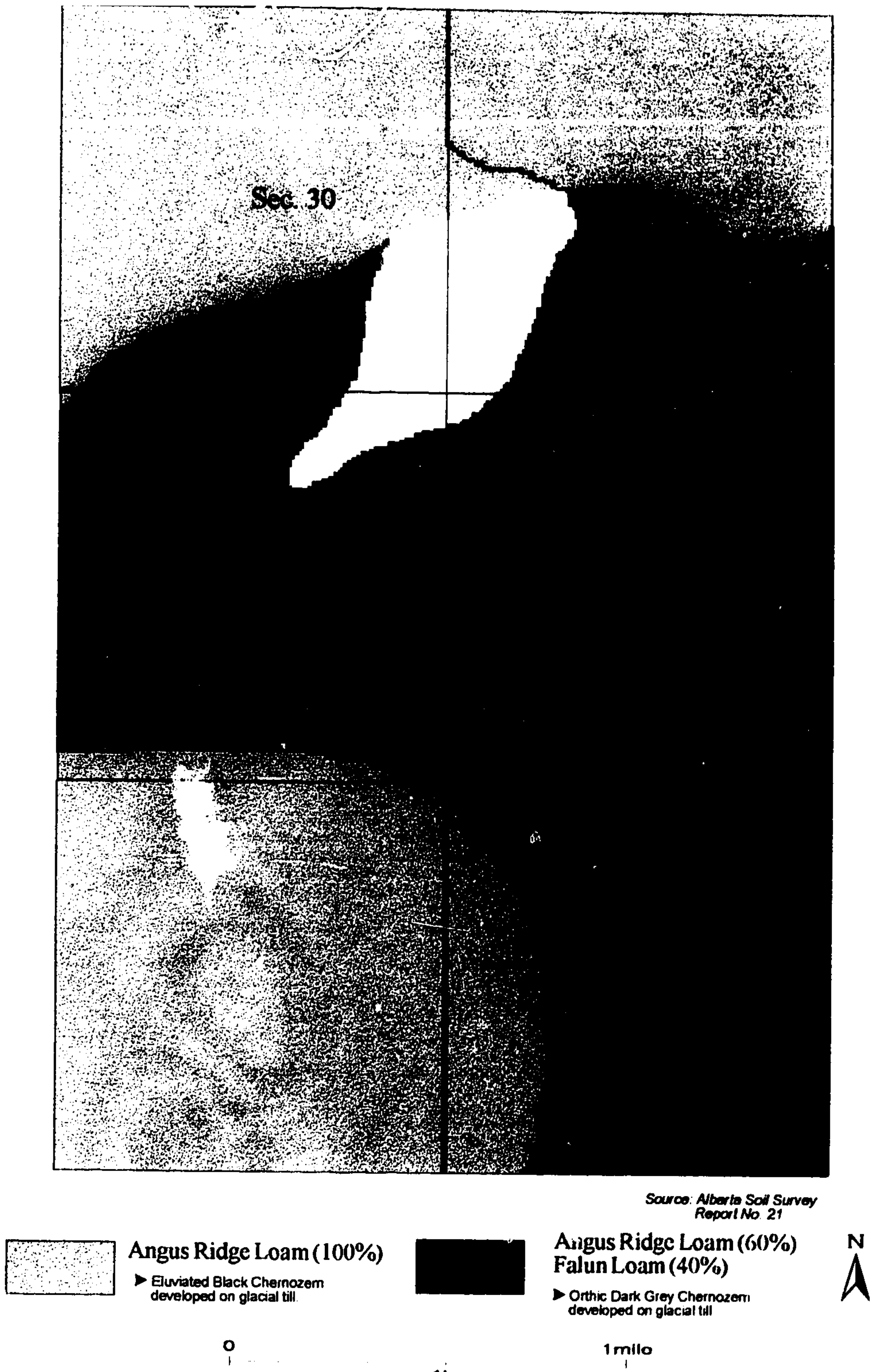


Figure 3.3 Soil associations in study area, Township 51, Range 23.

study site is in the black s[illegible] zone. The area is almost [illegible]mpletely dominated by an eluviated black chernozer[illegible]iation known as the Angus Ridge Loam (Figure 3.3). The Angus Ridge Loam is formed in medium textured (loam to clay loam) material that contains stones. This association occurs on level to rolling topography and is often associated with Orthic Black chernozems (which lack a light coloured subsurface (Ae) horizon) and Solodized Solonetz (which have a hard round topped columnar subsoil (Bnt) horizon). The native cover of this soil association is described as Parkland, consisting of tall grasses, shrubs and deciduous trees.

Digital Elevation Model Data

The DEM used in this research was surfaced from contour lines extracted from a 1:5000 orthophoto with 1 metre contour lines, available to the public from the City of Edmonton, Alberta. Orthophoto products are corrected for terrain, camera, and perspective distortions, and are transformed to an orthographic projection. The contour lines plotted on the surface of the orthophoto were stereo-compiled. The stereo-compilation process requires a stereoplotter operator to set a floating dot at a specific elevation and then to trace the dot along the contour. All contours are systematically traced in a clockwise or in a counter-clockwise direction in order to avoid stereo-compilation errors that over- or under-estimate the location of the contour (Avery and Berlin, 1992).

The orthophoto was scanned at a resolution of 200 dots per inch (dpi). This resolution was sufficient for the scanning software to find enough matching features to combine the various swaths into one large scanned image. This data set was then resampled to a resolution of 100 dpi in order to make the image a manageable size for image processing on an IBM 486 personal computer.

Contour Line Extraction

The scanner used is a form of charged coupled device (CCD) which is a silicon array sensing system. It scans in 12 cm swaths and the scanning software correlates the swaths and then combines the swaths to create a final image. The correlation procedure works best if the swaths are parallel and have a 2 cm overlap. A special scanning table was constructed to ensure that these criteria were met. A frame of 2.54 cm by 2.54 cm aluminium-angle was constructed to keep the scanner tracking in a straight line. The frame has 1.5 cm pins that mount into a backing board; holes were then drilled into the board at the correct 2 cm spacing providing the required optimal overlap.

The CCD sensing system detects varying grey tones through the breaking of molecular bonds in the silicon array sensor. When molecular bonds are broken electrons are released and maintained in a region called a potential well. The degree of molecular breakage is then digitally recorded as a pixel. The intensity of the pixel is, therefore, proportional to the amount of light that hits the area being scanned.

The contour lines are a uniform black tone on the original orthophoto. Due to varying background intensities, the CCD recorded the contour lines with varying intensities. The contour lines are, however, still regionally the lowest grey level value (GLV). To account for this variation a number of different threshold values were applied to the image. Digital masks for each of the threshold values were selected and the non-contour information deleted. The contours which remain were then reclassed to a GLV = 0 while all non-contour areas were assigned a GLV = 255. All of the contour lines were checked for completeness and separation. The final result of this process is a binary contour map (Figure 3.4a).

Coding and Automated Digitizing of Contours

Each contour line was then coded with a GLV that corresponded to elevation above a predetermined reference level. In the study area, the lowest contour is 727 metres; therefore, a reference level of 700 metres was selected. All contour lines were coded sequentially from this reference level; for example, the 727 metre contour line was given the GLV = 27. The coding of the contours progressed from the lowest to the highest elevation (Figure 3.4b). After each contour was coded, the mask threshold was incremented by one so that the last contour was masked. This technique ensures that the coding is accurate, especially in areas of close contour spacing, as it prevents areas that are already coded from being mistakenly re-coded.

This raster image was the input for the RAST2XYZ (Hemenway, 1995a) program. RAST2XYZ automatically digitizes a unique X, Y, in either UTM or latitude longitude, for every grid cell not coded with a GLV = 255 or GLV = 0. A Z-value is recorded that is equal to the GLV of the pixel and is added to the reference level to obtain the proper elevation of the contour line. The program assumes that the grid cell spacing is equal and square. The automation of this traditionally manual process is thought to be as accurate as the manual process and reduces the probability of operator error.

The output was an X, Y, Z file that contained 230,805 observations. As the sample was large, the points file was filtered to remove points within specific small

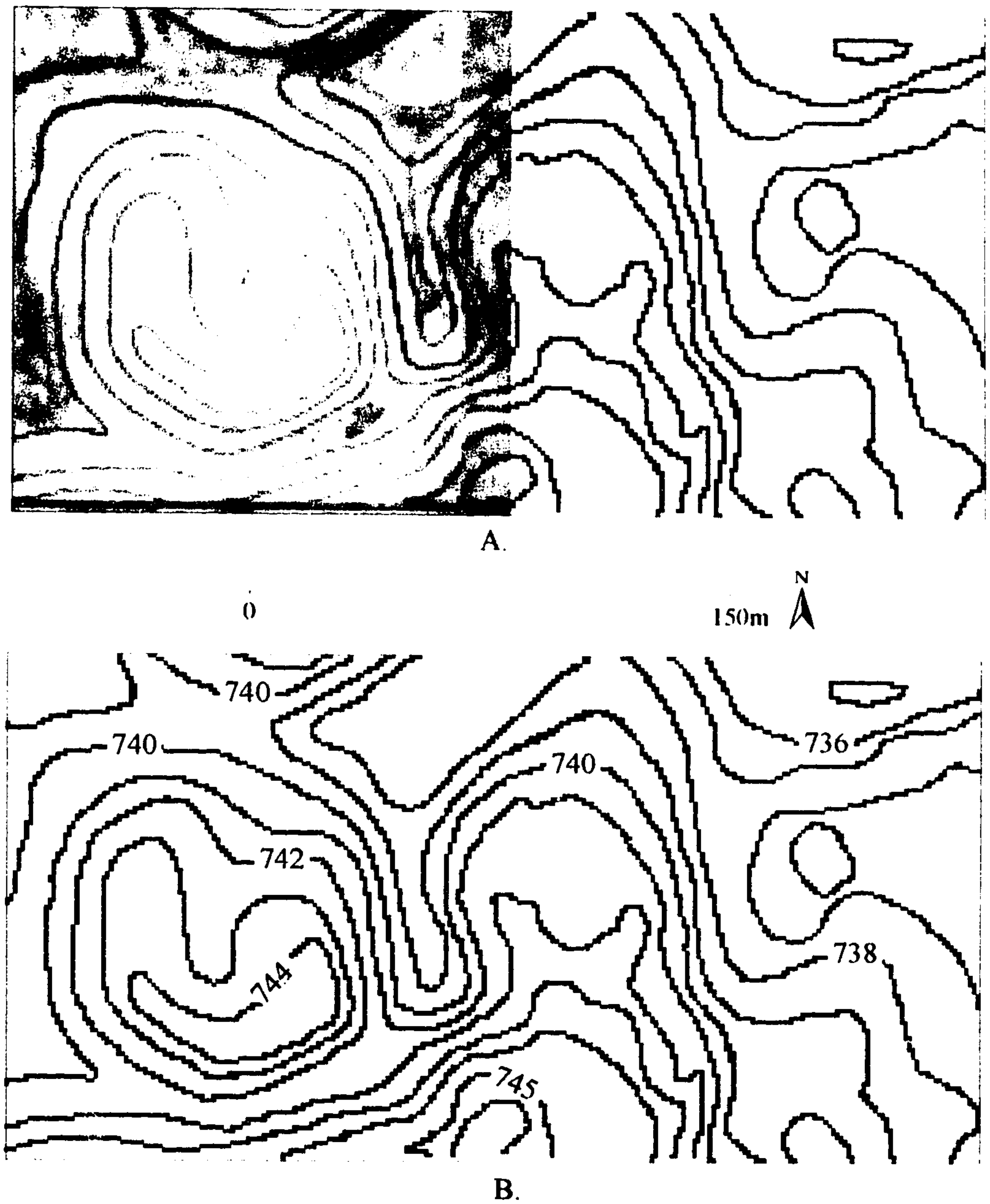


Figure 3.4. A and B. Contour Extraction and Coding. Figure 3.4a shows the process of contour extraction. Figure 3.4B shows the process of contour coding where the contours are digitally labeled according to their elevation above a predetermined reference level.

distances. The PFILTER (Hemenway, 1995b) program was used to reduce the total number of points to 13,848 points, a 94% reduction in the amount of points. The reduction of point density is necessary in order for the surfacing program to efficiently compute the DEM.

Geostatistics

The study of geostatistics is based on the principle of the regionalized variable which has properties intermediate between a truly random variable and a completely deterministic variable. Many features that have geographic distributions show this type of relationship, for example, elevation (Evans, 1972; Oliver and Webster, 1986). There is local spatial dependence expressed in the way changes in elevation occur. This property is referred to as spatial auto-correlation, which means that the closer two variables are to each other in space the more likely they are to be related. The problem with variables that exhibit this property is the way in which the change is expressed. The change in the variable is so complex that it cannot be described adequately by any deterministic function (Oliver and Webster, 1986; Davis, 1986).

The concept of spatial auto-correlation is the basis for all surfacing routines that involve the interpolation of an elevation from functions (as in analytical surfacing methods) or directly from the distribution (as in numerical surfacing methods). This fact links geostatistics to surfacing. A question often asked is "what is the appropriate resolution that the data should be surfaced at in order to adequately represent the feature?" The current approach to the solution of this problem is to use rules of thumb or to surface at a number of different resolutions and use the elevation model that "looks" the best (Burrough, 1986).

The theory of geostatistics and the concept of the regionalized variable make it possible to define the criteria for an appropriate spatial resolution. More importantly, geostatistical theory can define the nature of the variance of the landform. The geostatistical measure that describes the rate of change of the regionalized variable is known as the semivariance. Semivariance is measured for a specific orientation and gives a measure of the degree of spatial dependence of the variable along this orientation. The variable measured can be any continuously varying property, for example, elevation, water content, or organic matter. If the spacing between variables along a line is some distance Δ, the semivariance can be estimated for distances that are multiples of Δ

$\gamma_h = \Sigma_i^{n-h}(X_i - X_{i+h})^2/2n$ where X_i is a measure of the regionalized variable taken at location i and X_{i+h} is another measurement taken h intervals away. The equation, therefore, represents the sum of the squared differences between pairs of points separated by the distance Δh. The number of points is n, so the number of comparisons between pairs of points is n-h (Davis, 1986).

The usual way to represent the relationship between semivariance and distance is in the form of a semivariogram, where semivariance is the Y axis and h (distance) is represented on the X axis. Semivariance can be displayed graphically along any orientation. For example, if there was a specific orientation to the data, the semivariance can be measured with respect to any orientation. A further extension of the theory makes it possible to measure the semivariance with respect to every orientation (referred to as direction 0).

Figure 3.5 shows a number of idealized semivarigrams. By analysing the shape and a few critical features, the underlying structure in the data can be resolved. Figure

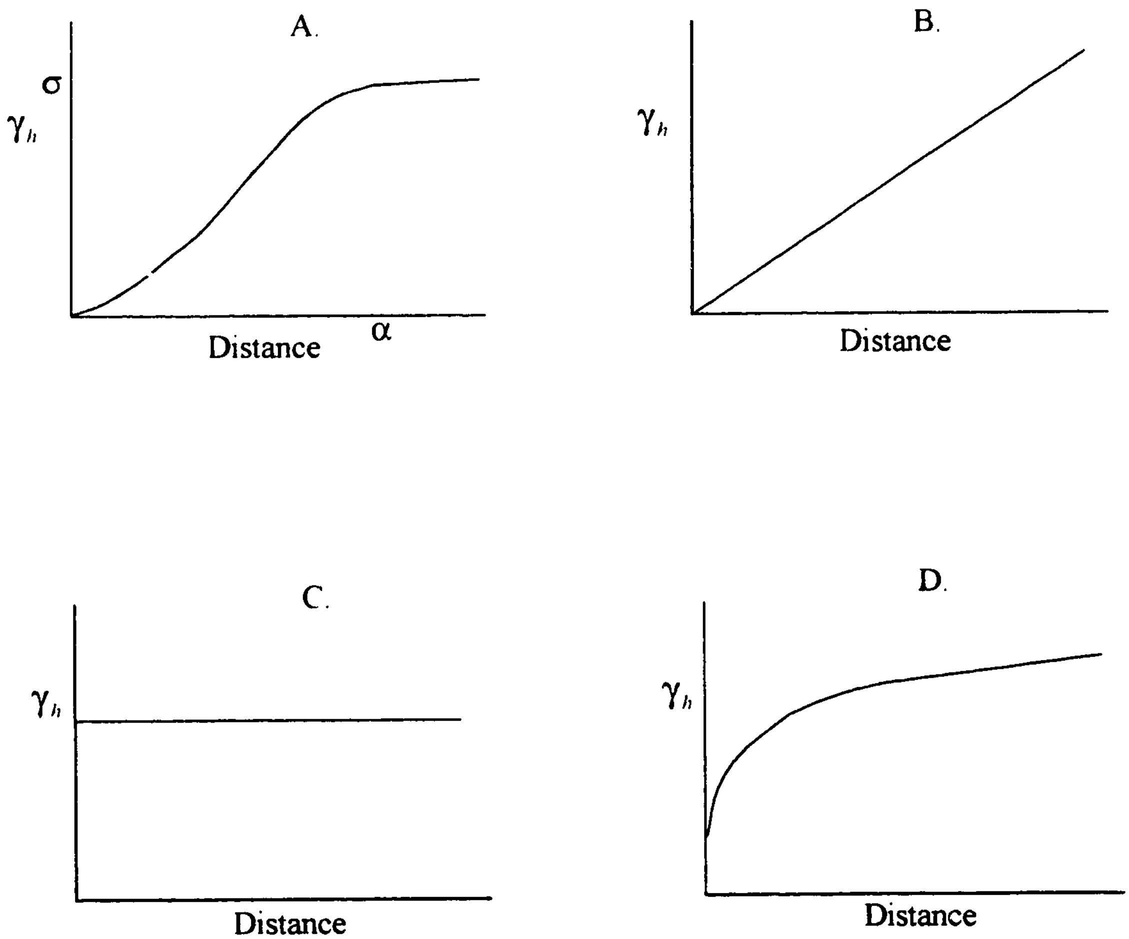


Figure 3.5. Idealized Semivariograms. Source: Davis, 1986.

3.5a shows a parabolic semivariogram shape; in this case, the regionalized variable shows excellent continuity. Figure 3.5b shows the linear form where the regionalized variable has moderate continuity. The horizontal form, Figure 3.5c, shows a random variable with no spatial auto-correlation. Figure 3.5d shows the nugget effect, which indicates the apparent failure of the semivariogram to go through the origin. This condition indicates that the regionalized variable is highly variable over a distance less than the sampling interval.

In Figure 3.5a, the point where the semivariance levels off is called the sill (σ). The sill implies that there is no spatial dependence between the data points because all estimates of variance differences are invariant with distance. The distance at which the sill occurs (α) is called the range. Within the range, the closer the sites are the more likely they are to be similar. Another important and unseen feature of the semivariogram is the lag over which the variance is estimated. The size of the lag is important, as it indicates over what scale the most useful pattern can be extracted from the background noise (Davis, 1986).

One current limiting factor in the application of geostatistics is the finite limit of the data points that may held in computer memory. The current limit is around 1,000 points. In this study, the DEM was surfaced from a point data set of 13,848 points. This number exceeds the semivariance program' s functional limits. For analysis, a program was written to reduce the number of points to 802 points (Figure 3.6). A systematic sampling scheme was used in place of other point reduction schemes which are based on distance, as distance is essential to determining the nature of the semivariogram.

Figure 3.7 shows the semivariogram computed for the 802 point data set. This semivariogram shows that the regionalized variable is fairly representative of the

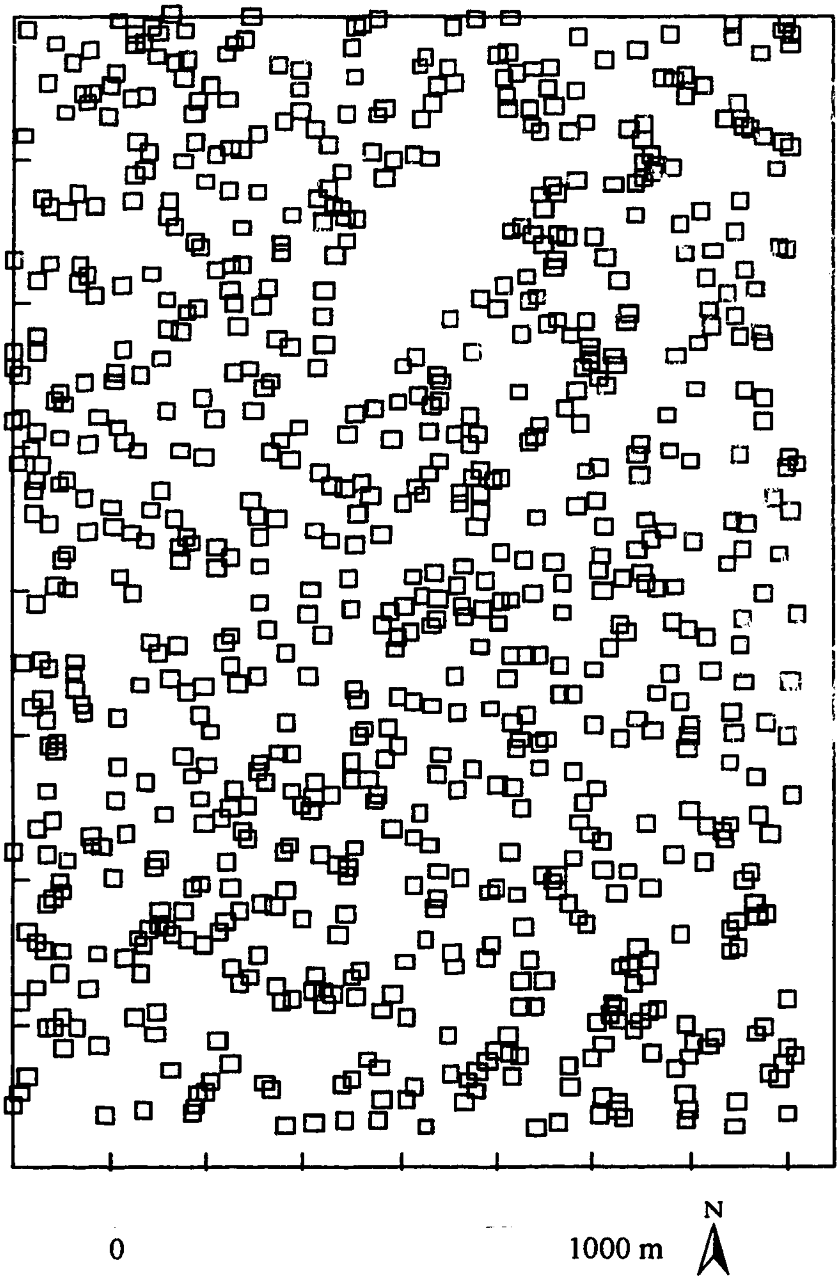


Figure 3.6. Distribution of Semivariogram Sample Points.

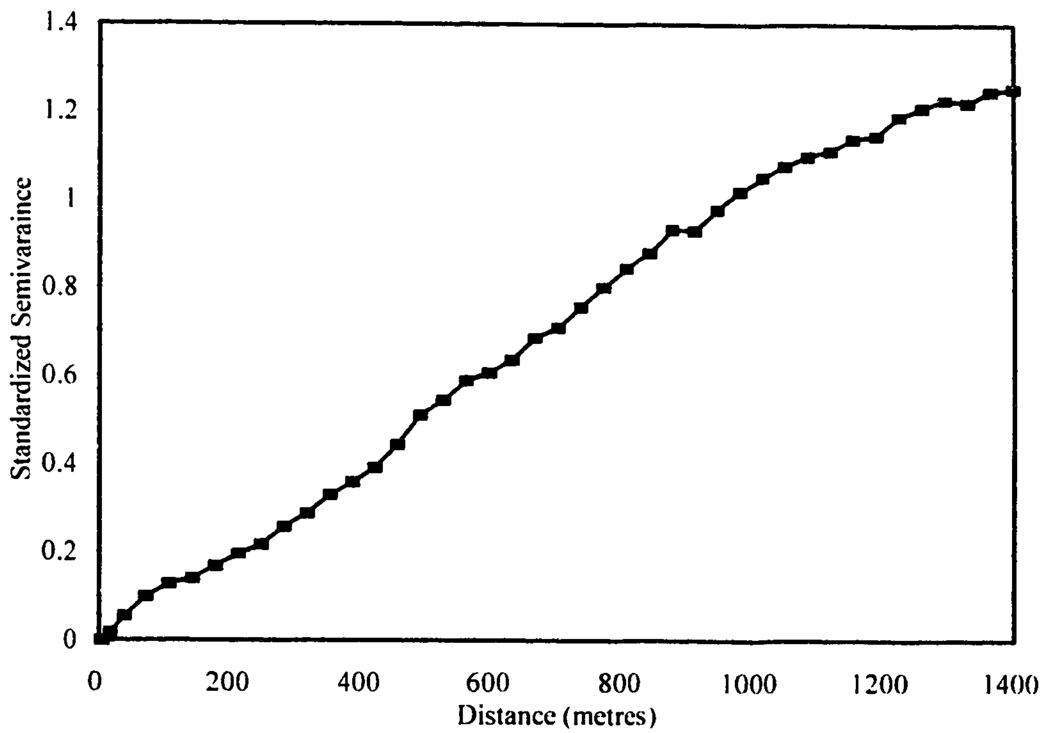


Figure 3.7. Semivariogram of Entire Data Set.

idealized parabolic form (Figure 3.5a). This graph is displayed with the standardized semivariance. In this case, a standardized semivariance of 1.2 is equal to a semivariance of 25 metres. The standardized data are displayed because the relative changes are easily interpreted in this form. The semivariogram shows good continuity over the entire area with the semivariance equal to the topographic relief in the area. The other feature of this diagram is the number of areas within the semivariogram where the regionalized variable is behaving with continuity over certain distances, for example, from 0 to 160 metres and from 420 to 600 metres. These points on the semivariogram indicate the dimension of the small- and medium-scale landform in the area.

Figure 3.8 is an enlargement of the region from 0 to 180 metres. The most important feature of this graph is the point where the semivariance is close to zero and rises sharply. This is the distance between points that grid cells have to be to show the variance in the data. In this case, the distance is 4.05 metres. This is the most appropriate resolution for surfacing the data in order to capture the large-scale variation in the data.

The spatial continuity that the semivariogram displays in the first sub-range describes the average scale of the landform in the area. The semivariogram shows that any point in the data set is most like its neighbours up to a distance of 160 metres and that the variation between these points is at most 3 metres. Interpretation of the original orthophoto indicates the hummocks are around 160 metres apart and they average 3 metres in height.

The final observation is that the lag, or distance that the regionalized variable was sampled, was 40 metres to extract the maximum information with the least noise. This

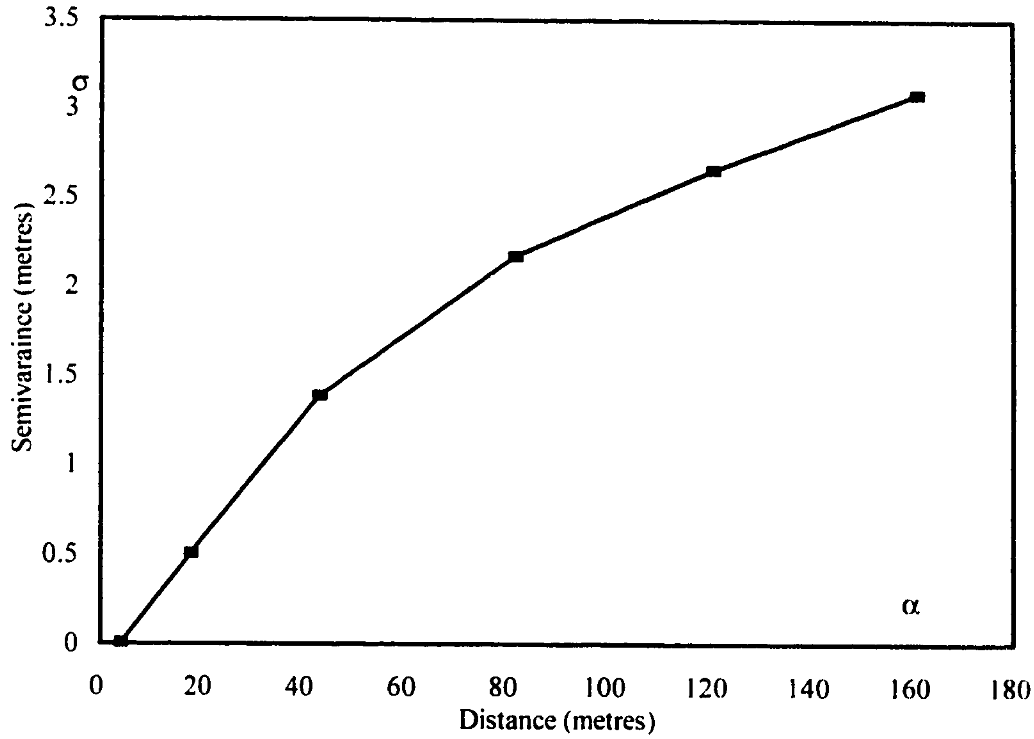


Figure 3.8. Enlargement of Semivariogram Sub-Range.

distance, although arrived at by trial and error, is the appropriate distance that the data should be sampled at to obtain a reasonable representation of the nature of the landscape

DEM Generation

The X, Y, Z file was surfaced using QSURF (Hemenway, 1995c) which finds the solution to a set of multiquadric equations of topography. Multiquadric equations of topography, given a discrete set of data on a topographic surface, reduce the discrete data to a continuous function. The solved set of functions exactly fits all of the original points and provides a reasonable interpolation at intermediate points. In areas where there is little data, the derived equation treats the surface as neutral (Hardy, 1971). Using the results of the geostatistical analysis, a spatial resolution of four metres was selected to produce a surface grid of elevations.

Field Methodology

The purpose of the field methodology was to obtain geo-referenced sample locations where data were collected. These sample data were then used to check the accuracy of the model. The other purpose of the field phase of the project was to check that the landform classification was accurate.

The first step was to select one of the six quarter sections in the study area at random and to seek permission to conduct a soil survey from the land owner. The section selected was the south-east quarter-section of section 19, township 51, range 23, see Figure 3.3. The samples were collected on two days, September 30 and October 1, 1995. Weather conditions were good for both days. The locations of the sample points were chosen by starting at one field corner and then walking to a point. Figure 3.9 shows the distribution of points in the field.

The following procedures were conducted at each sample point:

1. the location of the sample site was recorded using a Trimble Basic Plus 6 channel Global Positioning System (GPS) receiver.
2. notes were taken on the landscape position (crest, side slope, or depression).
3. using a Dutch auger, the depth of A-horizon and the depth to C-horizon were measured.
4. using a standard soil probe, a surface soil sample was taken and bagged.

Laboratory Analysis

Laboratory analysis of the soil samples was conducted to meet two objectives; to accurately classify the soil types, and to check model assumptions. The soil samples were classified using the Canadian System of Soil Classification (Agriculture Canada, 1987). The second reason for the laboratory analysis was to check to see if the parent material was the same at all of the sites so that the assumptions made in the model were realistic.

The first phase of the lab analysis was to gather diagnostic information on the physical properties of the soil samples for classification. The following physical properties were measured:

1. soil moisture content,
2. soil organic matter content,
3. percent sand,
4. soil colour.

The laboratory techniques used to measure these variables followed the Methods Manual for forest soil and plant analysis published by Forestry Canada (Kalra *et al.*, 1991). This manual describes the techniques in detail.

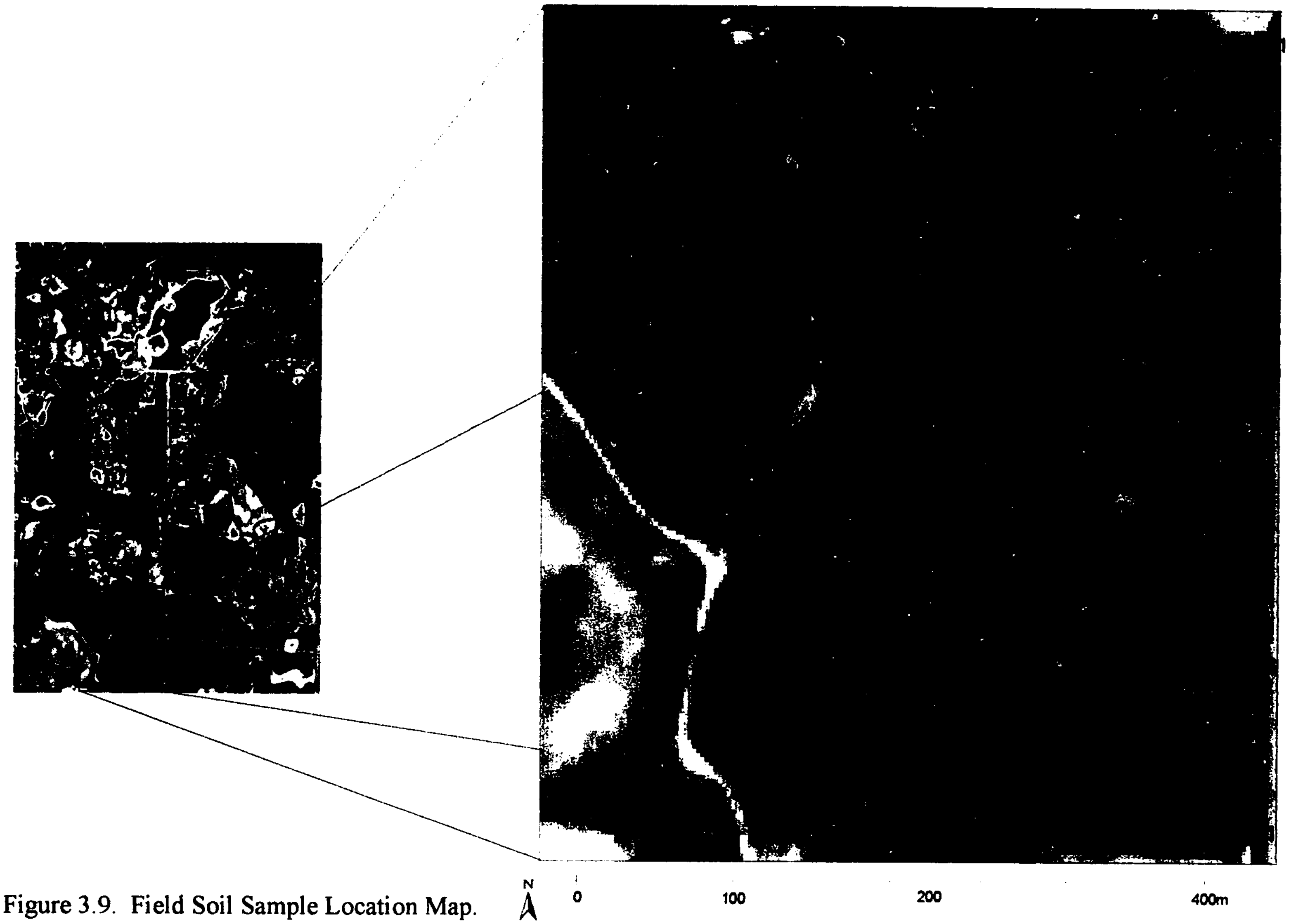


Figure 3.9. Field Soil Sample Location Map.

Soil moisture content is determined by weighing a field-fresh sample of soil and placing the sample in a forced-air oven at 105° C for 48 hours and then re-weighing. The loss in weight is expressed as a percentage of the original soil weight. There may be some loss of organic matter, but this source of error is not considered serious (Kalra *et al.*, 1991).

Samples were then taken from the oven dry soil and used to measure soil organic matter content. Organic matter is oxidized at a temperature of 375° C and can be measured as a function of sample weight loss. The samples were placed in preheated porcelain crucibles and weighed. The crucibles were then placed in a furnace at room temperature and the heat was raised to 375° C. The samples were left in the furnace for 24 hours. The furnace was then cooled and the samples were weighed to obtain a measure of the amount of organic matter by loss on ignition (LOI). This technique gives a reasonable estimate of organic matter that is accurate for most descriptive purposes (Kalra *et al.*, 1991).

Soil colour was measured using a Munsell colour chart. The oven dry soil was used to determine the colour as this removes any differences in soil colour that is indicative of moisture differences. It is also advisable to conduct this procedure in the lab as lighting conditions are uniform.

Percent sand was measured by sieving the samples used to measure organic matter content by LOI. These samples were ground with a mortar and pestle, weighed and passed through a 250μm sieve. The amount of sample that passed through the sieve was then re-weighed to measure the amount of sand that was screened by the sieve. This gives a measure of the medium and coarse sand fraction of the sample.

Particle size analysis was conducted to obtain a measure of the relative proportions of particles in dimension classes. The basis for all sediment analysis is Stokes' law which states that a particle falling due to gravity, in a viscous liquid, is acted upon by three forces: a gravitational force acting downward, a buoyant force acting upward, and a drag force acting upward.

Particle size analysis is based on the fact that the measured equilibrium velocity of a particle through a viscous medium, resulting from the action of gravitational force can be related to the size of the particle by Stokes' law. For spherical particles, Stokes' law is: $D = kv^{1/2}$

where D is the diameter of the particle, v is the equilibrium sedimentation velocity. The expression of the medium that the particles are suspended in is k which relates the fluid's viscosity and density. In general, this equation is correct if the particles are spherical. In practice this condition is rarely the case and results in the introduction of some error, usually no greater than three percent (Kalra *et al.*, 1991).

The most common way of determining sediment size distributions is to disperse particles in a fluid and stir to ensure that the mix is homogeneous. The mixture is then left undisturbed while it undergoes sedimentation. The density of the fluid is measured at a number of different time intervals to measure the amount of sediment produced; from this the diameter is calculated.

In this study a Sedigraph 5100 was used to measure the particle size distribution. The Sedigraph uses a finely collimated X-ray beam to measure particle concentration in terms of the transmitted intensity of the X-ray beam through the suspension relative to the suspension fluid without sediment.

This technique is useful as the X-ray beam is finely calibrated and is extremely small to precisely measure the sediment in suspension. The X-rays also do not disturb the suspension during sedimentation. As the process is relatively automated, the potential for errors is reduced. The other benefit is that the process is fast and accurate as several duplicate samples can be processed in one run.

Coakley *et al.* (1991) conducted an analysis of the accuracy of the Sedigraph 5100. This study showed that the instrument is accurate to within ± 1%. The only significant deviation to this measure was for particles in the silt fraction that showed an under-prediction of 3% to 5%. This error is accounted for by restriction in the original pump design not maintaining sufficient velocity and turbulence to keep particles of this size in suspension (Coakley *et al.*, 1991).

Summary

This chapter has described the nature of the study area, defined data requirements, and outlined the methods used for data collection. The section on geostatistics describes the use of geostatistical theory as a tool to define the topographic parameters of the study area. Using the results of the geostatistical analysis, an objective approach was used to select the resolution of the DEM. This technique, though the analysis of semivariance, allows for the selection of an optimal resolution for surfacing point distributions. The soil survey and laboratory analysis provide data for testing the hypothesis that soil type is a function of landform in localized areas.

CHAPTER 4

MODELLING

The purpose of this chapter is to present the methodology used to classify landforms based on geometric signatures. Modelling is a subjective process; therefore, the definition and concept of a model used in this thesis are discussed. The techniques used to extract model parameters and classification procedures are also covered in an in-depth fashion. The last section of this chapter describes the method used for classification of soil type. This section is important as it defines the evidence used to verify that the association between landform and soil type is present and that in this area the measure of landform is sufficient to explain the soil types present.

Models are defined as "selective approximations which, by the elimination of incidental detail, allow some fundamental, relevant or interesting aspects of the real world to appear in some generalized form" (Chorley and Haggett, 1967, p.23). One fundamental feature of a model is that its construction involves a highly selective approach towards information content. Most models in geography seek not only to eliminate noise but less important signals as well.

Models are constructed so that the variables selected are retained as they contribute to an overall view of an underlying structure or pattern which may not be otherwise apparent. In this respect models are often thought of as "pattern seeking" (Chorley and Haggett, 1967). Chorley and Haggett point out that the pattern-seeking nature of models leads to an inherently suggestive quality. The authors point out that this suggestive nature leads the investigator to some greater insight, this implies that the model structure has greater implications than the study of the component parts (Chorley and Haggett, 1967).

Huggett (1975) proposes two different, but partly complementary, means of modelling the soil system. The first approach is to implement an isomorphic model so that every variable in the system is an element in the model. The alternative approach is a homomorphic model. A homomorphic model groups or combines variables to form a single element. Huggett states that the homomorphic model is the most appropriate model because it views the soil system from a macroscopic (general structure) perspective rather than focusing on detail.

The principal difficulty encountered with this type of research approach is defining model parameters. In the soil system, variables change in response to many different spatial and temporal dimensions. Soil properties vary not only in space but also through time, and often respond rapidly with the level of soil conservation practised (Huggett, 1975; Gregorich and Anderson, 1985). Traditionally these conditions have made the parameterization of isomorphic soil type models impractical, if not impossible (Huggett, 1975).

A method for determining homomorphic model parameters is to look at existing studies that have attempted to classify the relationship between topography and soil distribution with the use of DEMs (Pennock *et al.*, 1987; Lee *et al.*, 1988). These studies found an association between landforms and erosional or depositional elements in the landscape. The variables that are common to all of these studies are the first and second derivatives of elevation (slope and curvature). The usual approach to classification of landform in these studies is based on the heuristic classing of the groups in a GIS (Moore *et al.*, 1993).

Traditional methods of landform classification are often based on the field experience of the person doing the classification (Dalrymple *et al.*, 1968; Young, 1972;

Pennock *et al.*, 1987; Pennock and DeJong, 1987, 1990; Martz and DeJong, 1987, 1991; Martz, 1992). A more recent approach to landform classification is based on using frequency-based contextual classifiers. These classifiers use frequency counts of classed morphometric parameters calculated from neighbourhoods. These counts are then used in a discriminant analysis to classify landforms (Schmid-McGibbon, 1993). This technique is different from traditional landform mapping techniques because it is statistically based and is replicable.

Extraction of the Geometric Signature

The selection of appropriate variables to be input into a classification model is the most important step in the classification procedure. Geomorphometric measures derived from DEM's are at the foundation of the automated classification of geomorphic surfaces. The process most commonly used for the extraction of these variables is neighbourhood processing. Neighbourhood processing involves the roving of an odd-number sized window through a grid of elevations. As the window is moved to each successive position, parameters are calculated and assigned to the location of the centre cell of the window in a new convolved data set.

Differential calculus is the study of rates of change. Using the method of finite difference calculus developed in mathematics it is possible to derive useful information from DEMs. There are several different methods for the calculation of the derivatives of elevation. Evans (1972) suggests that analytically calculating the derivatives from fitting a third order polynomial to a three-by-three matrix is the most appropriate method. This analytical approach to calculating the derivatives has been widely implemented (Franklin, 1987; Zevenbergen and Thorne, 1987). The other method involves finite differences from calculus. There are two different numerical methods for calculating derivatives using finite differences. The first method is a direct application of finite difference calculus and involves the vector sum of the partial derivatives in X and Y (Eyton, 1991). This method is often referred to as the four nearest neighbour approach. The other method uses the eight neighbours in a 3 by 3 matrix and a weighting to account for the different distances between the centres of the cells. The difference between cells along rows or columns is 1 while the difference on the diagonal measures is $\sqrt{2}$ (Eyton, 1991).

The first derivative of elevation describes the rate of change of elevation, or the slope of the landform. Slopes are easily calculated from DEMs, as a DEM represents a systematic sample of the continuous landscape. Slope is the fundamental measure of landscape classification indices. Slope steepness, which determines the intensity of the shear stress acting upon a surface, is the controlling factor on such processes as soil erosion, runoff, and soil creep. Slope, therefore, defines the direction and magnitude of geomorphic work (Strahler, 1956).

Second derivative measure of elevation, the rate of change of slope, represents the curvature of the landform. This measure defines the convex, concave, and straight segments of the landform. To avoid directional bias associated with the computation of the second derivative in the row and column direction, as proposed by Pike (1988), the second derivative is calculated in the direction of maximum slope and then orthogonal to the down slope measure. This technique, therefore, yields two useful measures of curvature: one down-slope and the other across-slope (Eyton, 1991).

Hodgson (1995) tested the accuracy of the different methods of calculating the derivatives and found that the method based on the correct application of finite difference calculus gave the best estimate of the slope. Although Hodgson did not directly test the method proposed by Evans (1972) of fitting a third order polynomial, tests have shown that this method is similar in accuracy to the computation of the derivatives using the eight neighbours. The method of calculating the derivatives of elevation, using finite difference calculus, proposed by Eyton (1991) was implemented in this work using TERRA FIRMA (Eyton, 1992).

The next step in the process is to class the individual maps. There are two reasons for classing the derivative measures: 1. the process of homomorphic modelling requires that the model variables are grouped into functional elements; 2. the second reason for using classed maps is that they provide a macroscopic (general structure) perspective rather than focusing on incidental detail. The result of this approach is that the class selection for the maps is the most important variable.

In this thesis the approach that was used was to find a number of different methods of classing slope, and the two curvatures (across-slope and down-slope curvature). The result of this study indicates that there is one common method of representing measures of curvature while there is a great deal of variation in the method of classifying slopes. A general interpretation of landform curvature classification has been presented by Young (1971), where curvature classes are based on degree of curvature per 100 metres.

The classification of slopes into functional units is dependent on the environment where the slope classification was developed (Dalrymple *et al.*, 1968). Measures of curvature are more general in nature and are not seen as limiting factors in the landscape. Given this fact, the slope classification implemented was suggested by the Expert Committee on Soil Survey (1987). Figures 4.1, 4.2, and 4.3 are the classed maps of the

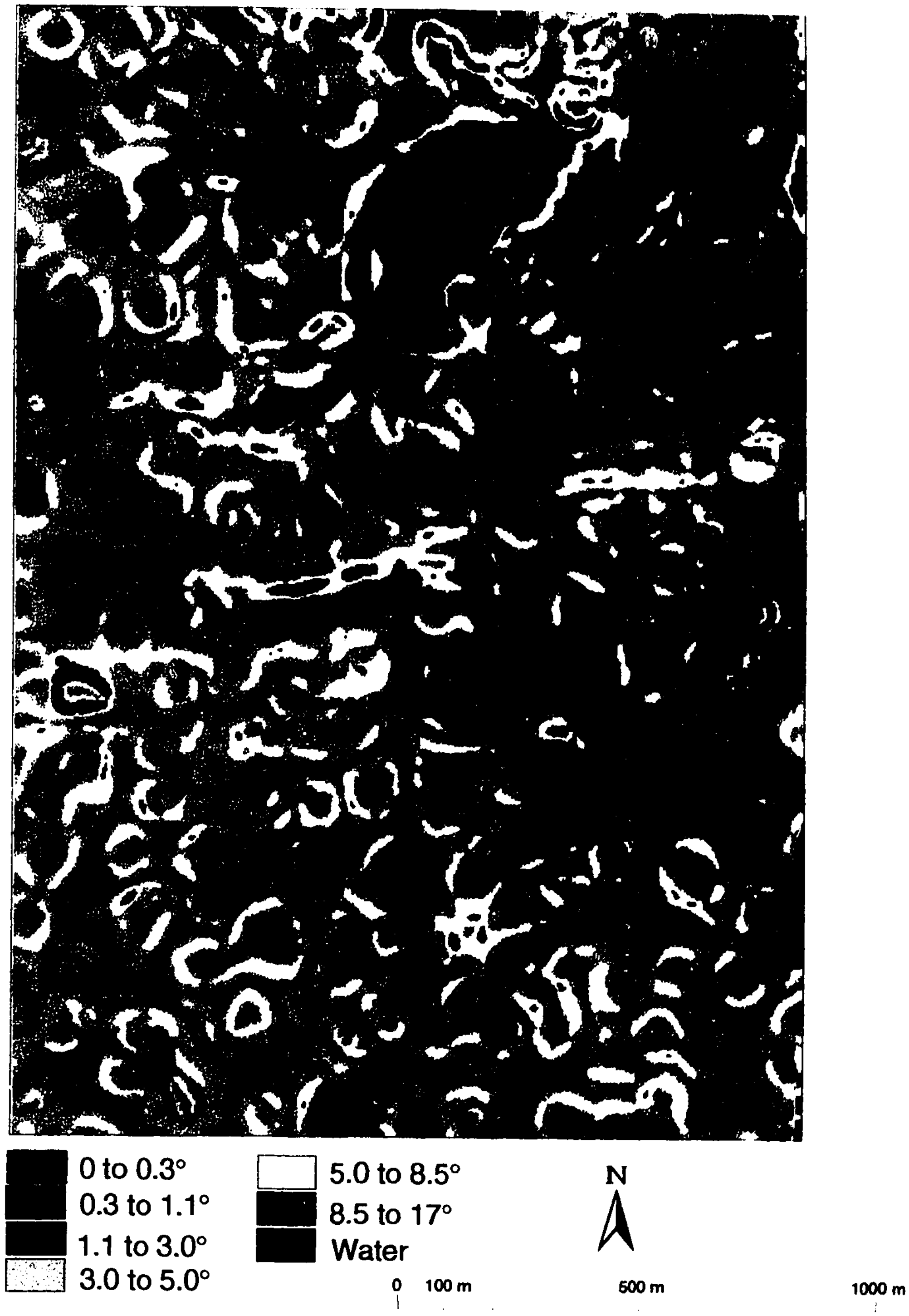


Figure 4.1. Slope Map.

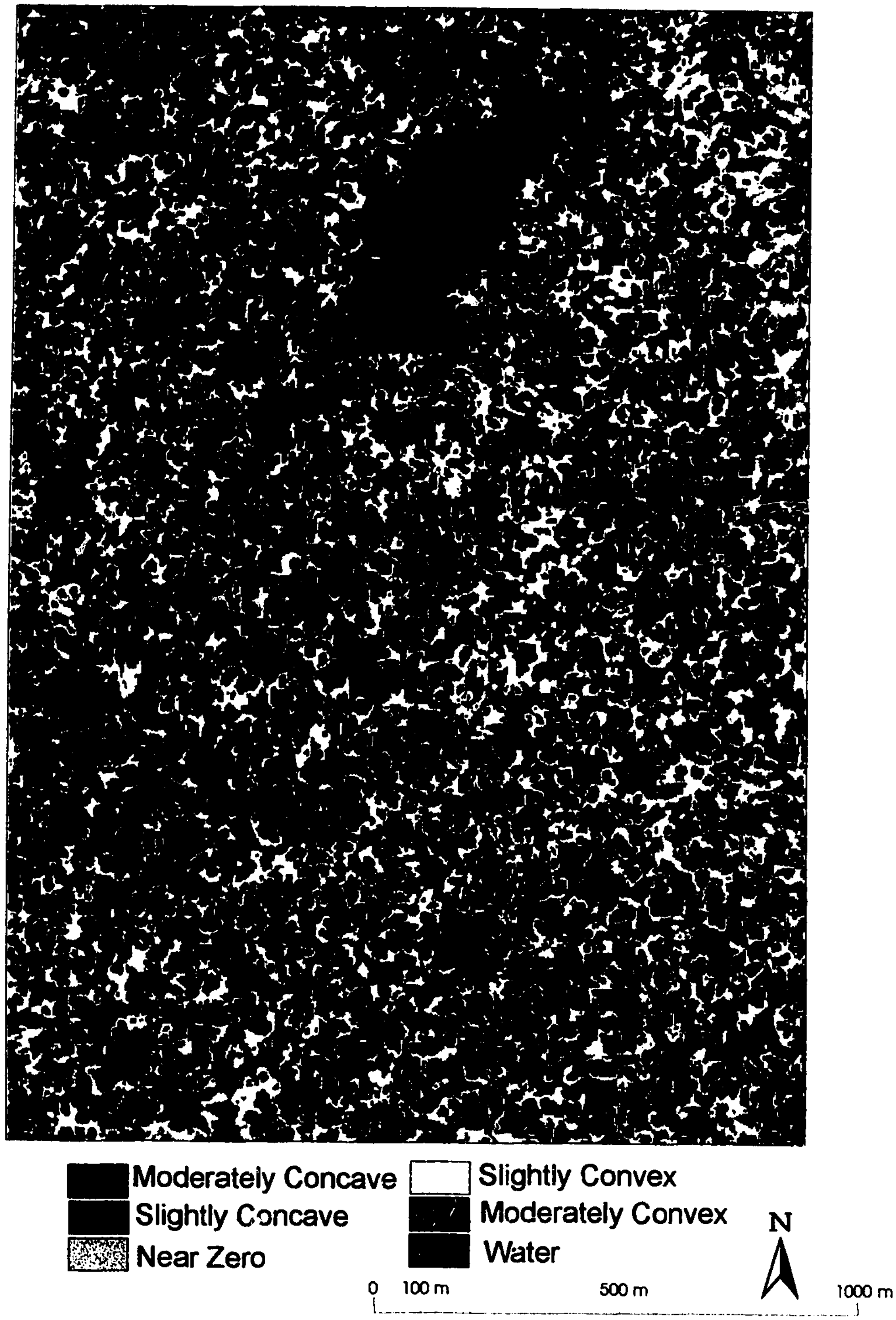


Figure 4.2. Across-Slope Curvature Map.

Figure 4.3. Down-Slope Curvature Map.

derivatives of elevation. Theses figures show that all of the mapped classes display significant spatial continuity. Figures 4.4, 4.5, and 4.6 are the histograms of each of the classed maps. It is important to check if the distributions of the variables meet with current understanding of the nature of the distributions. Figure 4.4 is the histogram of slope classes. The histogram shows that slope, in this environment, is as expected with the largest frequency of slopes from 1.1 to 5.0°. The interpretation of the two curvature histograms shows what is expected. The distribution of curvature, either across slope or down slope, should be somewhat bimodal. The reason for this is that there are few natural features that display any flatness.

The other important consideration is the independence of the variables. Before any classification is undertaken it is necessary to check that the data input into the classification procedure is measuring different parameters (Evans, 1972; Weibel and DeLotto, 1988). This at first glance seems obvious; however, since the data have been classed it is a necessary procedure. In order to check for independence, principle components analysis (PCA) was implemented. The objective of PCA is to reveal a simple underlying structure present in a set of multivariate data. The structure in the data is expressed in the pattern of variances and covariances between the variables and the similarity between observations. In this analysis it is important to make sure that the data are not inter-correlated and are therefore representative of different features (Davis, 1986).

In this case PCA analysis provides two useful tools for interpretation. The first is the correlation matrix, shown in Table 4.1a; the correlation matrix shows the strength of relationship among the variables. This table shows that there is little correlation among the variable with the highest coefficient of correlation being $r = 0.5527$ for variable 2

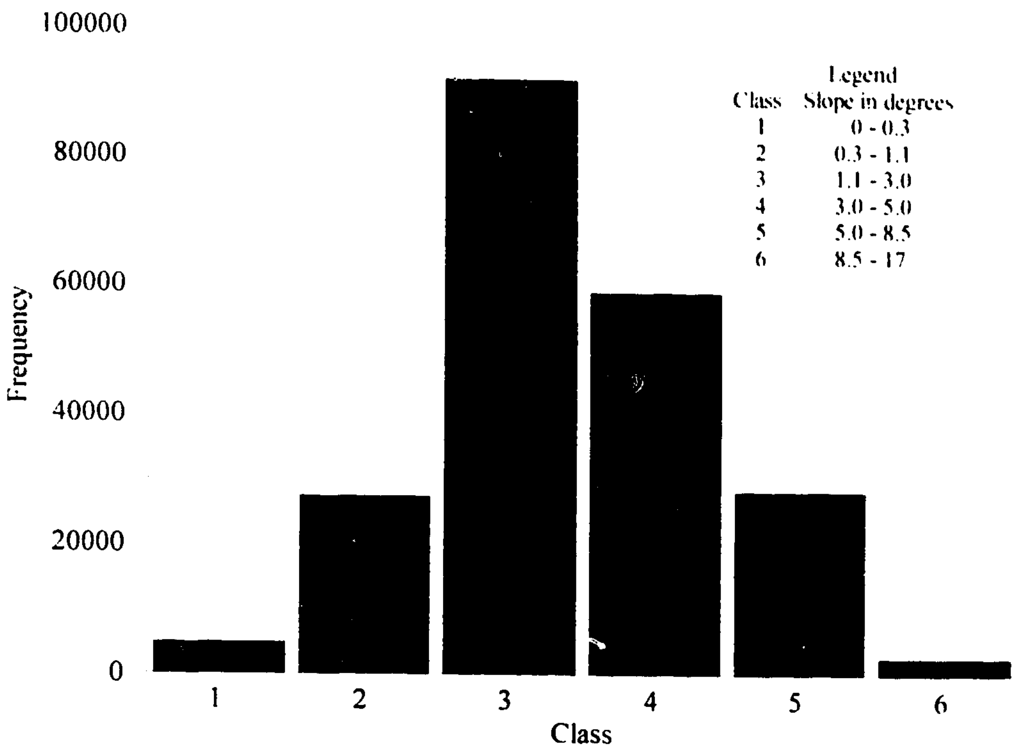


Figure 4.6. Histogram of Slope Distribution.

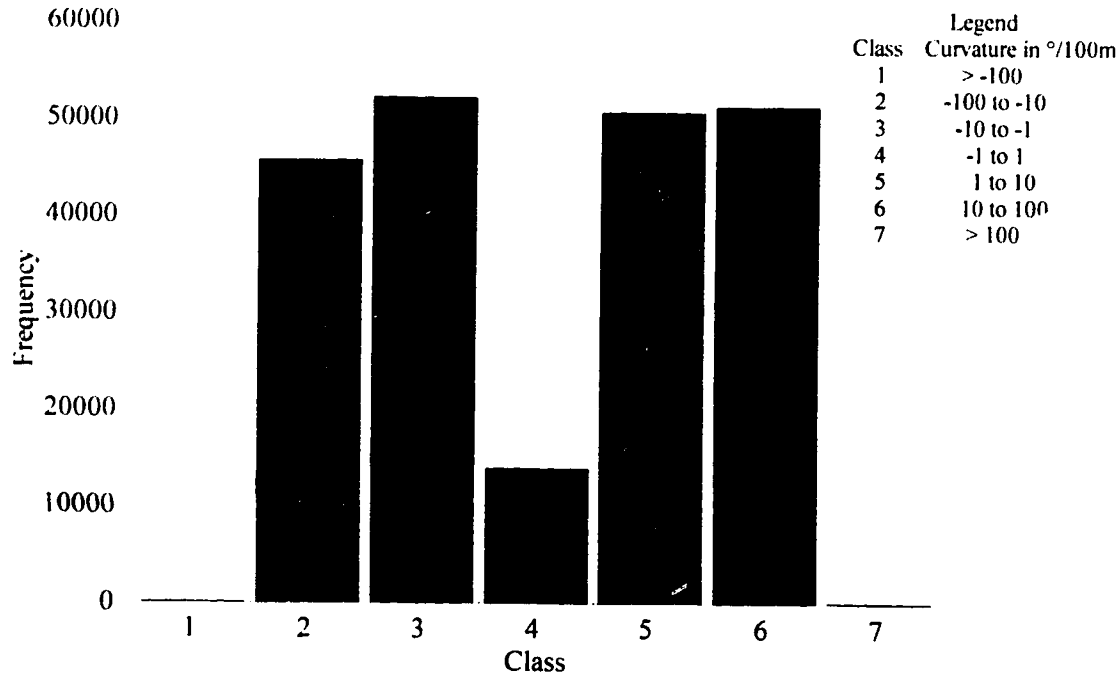


Figure 4.6. Histogram of Across-Slope Curvature Distribution.

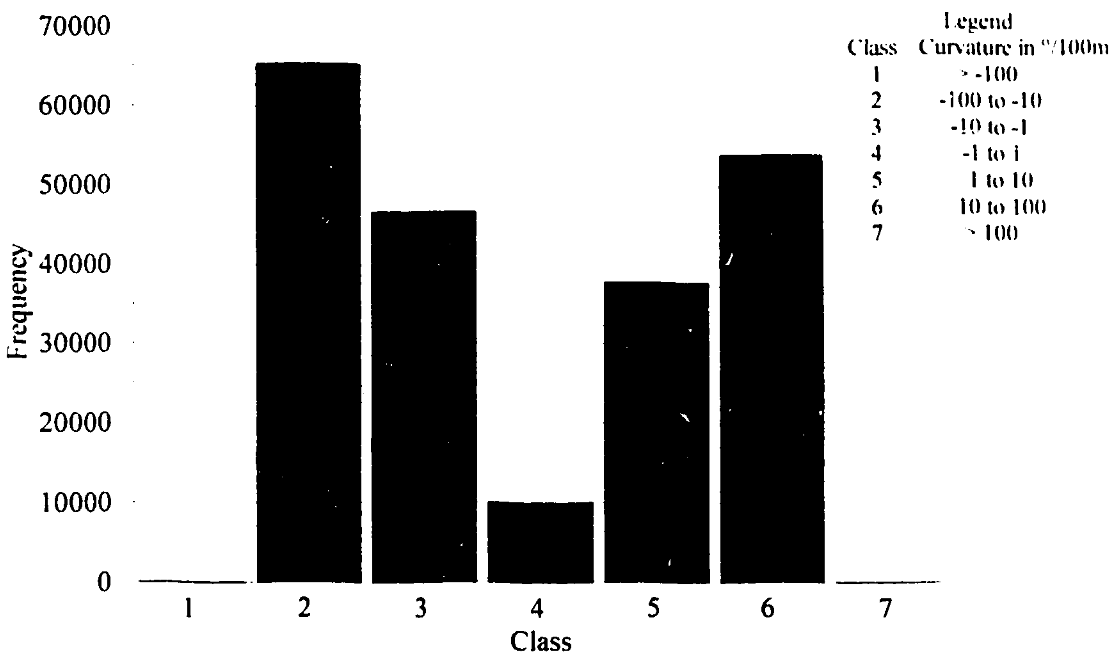


Figure 4.6. Histogram of Down-Slope Curvature Distribution.

Table 4.1 A and B. Results of PCA.

A. Correlation Matrix:

	1	2	3	Labels:
1	1.0000	0.3082	0.0233	1=Slope
2	0.3082	1.0000	0.5527	2 = Across Slope Curvature
3	0.2331	0.5527	1.0000	3 = Down Slope Curvature

B. Eigenvalues:

	Eigenvalue	Variance Explained
PC1	1.7489	0.583
PC2	0.8104	0.2701
PC3	0.4407	0.1469

versus 3 which explains 30.54% of the total variance (r^2). Table 4.1b shows the eigenvalues and the variance explained by the eigenvalues. An eigenvalue is the measure of the length of each component.

In PCA each of the components is plotted orthogonally to all other components; therefore, the interpretation of the length of the components, as expressed by the eigenvalue, can explain the strength, or lack thereof, of the correlations. For example, if the first and second principle components are approximately the same length, then the ellipse that could be drawn to describe the two components would be circular. This would show that there was little correlation between the two components and the variables are therefore measuring different features (Davis, 1986). In Table 4.1b, the eigenvalues do show some correlation, but the correlation is weak. From this it was concluded that the variables used as inputs into the classification procedure were measuring different aspects of the geometric signature.

Classification of Geometric Signature

The classification of geometric signature is based on the image classification techniques used in the field of remote sensing. The concept of a spectral signature states that the spectral response of a feature is sufficient to accurately distinguish different targets. The classification of features in remote sensing is conducted through the use of statistical classifiers. The training fields are areas where data are collected to build statistical classifiers. There are two basic approaches to the selection of training fields, supervised and unsupervised.

Supervised training field selection requires that the analyst select areas where data are gathered to develop classification functions. The analyst, therefore, defines useful classes and then examines their statistical separability. This technique requires a thorough knowledge of the geographic area and substantial reference data to which the data apply (Lillesand and Kiefer, 1987).

In the unsupervised approach, the number of legend categories or classes is not known *a priori* but, rather, cluster analysis is used to find natural groupings. Using this approach to training field selection, the classifier identifies the distinct classes present in the data. The classes are based on statistical separability (natural groups) and their information utility is defined *a priori* (Lillesand and Kiefer, 1987).

There are several approaches to sampling data in unsupervised training field selection. The method implemented by TERRA FIRMA (Eyton, 1992) consists of two procedures: a systematic sampling design where the analyst selects the sampling effort, and cluster analysis to determine the optimal number of natural groupings in the data. The method for defining an appropriate distance to sample the data at is often arrived at through experience and has no real quantitative validity. The approach used in this thesis was to sample the data at the same distance interval (lag) used to model the semivariance. This distance was 40 metres, therefore, the images were sampled every 10 rows and every 10th pixel along the row. This resulted in a data set with 2280 observations.

There are numerous clustering algorithms that can be used to determine the natural groupings in a data set. The clustering method used by TERRA FIRMA is called the K-means approach. Using the K-means approach the analyst defines the initial number of clusters (k); these clusters are then designated as initial "centroids" of clusters. A matrix of similarities between the k centroids and the n observations is calculated; the observations are then assigned to the cluster whose arbitrary mean vector is closest. After all of the observations have been placed in clusters, new centroids for the k points are calculated and the process iterates until there is little change in the location of the centroid positions (Davis, 1986).

Further analysis of the nature of the variance gives an indication of the optimal number of clusters or groups that exist in the data set. One method of determining the optimal number of groups based on variance measures is a plot of the f-ratios. The plot of the f-ratios shows how the value of the f-ratio changes with the number of clusters (Figure 4.7). An f-ratio is defined as: $F = \dfrac{\text{between group variance}}{\text{within group variance}}$. Optimal groupings for cluster analysis occur when the within-group variance is minimized and the between-group variance is maximized (Johnston, 1991). This means that there is more "distance" between the groups or clusters than the intra-group distances. When this situation occurs the plot of the F-ratios increases towards an optimal solution, then drops sharply as a sub-optimal condition occurs. Figure 4.7 shows that optimal solutions occurred at 9 and 11 groups.

It is possible to have more than one optimal grouping because, by definition, cluster analysis is meant to indicate natural groupings in the data set. Natural groupings, in this case, are a function of the level of generality imposed on the data. For example, if 9 was selected as the optimal number of groupings, the output would be a relatively generalized map. If there is any inherent structure within these 9 groups you could select 11 or any other higher numbered optimal solution will yield a more complex classification (Davis, 1986).

While cluster analysis defines the optimal number of natural groups present in the data, it does not define the relationship between the groups. There is a wide variety of multivariate statistical techniques that can be used to define this relationship (Lillesand

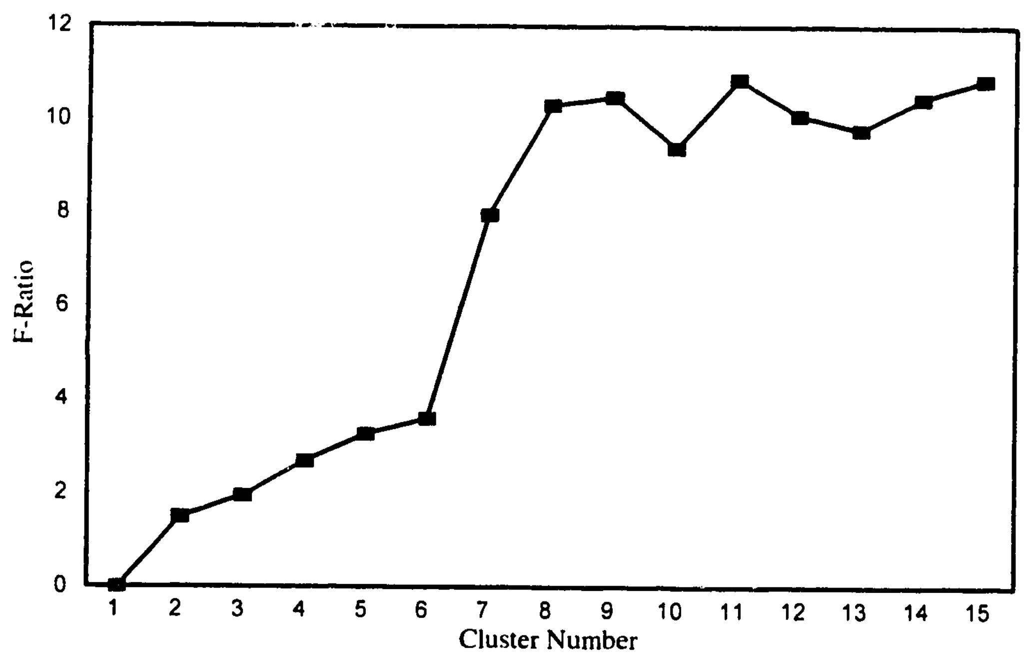


Figure 4.7. Graph of F-Ratios Versus Cluster Numbers.

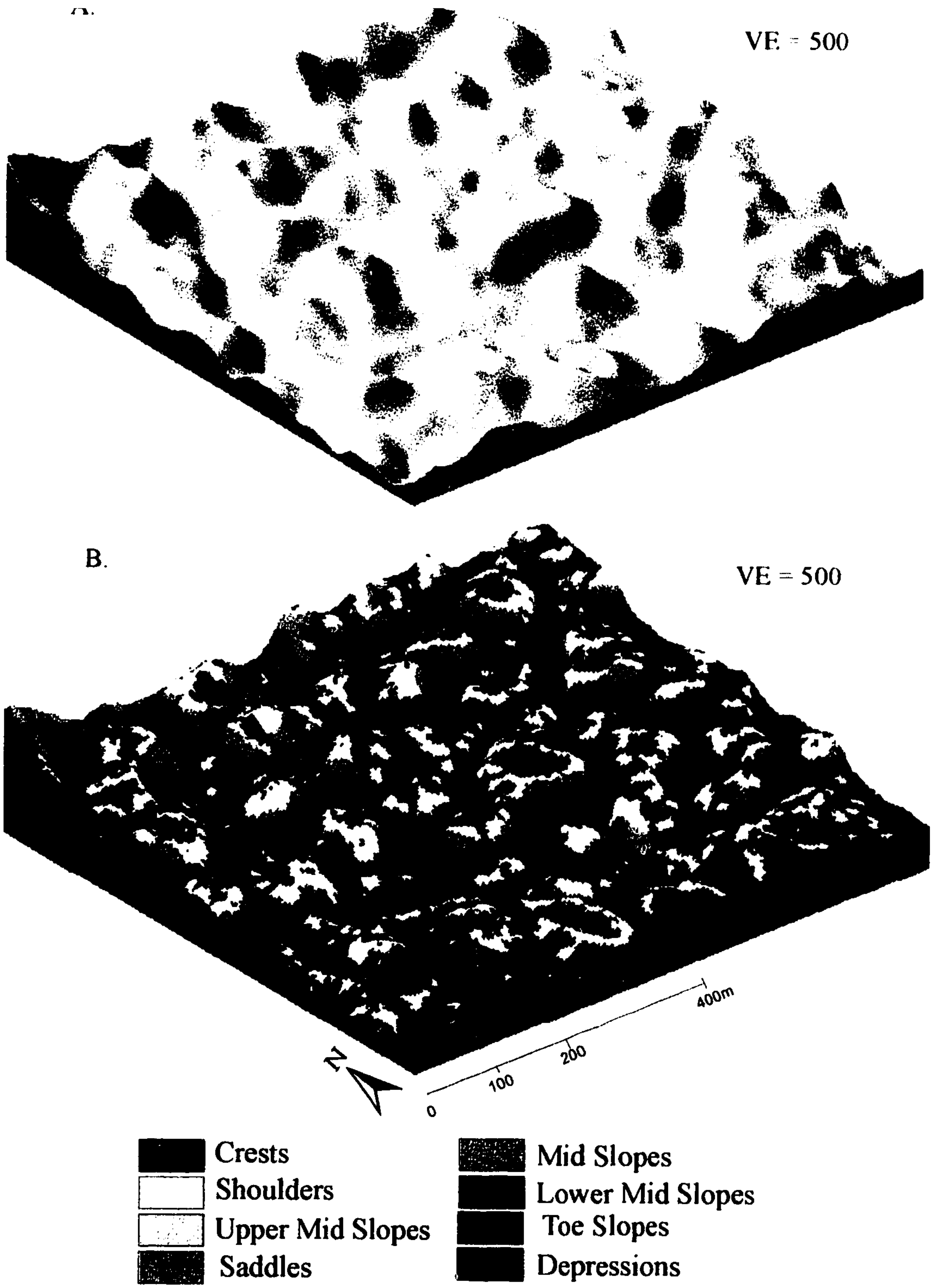
and Kiefer, 1987). The CLASS module in TERRA FIRMA (Eyton, 1992) was used to develop discriminant analysis classification functions. Discriminant analysis is a powerful multivariate technique that is often used to discriminate between two or more classes. Discriminant analysis finds rules or classification functions that partition data space to classify all other unclassed data (Davis, 1986).

The result of the discriminant analysis classification is a map that represents the optimal number of landform classes in the area based on the shape signatures that were extracted from maps of slope, across-slope curvature and down-slope curvature (Figure 4.8). The last step in the procedure is to develop a post-classification legend so that the classes have meaningful names. The area outlined in Figure 4.8 is shown as a series of perspective plots in Figure 9. Figure 4.9a is the hillshade ɩped over the DEM while Figure 4.9b is the landform classification draped over the DEM. It is useful to view the landform classification as a perspective plot in conjunction with the hillshade perspective plot as it shows the relationship between the landform as seen in the hillshade and the classification. Using this plot meaningful names were given to the classes.

Soil Classification

The objective of the field phase of the project was to classify the soils present in the area. Using the 1:250 000 soil map sheet 83-H the soil associations were identified. The soil association information is valuable as a tool to assess the probable mix of soil types at a higher level of soil mapping. In the study area the only difference in the soil associations is the mix of two components (Figure 3.3). This difference is a reflection of the differing mix of landforms in the area.

Figure 4.8. Map of Geometric Signature Classification .



'igure 4.9. Legend Category Development.

The 1:250 000 soil map indicates that the parent material from which the soil was developed is glacial till. Field observations and laboratory analysis indicate that the surficial deposit present is not a till but rather a glacial lacustrine deposit. By definition tills are unstratified and unsorted, consisting of clay, sand, gravel and boulder-sized particles in any proportion. The sediment sampled in the area consists of well-sorted silt-sized particles. There were no boulders or gravel-sized particles present in any of the study sites. Therefore, the sediment was most probably deposited by water in a glacial lake. It is possible that the lacustrine deposits have been deposited over top of till at a depth greater than 120 cm (the maximum depth that was sampled). In this case there would be little difference in the soil types that formed on the lacustrine deposits.

Using the Canadian System of Soil Classification (CSSC) the samples were then classified. The CSSC uses a number of different diagnostic criteria specific to the soil order. In the CSSC there are three different levels of soil description. The highest level of generalization is the soil order; soil orders are then broken down into great groups, and the great groups are then further subdivided into subgroups. Soils are most commonly mapped at the association level, a level of generalisation not defined in the CSSC. Soil associations are mixes of subgroups where the terminology is specific to geographic location rather than taxonomic differences.

The level of soil mapping used in this study was the subgroup or soil-type level. The 1:250 000 soil map of the area defines the soil great group, soil order, and soil associations in the area. The soil association information indicates the range of expected soil types that can be found in the area. Table 4.2 is a list of the CSSC diagnostic criteria for the four soil types found. Using these criteria the samples were classified. Appendix

1 is a table of the data collected and used to classify the soil types. Appendix 1 is a table of the data collected and used to classify the soil types.

Summary

This chapter presented the methodology used to classify landforms based on geometric signatures. Traditional methods of landform classification are based on the field experience of the researcher doing the classification (Dalrymple *et al.*, 1968; Young, 1972; Pennock *et al.*, 1987; Pennock and DeJong, 1987, 1990; Martz and DeJong, 1987, 1991; Martz, 1992). Pike and Rozema (1975) conceptualized the geom[illegible]gnature as a set of measurements that abstracts the essential shape of each type of topographic surface and distinguishes it uniquely from other surfaces. In this study, geomorphometric measures derived from DEMs were used to classify landforms. The last section of this chapter describes the method used for the classification of soil type. The soil classification was used to verify that the association between landform and soil type is present and in this area the classification is sufficient to explain the soil types present.

Table 4.2. Soil Types and Diagnostic Criteria.

Soil type	Diagnostic criteria
orthic black chernozem	B-horizon at least 5 cm thick and lacks alkaline earth carbonates. Lacks an Ae horizon at least 2 cm thick and shows no evidence of gleying within 50 cm of the surface.
eluviated black chernozem	Ae horizon greater than 2 cm thick. Weakly to moderately illuvial Btj or Bt horizons.
calcareous black chernozem	Weakly developed B horizon that contains alkaline earth carbonates (Bmk).
gleyed black chernozem	Faint to distinct mottles within 50 cm of the surface.

Source: Agriculture Canada Expert Committee on Soil Survey, 1987.

CHAPTER 5

ANALYSIS

The purpose of this chapter is to test the hypothesis that there is a relationship between soil type and landform and that the relationship can be characterized as a function of terrain derivatives. In this study several different types of data have been collected. It is therefore necessary to use several statistical techniques to analyse the nature of the various relationships. The significance level used to distinguish significant from non-significant relationships is 0.001. This conservative level was selected as the qualitative relationship between soil type and topographic position is well defined. If the relationship can be quantitatively measured then the same strong relationship should exist.

Statistical Testing of Sediment Particle Size Distribution

At the foundation of all modelling experiments are a number of base assumptions. The conceptual model of soil formation indicates that a soil is a function of climate, time, organisms, relief and parent material (Jenny, 1941). At the spatial resolution involved in this study, it is reasonable to assume that the climate, time and organisms are constant. Therefore, the only influential variables are topographic relief and soil parent material. When possible, all assumptions should be tested to ensure that the assumptions made are valid.

Statistical testing was conducted to verify that the sediment samples were drawn from the same population. As the data are not normally distributed the usual method of testing for a significant difference, analysis of variance (ANOVA), is statistically invalid. The non-parametric equivalent of an ANOVA is the Kruskal-Wallis H-test. The K-W

H-test is designed to determine whether there is a significant difference among three or more samples. The H-test assumes that the underlying variable has a continuous distribution, and requires at least an ordinal level of measure. The null hypothesis is that the data are from the same population (Ebdon, 1990).

Figure 5.1 is the log/normal graph of sediment size versus percent weight in the fraction as measured by the Sedigraph 5100. This distribution shows that the majority of the sediment samples are in the silt fraction (62.5 to 1μm). The samples are composed of glacio-lacustrine sediment and not glacial till. The results of the K-W H test revealed a value of the H statistic (corrected for ties) of 5.8717 with 24 degrees of freedom. The relationship is significant at the 0.001 level. The samples are, therefore, from the same population. The within-group differences that are evident in Figure 5.1 are not related to geographic position, but rather to the error associated with the Sedigraph 5100 in the silt fraction as described in Chapter 3.

Classification Accuracy

In this study, two types of analysis are necessary to test the hypothesis that soil types are a function of topographic shape. The first measure is an estimate of classification accuracy; the other necessary measure is map accuracy. These two measures are not often undertaken. Measures of classification accuracy based solely on the training field data are usually calculated at the time of the classification procedure and many observers report this measure as a means of map accuracy. What this statistic measures is the accuracy of the classification and has little to do with the accuracy of the map. The usual method of assessing classification accuracy is a measure called overall correct classification. Table 5.1 shows the classification confusion table with an overall

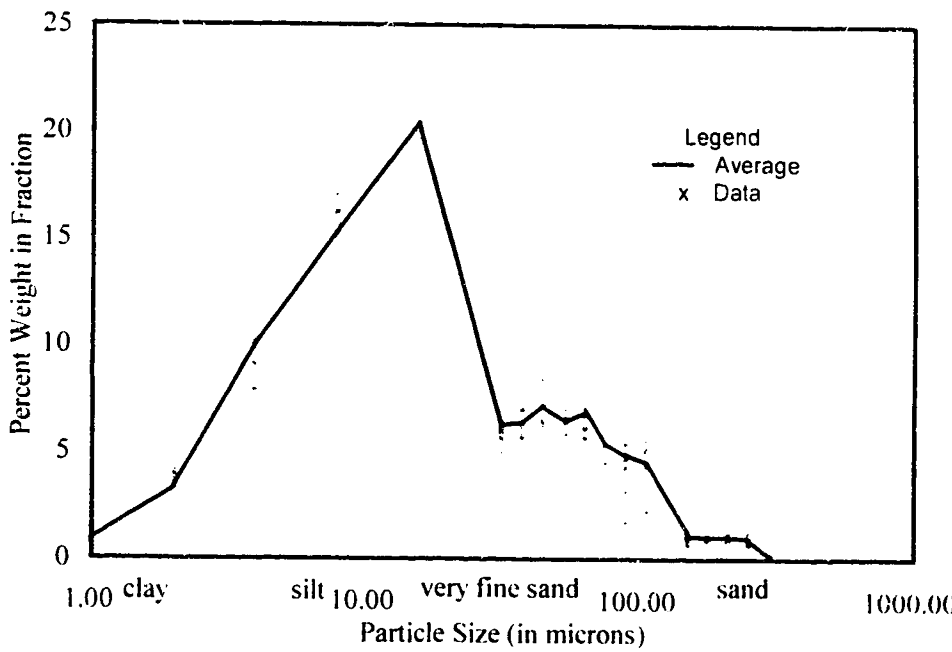


Figure 5.1. Particle Size Analysis.

Table 5.1. Confusion Table (%).

	Lower Mid-Slopes	Depressions	Crests	Saddles	Mid-slopes	Upper Mid-slopes	Water	Shoulders	Toe Slopes
Lower Mid-Slopes	100	0	0	0	0	0	0	0	0
Depressions	0	97.33	0	2.67	0	0	0	0	0
Crests	0	0	100	0	0	0	0	0	0
Saddles	0	0	0	100	0	0	0	0	0
Mid-slopes	0	0	0	0	98.73	1.27	0	0	0
Upper Mid-slopes	0	0	0	0	0	100	0	0	0
Water	0	0	0	0	0	0	100	0	0
Shoulders	0	0	0	0	0	0	0	100	0
Toe Slopes	0	0	0.37	0	0	0	0	0	99.63

OVER-ALL CORRECT CLASSIFICATION = 99.30 %

correct classification of 99.3%. A confusion table is a measure of Mahalanobis distance. The number of misclassifications is calculated by counting the number of observations closer to another group's mean (or centroid))than to their own (Davis, 1986).

Table 5.1 also indicates the areas of confusion as areas of misclassifications as a percent of the pixels that may have been misclassified. The following groups show some degree of misclassification: depressions, mid-slopes, and toe slopes.

The group classified as depressions showed 2.67% confusion with groups that were classified as saddles. This can be explained as these two areas have similar characteristics in across-slope and down-slope curvature and are mainly discriminated based on magnitude of slope. In this case, the depressions have low slopes while the saddles have medium slopes.

Mid-slopes were confused 1.27% with upper mid-slopes. These two landforms are similar in many respects with the upper mid-slopes having a greater degree of down-slope curvature. The last group that showed confusion was the toe slope group. Toe slopes were confused 0.37% with crests. This is explained as toe slopes are located at the base of hummocks and have a low slope and little across-slope curvature and some down-slope curvature. As a functional description, this shape this differs little from the description of crests. Crests differ from toe slopes by having a greater degree of across-slope curvature. If shape alone is considered, toe slopes could be thought of as small size basal crests.

Map Accuracy

The sample sites involved in this study were surveyed using differentially corrected GPS points. These points were spatially registered to the DEM and, therefore, to the landform classification. Figure 5.2 shows the distribution of sample points overlaid on the landform classification. The map classification was checked by overlaying the vector GPS points on the landform classification map and recording the landform unit where the GPS point was recorded. The landform class information was then added to the table of soil attributes. The objective of testing is to ensure that the variability of the soil properties within mapped units is less than their variability in the soil landscape as stated by Beckett and Burrough (1971).

The hypothesis tested was:

H_0 = The two samples have come from a population in which there is no relationship between soil type and landform unit. The observed difference is merely due to chance in the sampling process.

H_1 = There is a real relationship in the population between soil type and landform unit.

Chi-square was the statistical technique used to test the strength of the relationship between the two distributions. The chi-square test is restricted to nominal (frequency) data and is non parametric. It is, therefore, an appropriate method of evaluating map data (Campbell, 1991). The significance level used to distinguish significant from non-significant relationships was 0.001.

Campbell (1991) suggests that an appropriate method for measuring the strength of association between two maps is the quadrat approach, where the maps to be tested are divided into areas and the class that dominates the area is recorded. This technique is

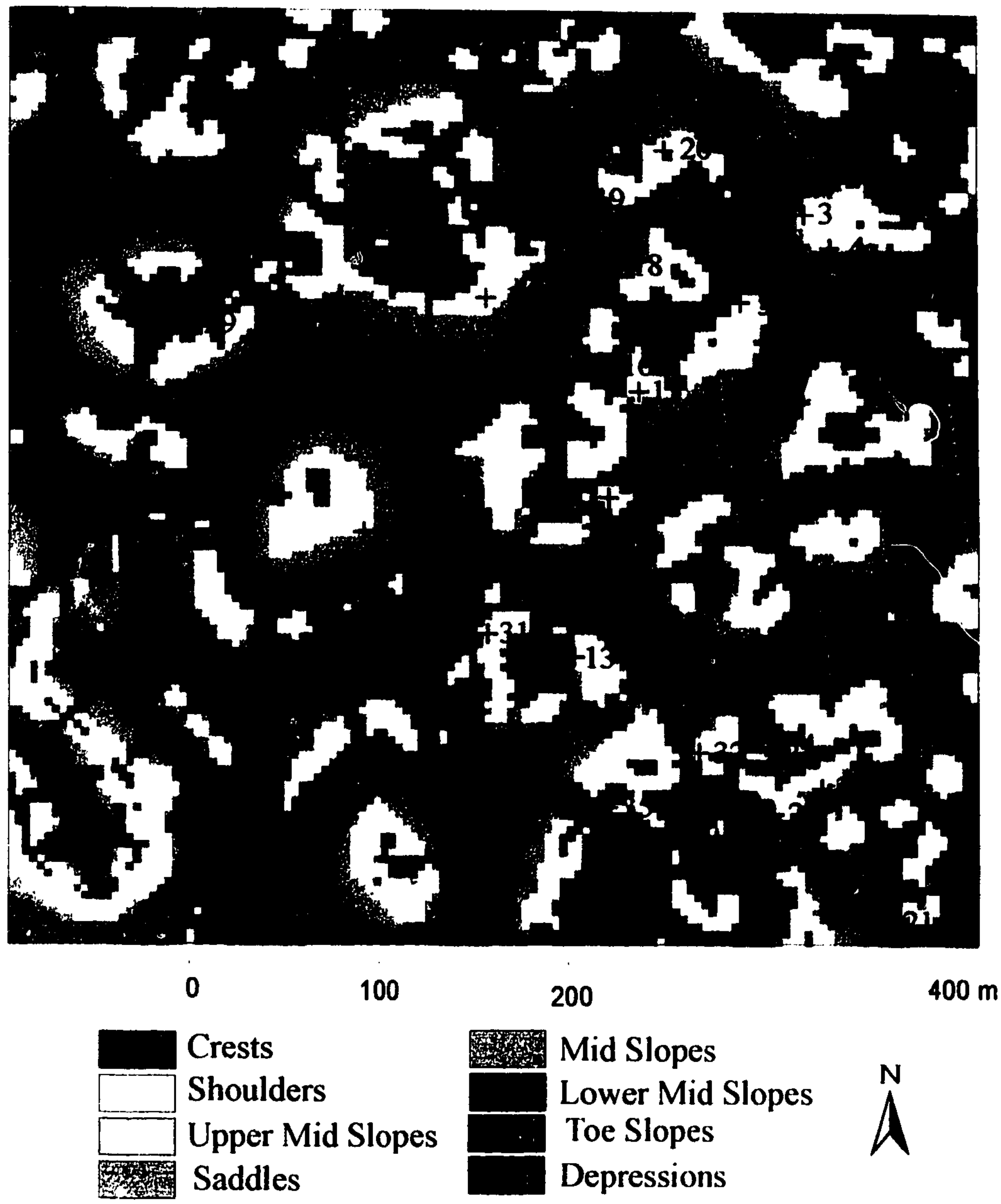


Figure 5.2. Landform Classification Subset With GPS Soil Survey Points.

analogous to taking a vector point, such as GPS data, and converting it into raster data. This was the technique used to place the GPS surveyed point in the correct pixel on the landform classification.

The GPS data points were differentially corrected using Trimble Navigation's PFINDER software. The PFINDER software performs differential correction on the input data and averages all of the corrected points. The base station used for the differential correction information is located in Red Deer, Alberta and is operated by Alberta Transportation and Utilities.

Out of the 35 sample sites, 2 (5.7%) fell between two pixels. The sample points were assigned to a pixel based on soil characteristics and landform position recorded in the field. For example, at one site the sample was taken on a slope shoulder. On the map, the GPS sample point plotted between a shoulder and a depression; therefore, the point was assigned to the shoulder class. This is a reasonable procedure as the error associated with the GPS points was ±2m. Therefore, with 4 m pixels if the point is moved ±2m it will move from the edge to the centre of the pixel.

The chi-square test compares the observed frequencies of a variable with a set of computed expected frequencies. In this test H_0 is rejected if the computed value of chi-square is greater than the critical value. In this study the critical value was 42.31 and the calculated value of chi-square is 51.547; therefore, H_0 is rejected at the 0.001 significance level. Therefore, the relationship between soil type and landform is significant.

What this statistic does not address is the strength of the relationship. In order to calculate the strength of the relationship Spearman rank correlation was calculated. Spearman rank correlation is a non-parametric version of the Pearson product-moment correlation. Spearman rank correlation is appropriate for ordinal or interval data that do not satisfy the normality assumption. The coefficient computed has a range from -1 to +1 where the sign of the coefficient indicates the direction and the value indicates the strength of the relationship. Figure 5.3 is a graph of the landform units versus soil types. The result of the correlation analysis was an r value of 0.87009. The correlation is therefore not only significant but strong and positive.

Summary

This chapter has demonstrated, through the use of several different statistics that the relationship between soil type and landform can be mapped for local areas based on the classification of landform. It has also shown that the assumptions used in the model were reasonable.

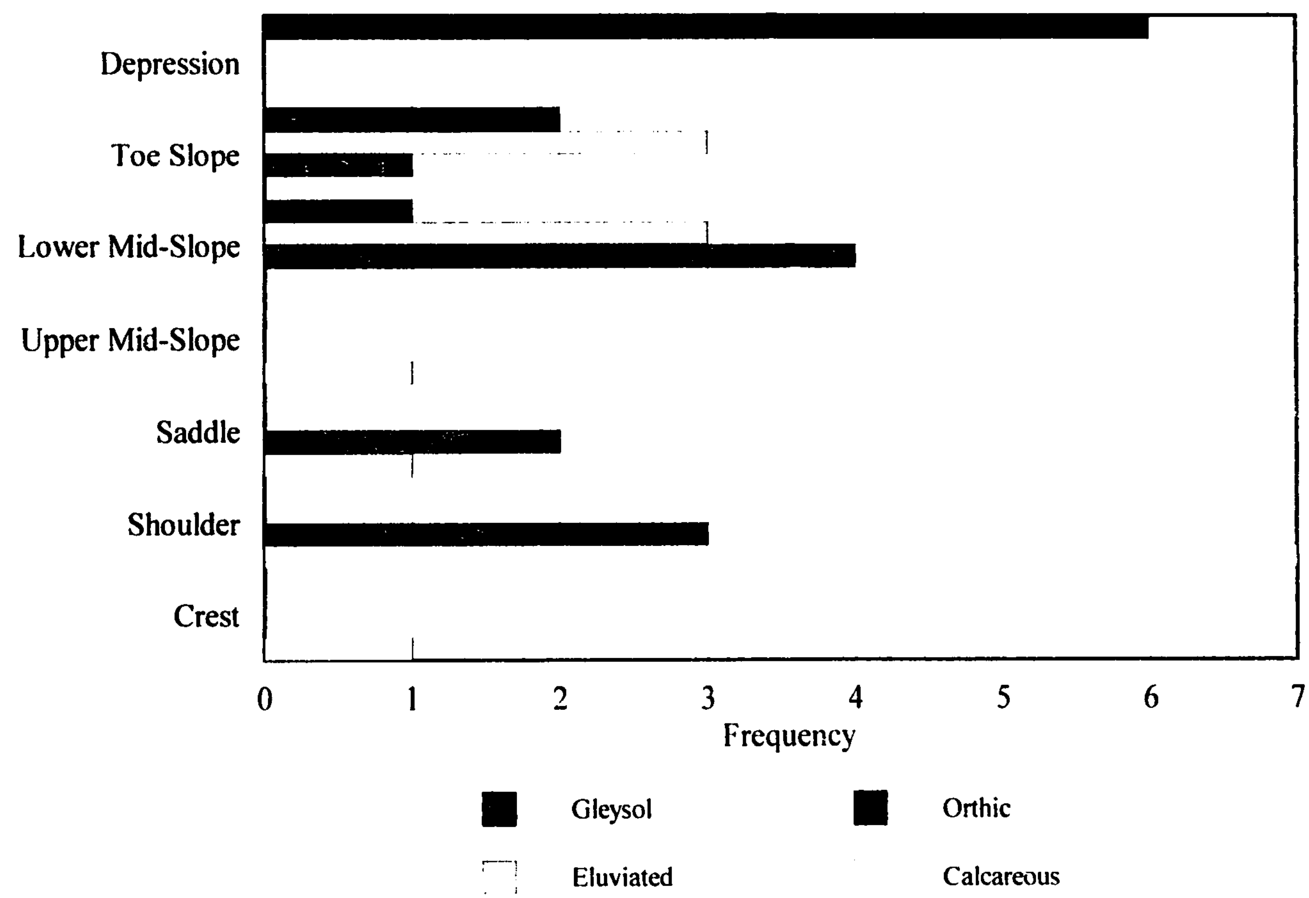


Figure 5.3 Landform Unit Frequency Plotted Against Soil Type.

CHAPTER 6

DISCUSSION AND CONCLUSIONS

Geographers are trained to divide the landscape into discrete units and visualize the interactions and processes affecting the landscape. Manual methods of soil mapping require tacit knowledge. Tacit knowledge is knowledge acquired through practice and experience. Interpreters who have acquired this type of knowledge usually cannot easily define the rationale for decisions used in the mapping process (Hudson, 1992). The development of automated landform mapping techniques will allow for the quantification and objective implementation of this type of geomorphic mapping.

The objective of this study was to map the relationship between soil and landform at a scale and resolution suitable for environmental modelling and site-specific farming. The current approach to high-resolution soil mapping is airphoto interpretation in combination with a grid survey. The result of this thesis is an automated mapping technique that allows for the accurate characterization of the soil landscape based on the relationship between soil type and landform.

In this study, geomorphometric measures derived from DEMs were used to classify and map landforms. Traditional methods of landform classification are based on the field experience of the researcher doing the classification (Dalrymple *et al.*, 1968; Young, 1972; Pennock *et al.*, 1987; Pennock and DeJong, 1987, 1990; Martz and DeJong., 1987, 1991; Martz, 1992). The method used to classify landform in this study was based on the concept of the geometric signature developed by Pike and Rozema (1975). Pike and Rozema (1975) conceptualized the geometric signature as a set of measurements that abstracts the essential shape of each type of topographic surface and distinguishes it uniquely from other surfaces.

An important consideration when conducting automated landform classification is the approach used to select training fields. Training field selection is important because the data gathered from training fields are used to build the statistical classifier. An unsupervised approach to training field selection was used in this research for two reasons. First, using this approach to training field selection, the classifier identifies the distinct classes present in the data. The classes are based on statistical separability (natural groups) and their information utility is defined *a priori* (Lillesand and Kiefer, 1987). The second reason for the selection of this approach to training field selection is that this approach is unbiased. The structure in the data is, therefore, not forced by the researcher.

Measures of classification accuracy based solely on the training field data are usually calculated at the time of the classification procedure and many observers report this measure as a means of assessing map accuracy. What this statistic measures is the accuracy of the classification and has little to do with the accuracy of the map. In this study the overall correct classification was 99.3%. This statistic measures the degree of statistical separability in the data. Therefore, the landform classes were statistically well defined.

The most often overlooked measure in studies of this type is map accuracy. In this study, map accuracy was assessed using the soil type data surveyed using GPS and overlaying these points on the landform classification map. The landform class information was then added to the table of soil attributes. The relationship between these data was then analysed using a combination of Chi-square to test for a significant relationship at the 0.001 significance level and Spearman rank correlation to test the strength of the relationship. The Chi-square test showed a significant relationship between soil type and landform. The result of the correlation analysis was an r value of 0.87009 which indicates that the relationship between soil type and landform is strong and positive and landform explains 75.7% of the total variance (r^2) in the soil type classes.

The results of this study indicate that there is a strong correlation between the landform units that were derived from the classification procedure and the soil types that were surveyed in the field. This technique should prove useful in soil mapping and other forms of mapping that require some form of landform analysis. This procedure is an improvement over the traditional methods as it provides an unbiased and replicable technique for mapping landforms.

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Appendix 1.

Sample #	1	2	3	4	5	6	7	8	9
A Horizon	63.500	30.480	25.400	12.700	17.780	30.480	63.500	30.480	43.180
C Horizon	91.440	120.000	88.900	78.740	73.660	120.000	120.000	91.440	88.900
Dish Weight (g)	2.184	2.191	2.208	2.182	2.194	2.202	2.199	2.199	2.195
Moist Soil + Dish (g)	67.670	50.896	81.620	88.020	62.720	85.780	84.540	67.290	65.220
Oven Dry Soil + Dish (g)	56.769	43.051	69.580	75.450	54.438	71.040	68.490	56.888	54.297
% H2O	16.646	16.107	15.161	14.644	13.683	17.636	19.492	15.981	17.331
Weight of Sample	8.717	9.415	11.851	9.262	10.747	8.410	8.040	9.066	9.142
Weight of Sand Fraction	1.373	1.409	2.335	2.585	2.963	1.947	2.335	1.591	1.806
% Sand	15.751	14.965	19.703	27.910	27.570	23.151	29.042	17.549	19.755
Colour (all 10YR)	[illegible]	5/2	6/2	6/4	6/3	6/2	5/2	4/2	4/2
weight of dish	[illegible]	11.393	11.651	12.948	13.183	10.905	13.586	11.260	13.638
pre-ignition weight(with dish)	[illegible]	21.763	24.349	22.785	24.554	20.030	22.407	21.089	23.800
post-ignition weight (with dish	[illegible]	20.845	23.525	22.232	23.960	19.336	21.653	20.351	22.799
organic matter content	[illegible]	8.852	6.489	5.622	5.224	7.605	8.548	7.508	9.850
Soil Type		1	3	4	4	1	1	3	3
Landform Unit		2	6	6	6	1	2	3	3

Soil Type Legend

1 = Gleysol
2 = Eluviated
3 = Orthic
4 = Calcareous

Landform Legend

1 = Depression
2 = Toe Slope
3 = Lower Mid-Slope
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Appendix 1.

Sample #	10	11	12	13	14	15	16	17	18
A Horizon	22.860	38.100	30.480	25.400	12.700	15.240	48.260	15.240	50.800
C Horizon	91.440	78.740	60.960	120.000	78.740	93.980	120.000	58.420	120.000
Dish Weight (g)	2.191	2.187	2.192	2.191	2.196	2.183	2.194	2.200	2.192
Moist Soil + Dish (g)	57.356	51.193	52.474	81.850	79.410	79.250	79.410	71.930	55.256
Oven Dry Soil + Dish (g)	50.319	43.449	44.647	69.560	69.050	66.230	65.880	62.200	39.650
% H2O	12.756	15.802	15.566	15.428	13.417	16.894	17.522	13.954	29.410
Weight of Sample	9.226	7.052	6.694	11.354	8.787	7.575	9.090	10.050	6.861
Weight of Sand Fraction	2.179	1.382	0.821	1.287	2.273	1.172	0.951	3.139	0.595
% Sand	23.618	19.597	12.265	11.335	25.868	15.472	10.462	31.234	8.672
Colour (all 10YR)	6/3	5/2	4/2	5/2	6/3	4/2	3/2	6/3	3/2
weight of dish	13.340	11.530	12.142	10.849	10.777	13.284	12.954	11.210	10.323
pre-ignition weight(with dish)	23.125	19.200	19.664	23.208	20.218	21.745	23.348	21.955	19.095
post-ignition weight (with disl	22.584	18.593	18.853	22.218	19.591	20.881	22.070	21.309	17.183
organic matter content	5.529	7.914	10.782	8.010	6.641	10.212	12.296	6.012	21.797
Soil Type	3	2	2	2	4	3	1	4	1
Landform Unit	5	2	3	3	6	6	1	6	3

Soil Type Legend

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Landform Legend

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Appendix 1.

Sample #	19	20	21	22	23	24	25	26	27
A Horizon	48.260	12.700	30.480	27.940	13.970	24.130	26.670	25.400	71.120
C Horizon	91.440	55.880	78.740	81.280	86.360	81.280	81.280	78.740	86.360
Dish Weight (g)	2.197	2.[illegible]83	2.205	2.206	2.206	2.194	2.203	2.206	2.217
Moist Soil + Dish (g)	83.680	105.880	52.788	39.633	89.520	72.030	69.530	80.310	57.482
Oven Dry Soil + Dish (g)	68.960	87.960	31.748	26.227	78.650	61.970	58.385	69.460	45.068
% H2O	18.065	17.281	41.595	35.819	12.449	14.405	16.554	13.892	22.463
Weight of Sample	9.622	11.7[illegible]	4.939	4.098	10.001	11.067	11.938	8.571	7.580
Weight of Sand Fraction	2.438	3.341	0.134	0.199	3.999	2.729	2.359	2.071	0.586
% Sand	25.338	28.364	2.713	4.856	39.986	24.659	19.760	24.163	7.731
Colour (all 10YR)	4/2	6/3	3/3	3/2	6/3	4/2	4/2	3/2	4/2
weight of dish	10.330	[illegible]	11.664	13.627	12.365	11.399	10.884	13.229	12.215
pre-ignition weight(with dish)	21.2[illegible]	[illegible]	18.669	19.481	23.074	23.519	23.926	22.638	21.234
post-ignition weight (with dish	19.993	[illegible]	16.623	17.742	22.427	22.493	22.861	21.852	19.829
organic matter content	11.592	7.[illegible]	29.208	29.706	6.042	8.465	8.166	8.354	15.578
Soil Type	2	4	1	2	4	3	3	3	1
Landform Unit	2	6	1	3	4	5	3	3	1

Soil Type Legend
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Landform Legend
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Appendix 1.

Sample #	29	30	31	32	34	35	36
A Horizon	12.700	44.450	30.480	25.400	17.780	38.100	30.480
C Horizon	72.390	80.010	52.070	81.280	33.020	93.980	66.040
Dish Weight (g)	2.188	2.213	2.188	2.213	2.191	2.183	2.198
Moist Soil + Dish (g)	90.390	66.390	82.310	85.690	85.640	86.310	74.310
Oven Dry Soil + Dish (g)	73.800	51.170	71.030	73.590	71.480	74.510	62.590
% H2O	18.809	23.716	14.079	14.495	16.968	14.026	16.252
Weight of Sample	8.454	5.838	11.188	8.128	9.681	8.960	8.907
Weight of Sand Fraction	2.826	0.293	4.182	1.910	3.033	0.736	1.267
% Sand	33.428	5.019	37.379	23.499	31.329	8.214	14.225
Colour (all 10YR)	5/2	3/2	4/2	4/2	4/2	4/2	4/2
weight of dish	12.559	11.103	11.276	11.388	12.243	11.466	13.147
pre-ignition weight(with dish)	21.999	19.008	23.704	20.250	22.856	21.598	22.918
post-ignition weight (with disl	21.048	16.982	22.524	19.548	21.964	20.471	22.103
organic matter content	10.074	25.629	9.495	7.921	8.405	11.123	8.341
Soil Type	4	1	3	4	4	2	3
Landform Unit	7	1	6	6	5	2	2

Soil Type Legend

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Landform Legend

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