AN EVALUATION OF AUTOMATED CLASSIFICATION TECHNIQUES UTILIZING LANDSAT DATA FOR SOILS MAPPING IN THE GRAND RAPIDS AREA, MANITOBA.

by

Walter R. Fraser

A thesis
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ABSTRACT

The use of automated classification techniques utilizing LANDSAT data was evaluated for reconnaissance level soils mapping in the Boreal Forest Region near Grand Rapids, Manitoba. Supervised and unsupervised automated methods were employed rigourously to determine their potential with a single image LANDSAT data base. Both methods yielded similar results, as 8 to 10 soil mapping groups were successfully recognized. A tradeoff existed between the number of classes delineated and classification performance. Traditional methods resulted in the delineation of 57 map unit components.

Automated methods provided several advantages, such as savings in expensive ground truth collection, uniformity of classification results, and ease of manipulation of the final map product.

Automated methods of soils mapping in a Boreal Forest environment were dependent upon the indirect detection of soil conditions through vegetative cover. The poor correlation between native vegetative cover, the major contributer to the spectral signature, and the underlying soil conditions was the main limitation in classification performance. Additional limiting factors were the LANDSAT data base and the restriction of current automated classifiers to pixel-by-pixel analysis. Automated methods also do not provide map units comparable to those produced by conventional techniques. Several methods of enhancing the legibility of automated map products were suggested.

Conventional reconnaissance level soil mapping methods rely on ground truth acquisition in key selected areas and skilled airphoto interpretation. At present, automated methods utilizing a LANDSAT data base do not provide a practical alternative to traditional methodology.

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Chapter I

INTRODUCTION

Most of the traditional pattern of urban and agricultural development in Canada has been limited to areas of most favorable climatic and soil conditions along the southern fringe of the nation. Future growth and expansion will require increased knowledge and utilization of adjacent regions to the north, within the domain of the Boreal Forest. This vast region, occupying over one third of the land area of Canada, is becoming the scene of increasing development of roads and urban centers supporting numerous resource extraction activities such as mining, oil and gas production, and hydro-electric projects, as well as fulfilling increased demands for agricultural land and recreational use.

A knowledge of the distribution of the earth's natural resources, such as water, vegetation, soils, and geological formations has long been recognized as a prerequisite for effective baseline planning and development purposes. A knowledge of the soil resource is of particular importance, as it represents the most stable, environmentally sensitive element of the landscape. An emphasis on the integrated effect of all factors of soil formation as expressed in the soil profile indicates a capability of interpretation of soil map units for a wide range of biological and physical uses (Mills, 1976).

Soil surveys in northern areas are often designed to serve general planning purposes for a variety of disciplines, and are therefore usually conducted at what has traditionally been termed a reconnaissance level. This lower level of survey intensity frequently depends upon less than ideal ground truth site data, which is difficult and expensive to acquire in remote areas. Consequently, soil surveys are conducted using small scale aerial photographs, with a heavy reliance upon conventional photointerpretation techniques, both for choosing ground truth sites and for delineating map unit boundaries and descriptions (Mapping Systems Working Group, 1981). Indeed, mapping of such vast land areas could not have proceeded on a systematic basis without the advent of aerial photography and photointerpretation techniques.

Many refinements to the now traditional use of black and white panchromatic aerial photographs have occurred. These include the use of cameras with special film and filter combinations which provide images with enhanced photointerpretive elements for various disciplines. In addition, the rapidly growing field of remote sensing has been the scene of many revolutionary technological advances in detectors, aerospace platforms, and interpretive capabilities within the last few years.

The use of satellites as platforms for multispectral scanners, which record quantitative reflectance information in discrete wavelength bands, has become feasible within the last ten years. The LANDSAT (formerly called ERTS) satellite series have been specifically designed for the study of land resources, and therefore offer many distinct advantages over other detector systems. Among the advantages are low cost and a unique synoptic viewpoint which allows for rapid and repetative coverage of large areas with a minimum of data calibration problems.

Coincident with these advances in detector design has been the development of digital computer classification techniques to store and interpret the vast quantities of data generated by orbiting multispectral scanners. The use of new machine processing techniques to interpret LANDSAT data has shown a great deal of potential for various types of land resource mapping applications since the first launching in 1972 (Landgrebe, 1973). The potential reduction of time consuming and expensive field investigations and a uniformity in mapping reliability over large areas are particular advantages which may be offered by such new remote sensing systems. Any new techniques which provide such a potential for enhancement of present soil mapping capabilities should be investigated.

The objective of the current study was to determine the potential of automatic computer methods of analyzing LANDSAT data for reconnaissance level soils mapping in the Boreal Region of Manitoba. This included an attempt to delineate with maximum accuracy as many functional classes as possible given the existing limitations of data and processing techniques. Inference of functional soils classes via automatic machine processing was accomplished from the only information available, which was spectral data recorded for each pixel.

The relative merits of conventional air photo techniques in comparison with these automated techniques was also evaluated. An assessment of the methodology required for the use of automated procedures in the routine production of conventional reconnaissance level soils maps was also an objective of this study.

Chapter II

LITERATURE REVIEW

Ever since the establishment of the study of soils as independent natural bodies by Dokuchaev over a century ago, one of the major aspects of soils research has been a study of the distribution of soils in the landscape.

Simonson (1959) indicated that different balances of soil processes result in soils with considerably divergent physical, hydrological, and chemical properties. Differences in soil properties which are related to environmental conditions inherent in their development are expressed in soil classification systems. Subdivision of the landscape into units based on soil taxonomic criteria can therefore provide valuable information in predicting the behaviour of these units, estimation of their productivity, and identifying their best uses. Therefore a knowledge of the distribution of soil types obtainable by soil mapping techniques can provide valuable interpretive information for a variety of planning purposes.

2.1 CONVENTIONAL SOIL MAPPING TECHNIQUES

The advent of aerial photography has provided a tool of enormous value for all land resource disciplines. Stereoscopic viewing of overlapping vertical aerial photographs, which provide a three dimensional image of the terrain features, has become a standard procedure.

Aerial photographs provide a true qualitative picture of the landscape in its infinity of detail (Leuder,1959). The many aspects of the analysis and interpretation of landscape features has been the subject of a multitude of technical papers and reference textbooks. Comprehensive general texts on the subject have been written by several authors, notably Leuder (1959) and Mollard (1957). Also prevalent in the literature are explanations of interpretive techniques for specific disciplines, such as geologic mapping (Gray,1960), soils mapping (Soil Survey Staff,1966), and land capability mapping (Gimbarzevsky,1965).

These photo-interpretive manuals have many basic principles in common. All of them stress the importance of a careful analysis of the many individual factors or elements inherent in the photograph, such as tone, texture, pattern, landform, cultural features, vegetation, and drainage and erosional feature analysis. A careful deductive and inductive evaluation of these photo elements by a skilled interpreter who is familiar with the area, in addition to ground truth information from key locations, are vital to the success and reliability of photo-interpretive mapping procedures. It is this complex, interactive process requiring the application and convergence of photographic information and the knowledge and experience of the interpreter that makes the subject both a science and an art. Therein lies both the problems of subjectivity and reliability as well as the potential success of photointerpretation as a mapping tool.

Early soil surveys were based largely on field observations, with information recorded on planimetric maps or planetable sheets (Soil

Survey Staff,1966). Mapping was based mainly on ocular observations, with a minimum of supplementary information, such as topographic and geological maps, to aid in the delineation of map unit boundaries.

The use of photointerpretive techniques for soils mapping has been described by various authors, mainly concerning mapping in agricultural areas where the terrain surface is visible directly (Soil Survey Staff,1966; Leuder,1959). Crown and Pawluk (1972) indicate that soils are conventionally differentiated by both surface and subsurface properties and therefore cannot be expected to have observable differences in all cases without ground truth information. Stereoscopic analysis of individual elements of the landscape, such as slope, relief, landform, and tone are indicative of parent materials, drainage, and surface soil conditions. A knowledge of the soils within the area allows the inference of soil conditions and the extrapolation of soil boundaries with a high degree of confidence.

A knowledge of the distribution of soil types in an area, when used in conjunction with aerial photointerpretation, allows for the production of reliable soil maps even though sampling may be limited to key areas.

The demand for soil surveys in mid-northern areas of Canada is based on the need for soils data for baseline planning purposes by a variety of user groups. These surveys are required at a low survey intensity, generally termed a reconnaissance level, with few ground truth sites and a strong reliance on aerial photointerpretation techniques. Soil conditions are based largely on inference from relief, drainage, vegetation, and mineral and organic landform analysis

(Thie,1972; Tarnocai,1974). Map units not only serve to characterize soil components, but also attempt to incorporate landform, vegetation, and climatic conditions as well. These soil surveys therefore provide a product that is fundamentally the same as a biophysical classification (Mills,1976).

Many refinements to the traditional use of black and white aerial photography have been made. Various film and filter combinations have provided reflectance information from selective portions of the visible and near infrared regions of the electromagnetic spectrum (National Academy of Sciences,1970). The utility of these products for soil resource and biophysical mapping in the Boreal Forest region has been investigated by Tarnocai (1972) and by Thie (1972).

2.2 THE USE OF NEW REMOTE SENSING TECHNIQUES FOR SOILS MAPPING

Rapid advances in aerospace sensors, platforms, and data analysis procedures have been made, particularly during the last twenty years. This has resulted in the coining of the comprehensive term "remote sensing" to refer to the measurement of environmental conditions at or near the earth's surface that is performed primarily by sensors on airborne or space vehicles (Gregory,1972). This has included a wide range of active and passive sensors covering a broad range of the electromagnetic spectrum (National Academy of Sciences,1970; MacDowall,1972).

It has long been recognized that reflected and/or emitted radiation received from objects in different portions of the electromagnetic spectrum can be characteristic of its source (LARS,1967). The advent of multispectral scanner systems (MSS) has permitted the simultaneous, quantitative measurement of terrain reflectance values in discrete wavelength bands.

2.2.1 LANDSAT Multispectral Scanner

The use of satellite mounted multispectral scanners was initiated on a systematic basis with the launch of the first of the LANDSAT satellite series (formerly called ERTS) by the National Aeronautics and Space Administration (NASA) in 1972. LANDSAT A, LANDSAT B, launched in 1975, and LANDSAT C, launched in 1978, are essentially similar in design and performance, although LANDSAT C has an additional detector which operates in the thermal infrared region of the spectrum. These satellites were specifically designed for the study of earth resources and therefore offer many potential advantages over other detector systems.

The LANDSAT satellites operate in a sun synchronous, near polar, circular orbit with a nominal altitude of 920 km. The orbit is such that each area of the earth's surface is covered repetatively every 18 days at the same mean solar time. The multispectral scanner system measures radiation in four wavelength bands covering the green (500-600 nm), red (600-700 nm), and two infrared (700-800 and 800-1100 nm) portions of the electromagnetic spectrum. These are referred to as bands 4,5,6, and 7 respectively. Bands 1,2, and 3 are used to refer to the spectral intervals of the return beam vidicon (RBV) camera system also mounted on the satellite. The MSS employs an oscillating mirror system to scan the earth's surface with 6 rows of detectors in each of the 4 bands at once. The active scan mode is from west to east, perpendicular to the orbital direction of the satellite. Spectral intensities in each band are sampled at 10 nanosecond intervals along each scan line and are recorded as digital values from 0 to 63. Each 185 km square LANDSAT "picture" represents approximately 2400 consecutive scan lines, with 3200 samplings of the instantaneous field of view (IFOV) along each line. This corresponds to picture element ("pixel") dimensions of 77m in a north-south direction and 58m in an east-west direction (Slater,1979), representing an area of approximately 0.45 hectares.

LANDSAT MSS data for most regions of Canada is transmitted to the Prince Albert, Saskatchewan ground receiving station, where it is recorded on magnetic tape (CCRS,1974).

The remote sensing platform and detector design of the LANDSAT MSS system provide quantitative reflectance data that has several unique advantages for analysis of land resources. The principle advantages are low cost, repetative coverage of all areas of the earth's surface. The scanner look angle from this altitude is less than 12 degrees over the entire 185 km width of the scan line, and all data for a single image is recorded within 30 seconds, minimizing differences in sun angle, atmospheric transmission path, instrument response, and weather flucuations that would otherwise result in substantial calibration problems. An additional advantage is the availability of LANDSAT data in many different forms. These include single and multiband photographic images, transparencies, and computer compatible tapes (CCT). The CCT format is ideal for data manipulation and analysis using computer processing techniques.

2.2.2 Use of LANDSAT Imagery for Soils Mapping

2.2.2.1 Manual Analysis Techniques

Interpretation of LANDSAT imagery for terrain analysis has been conducted by several methods. Black and white photographic images of individual bands or color combinations of several bands can be examined using conventional airphoto techniques. This type of visual analysis for land classification purposes has been conducted by various authors, notably Tarnocai and Thie(1974), Gimbarzevsky(1974), De Gloria and Carneggie (1975), and Thie (1976). The synoptic viewpoint provided by the very small scale (1:1,000,000) images appears useful only for making very broad delineations of large, simple land areas (Thie, 1976). These images are not satisfactory for stereoscopic viewing and the poor resolution characteristics do not make interpretation of enlarged satellite imagery a practical alternative to interpretation of conventional high altitude aerial photography. The small scale of the satellite imagery makes it extremely difficult to recognize landform, vegetation, or drainage features in any detail through the use of conventional manual interpretation techniques (Tarnocai and Thie,1974).

Visual analysis techniques have also been used with digitally "enhanced" LANDSAT imagery. These methods retain the human interpreters ability to extract spatial information with the computer or color additive viewer capability of image enhancement through contrast change, band ratioing, and density slicing techniques. This can also be accomplished by manual means. For example, Mack and Bowren (1975) demonstrated that by assignment of six step grey scale values to LANDSAT images of agricultural fields in several bands, that a classification "key" could be developed to identify certain crop types.

2.2.2.2 Automated Analysis Techniques

The quantitative reflectance information provided by the LANDSAT MSS can only be fully utilized by applying computer processing methods using data in a digital format. This format, combined with the sheer volume of digital information recorded for each image, makes the use of automatic digital processing (ADP) techniques an attractive new method for utilizing LANDSAT data for terrain analysis purposes.

These automated techniques are based on pattern recognition methods. The University of Michigan and the Laboratory for the Application of Remote Sensing (LARS) at Purdue University have been pioneers in the research and development of multispectral scanner detectors and computer analysis techniques (LARS,1970).

The two basic approaches are termed the supervised and unsupervised methods. The supervised approach allows the user to control the classification process by selecting training site data for each class of interest. The computer then compares the reflectance values of individual pixels in the map area to those of the training classes and invokes a mathematical decision rule to assign them to the appropriate class. It is termed "supervised" because the analyst has defined specific areas of known ground truth conditions for computer training (Fleming et al,1975). This is a time consuming and critical phase in the success of the classification scheme. A useful classification can be generated only by trial and error, as it is not known beforehand if classes of interest are spectrally separable (Thie,1976).

The second approach is known as the unsupervised method. Here the user selects a representative area and a clustering technique is employed to produce the most spectrally separable specified number of classes (Shlien and Goodenough, 1974; Hoffer,1973). The user then identifies the clusters or groups of clusters produced. This has the advantage of showing the most separable (spectrally distinct) classes immediately, without the need for extensive ground truth. The disadvantage is that the classes created may be difficult to identify and may not be of interest to the user.

Computer classification methods have been studied to determine their usefulness as a mapping and inventory tool for numerous disciplines, including forestry, urban studies, land use, soils, geology, agriculture, and water resources. It has often been found that the results from such a major shift in technologies cannot be expected to provide an exact match with classes recognized by traditional photointerpretation or ground truth sampling techniques. For many potential user groups however, the satellite/machine processing system has advantages in terms of data capture and processing using unbiased, uniform classification criteria that allow it to replace or supplement current procedures (Ellefsen et al, 1973).

2.2.2.3 The Application of Automated Analysis Techniques for Soils Mapping in Agricultural Areas.

The use of these new remote sensing methods for soils mapping has mainly been focused on the direct detection of soil differences on fallow or sparsely vegetated fields in areas where detailed soil surveys are required (Kristof,1974; Weismiller et al,1977; Kaminsky and

Weismiller,1978). Results were generally reported to be satisfactory, although classification using satellite surface spectral information alone cannot be expected to provide a one to one correlation with conventional surveys which apply both surface and subsurface properties as differentiating characteristics. An additional limitation is that classification is restricted to exposed soil areas. Despite these factors, Landgrebe et al (1973) and Sinclair (1978) concluded that machine interpretation methods can identify meaningful divisions of soils and were recommended as a supplement to conventional mapping techniques.

2.2.2.4 The Application of Automated Analysis Techniques for Soils Mapping under Vegetative Ground Cover Conditions.

Soil mapping within the Boreal Region of Canada requires coverage of vast areas, albeit in less detail and with more general classes of soils or soil-vegetation complexes. The reflected energy in such regions is mainly the signature of the vegetative canopy (Tarnocai,1972). Gimbarzevsky (1972) indicates the value and limitations of natural vegetation for terrain analysis as follows;

> Natural vegetation within a climatic region is very closely related to physical land characteristics and recognition of vegetation is frequently an excellent indicator of terrain conditions: kind of surficial material, moisture content, depth to underlying bedrock, etc. In the Boreal Region, for example, pure pine stands are usually associated with well-drained, medium to coarse textured materials, while black spruce may be used as an indicator of poorly drained, wet conditions. In addition to ecological characteristics of vegetation types and regional climate, the effect of forest fires, logging, insect damage and other factors should be considered in relating vegetative cover as an indicator of specific land conditions.

The main thrust of existing remote sensing studies of vegetative reflectance has dealt with the identification of vegetative types such as tree and crop types, or disease or stress factors which may be detectable (Tinker,1978; Philpotts et al,1974; Nichols et al,1974). Various authors have conducted detailed analysis of individual leaf reflectance conditions and developed models based upon the integrated effects of vegetation structures, density, and orientation (LARS,1970; Brach et al,1977).

Colwell (1974) indicated the possible effects of many parameters important to the prediction of vegetative canopy reflectance in different wavelength bands. These included leaf hemispherical transmittance, leaf area and orientation, characteristics of other components of the vegetative canopy (such as stalks, trunks, and limbs), soil reflectance, solar zenith angle, look angle, and azimuth angle. Colwell indicated that at very small scales the spacing and other relationships between trees becomes important. Significant differences in leaf reflectance of various species may not result in significant differences in vegetative canopy reflectance, all other things being equal. Unless the canopies were different in structural configeration or some other important parameter, they were indistinguishable on the basis of their near-IR canopy reflectance. LANDSAT resolution elements could only identify gross reflectance data integrated over a large (79mx79m) area, primarily based on the signature of the canopy reflectance. Tinker (1978) indicated that "in remote sensing, however, the reflectance of the canopy, subsequent to the interaction of solar radiation with the canopy components (including non-leaf structures), is the quantity of interest." Further research is necessary to identify the actual cause-effect relationships of a number of canopy reflectance parameters which may be discernable in operational remote sensing programs.

The use of vegetation as an indicator of soil conditions, while recognized as a useful field mapping and photointerpretive element, has not been extensively investigated using LANDSAT data and automated digital processing techniques.

The use of these techniques for biophysical mapping purposes has been successfully employed by Tarnocai and Kristof (1976) in classifying the terrestrial and aquatic environments in the Mackenzie Delta. The classes were separated according to spectral responses using an unsupervised approach and correlated with existing ground truth data. Because the cover types were closely related to other components of the ecosystem, it was possible to relate the landforms, parent materials, and soils to these classes.

Thie (1976) evaluated photointerpretive and automated techniques for biophysical land classification in the subarctic and northern boreal environment near Churchill, Manitoba. Automated classification methods allowed the satisfactory mapping of nine class groups. These classes were concluded to be too general to provide a satisfactory alternative to conventional biophysical methodology based upon airphoto interpretation and groundtruthing techniques.

No studies to date have attempted to evaluate the potential of automated computer methods of analyzing LANDSAT data as a supplement or alternative to conventional reconnaissance level soil mapping techniques in the Boreal Forest environment.

Chapter III

DESCRIPTION OF THE STUDY AREA

3.1 LOCATION

The study area is located in the north Interlake area of Manitoba, centered on the Grand Rapids mapsheet (NTS 63G), as indicated in Figure 1. Small portions of the adjacent sheets to the north (NTS 63J) and south (NTS 63B) were also included.

3.2 CLIMATE

The area is within a climatic region designated as Humid Continental (Dfb) by Powell and MacIver (1977). This region is characterized by moderately warm summers and long cold winters, with no dry season. The mean annual air temperature at Grand Rapids, the only location in the area for which data are available, is approximately -0.5 C. The mean annual precipitation is approximately 460 mm , of which 2/3 falls as rain from May 1 to September 30.

According to the Soil Climates of Canada (CDA , 1977), the area is classified as Cold to Moderately Cold Cryoboreal with a subhumid to humid unsaturated moisture regime. This indicates an area with a growing season degree day value of from 1000 to 2250, and a slight moisture deficit of from 2.5 cm to less than 13 cm during the growing season. More detailed investigations of ecoregions in Manitoba, partially based upon a study of Manitoba soil temperature sites (Mills et al, 1978), indicates that the study area is within the Low Boreal ecological subregion (LB1). This area is characterized by mean annual air temperatures of -1.1 to 0.2 C, with an average number of degree-days (the accumulation of degrees of temperature above a daily mean of 5 C) of 1220 to 1445.

3.3 RELIEF AND DRAINAGE

Elevation varies from about 310 m for the highest areas of the The Pas Moraine, in the south-western portion of the map area, to a low of 217 m ASL, the elevation of Lake Winnipeg. Relief is generally low, except for the escarpment delineating the eastern edge of the Moose Lake Plain, and the southern edge of the The Pas Moraine (Figure 2). Relief in these areas is 20-40 metres.

The Saskatchewan River flows into Lake Winnipeg at Grand Rapids, and is the site of a major hydro-electric power station. A large dike, up to 30 m high and 25 km in length, was constructed to the south and west of Grand Rapids, greatly expanding the size of Cedar Lake and providing a reservoir for the hydro-electric plant. The only other river within the map area is the William River, flowing from William Lake into Limestone Bay, in the extreme north-western corner of Lake Winnipeg.

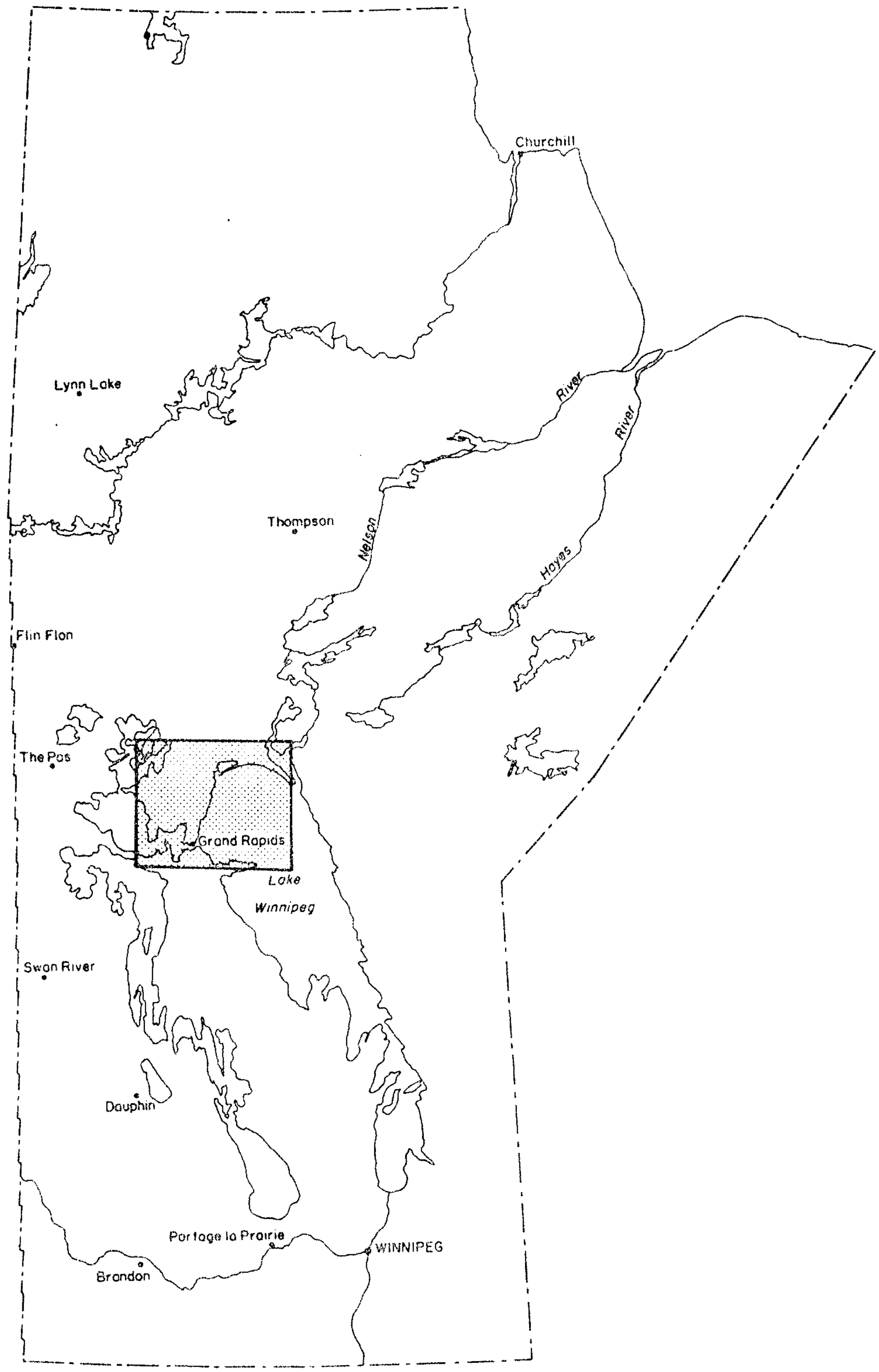


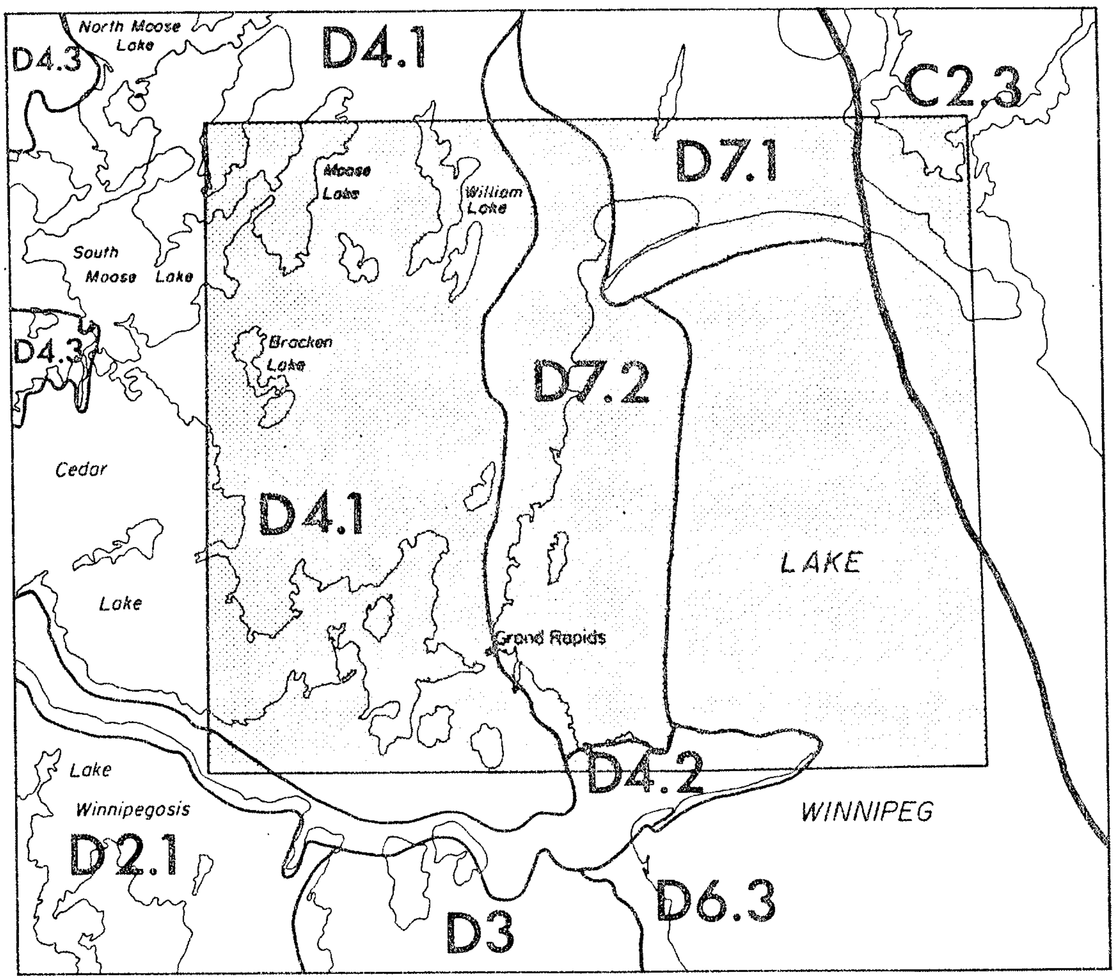
Figure 1: Location of the Grand Rapids study area.

3.4 PHYSIOGRAPHIC REGIONS

The entire study area is situated within the Manitoba Lowlands division of the Interior Plains physiographic region (Bostock,1970). Four physiographic subsections of the Manitoba Lowlands are recognized (Canada-Manitoba Soil Survey, unpublished data). These are the Moose Lake Plain, The Pas Moraine, the Grand Rapids Lowland, and the Hargrave Lowland (Figure 2).

The Moose Lake Plain occupies most of the western half of the map area. It consists of a level to gently undulating veneer of extremely calcareous glacial till, with numerous outcrops of dolomite bedrock of Silurian age. The area is dominantly well drained, with no well developed drainage network, and evidence of Karst features indicating rapid downward drainage through cracks and fissures in the bedrock.

A steep east facing escarpment separates this area from the Grand Rapids Lowland. This level to gently sloping lacustrine plain contains extensive organic deposits with lesser mineral soil areas of clayey lacustrine veneers overlying extremely calcareous till, and a network of north-south trending beach ridges. Drainage is generally very poor, accomplished through a series of small creeks and sloping fens, all ultimately flowing into Lake Winnipeg. Numerous springs, located in a discharge zone at the base of the escarpment, contribute to the poor drainage conditions. Drainage is also impeded by the beach ridges, which are oriented perpendicular to the normal west to east water movement.



REGION	DIVISION	SECTION	SUBSECTION
James	C Severn Upland	C2 Nelson River Plain	.3 Bloodvein River Plain
Interior Plains	D Manitoba Plan	D2 Westlake Plain	.1 Westlake Till Plain
		D3 Interlake Plain	
		D4 Cedar Lake Plain	.1 Moose Lake Plain .2 The Pas Moraine .3 Summerberry Lowland
		D6 Lake Winnipeg Lowland	.3 Sturgeon Bay Lowland
		D7 Minago Lowland	.1 Hargrave Lowland .2 Grand Rapids Lowland

Figure 2: Physiographic subdivisions of the Grand Rapids study area.

The Hargrave Lowland is located in the area immediately north of Lake Winnipeg. It is a level to depressional lacustrine plain, predominantly covered by organic deposits. This area is on the southern fringe of the Discontinuous Permafrost Zone (Tarnocai,1973) and contains some areas of organic soils, mainly in the form of frozen peat plateaus and palsas.

The Pas Moraine, the fourth major physiographic subsection, occurs in a continuous band along the southern portion of the map area. This is an extensive end moraine of extremely calcareous, very stony, loamy glacial till. The southern edge of the moraine is an escarpment up to 50 m in height, and is marked by a pronounced set of beach ridges at successively lower elevations, corresponding to lowered shorelines during the final stages of Lake Agassiz (Elson,1967). North of this escarpment, the moraine is a poorly drained, fluted, till plain which slopes gently to the north.

3.5 SOILS

Soils in the Grand Rapids area, classified according to the Canadian System of Soil Classification (CSSC, 1978), are dominantly Brunisolic, Gleysolic, and Organic (Canada-Manitoba Soil Survey, unpublished data). Well drained materials, chiefly tills derived from carbonate bedrock, exhibit predominantly Eluviated Eutric Brunisol profiles. Well drained, fine textured lacustrine sediments usually have Orthic Gray Luvisol profiles. Poorly drained mineral soils are normally Rego Gleysols, covered by a thin surface layer of Sphagnum moss.

Extensive areas of organic soils occur, particularly in the Grand Rapids and Hargrave Lowlands. These soils are dominantly Typic Mesisol and Typic Fibric Mesisols, developed from fen peats with thin overlays of fibric Sphagnum peat. Smaller areas of Terric Mesisols developed from fen peat, and from fibric and mesic forest peats, occur in all four physiographic subsections. Organo Cryosols occur in palsas and peat plateaus in the Hargrave Lowland, and in a few scattered areas in the Grand Rapids Lowland.

Chapter IV

METHODS

4.1 DESIGN OF INVESTIGATION

In order for a realistic appraisal to be made, a large area was chosen for analysis, to approximate the areal extent and variety of conditions encountered within a typical reconnaissance mapping project in the Boreal Forest Region. The recognition of soil types in such a study is highly dependent upon the associated vegetation types. The Grand Rapids area was chosen because there has been little disturbance by man's activities such as logging, farming, or urban development. Adequate access to training and test sites provided by recently developed roads through previously inaccessible portions of the map area was an additional reason for selecting this area. Although large areas support non-climax vegetation due to forest fires, it was felt that this is a natural condition under which automated mapping systems should be realistically tested to evaluate their potential for soils mapping.

The work was carried out in a similar sequence to that conducted by Thie (1976), in order to minimize the bias that may have resulted from experience gained by the author in employing subsequent interpretive methods. The steps involved were as follows;

1. An initial photo-interpretation and field analysis was carried out in order to provide an overview of the physiography, soils,

and vegetation relationships expected to be encountered within the study area. This preliminary investigation was considered a basic prerequisite step for either conventional or automated soils mapping methods.

2. A supervised automated classification procedure was carried out, using the LARS software package developed by Purdue University. This was conducted on an in-house basis, using the computer facilities of the University of Manitoba. Potential training and test sites were delineated on aerial photographs and were verified by existing ground truth information and further field investigation where possible.
3. An unsupervised automated classification precedure was carried out using components of the LARS computer software package. This was done after completion of the supervised classification, so that results would not bias the selection of supervised training classes.
4. A detailed photo-interpretation using black and white aerial photography and ground truth information was conducted to produce a conventional 1:125,000 scale reconnaissance soil map of the Grand Rapids mapsheet for the Manitoba Soil Survey Unit. This mapping was useful for comparison of conventional techniques and results with the two automated classification procedures.

Appendix D illustrates the final classification maps and legends produced by the supervised, unsupervised, and conventional methods.

4.2 AQUISITION OF REMOTE SENSING IMAGERY

Conventional small scale panchromatic black and white photographs were obtained for the entire study area. The photos were taken from a height of 12,200 m ASL in the late fall of 1971, using a 152.4 mm lens. The resulting photo scale is approximately 1:78,000. These were the photos later used in the production of the Grand Rapids Reconnaissance Soils Map (Can. Man. Soil Survey, unpublished data), produced by conventional photointerpretation techniques.

Black and white aerial photographs of the study area, taken in October,1953, were also used. The flight was made at a height of 10,700 m ASL with a 152.4 mm lens, resulting in a photo scale of about 1:68,000.

Both sets of photographs were obtained on loan from the Manitoba Soil Survey Unit for the duration of the study. These photos are also available through the National Air Photo Library in Ottawa.

Various inventory facilities of the Manitoba Remote Sensing Center were employed in order to determine the best available LANDSAT data for the study area. These included data tables and printouts from the LANDSAT Imagery Catalogue, showing the image quality for LANDSAT images of any given area in Canada (CCRS, 1975). In addition to this, mirofilm images (microfiche) were examined to evaluate potential images. The imagery desired was for the mid summer period, with a minimum of cloud and haze cover, and to be relatively free of striping, dropouts and other errors. The image finally selected was taken on July 27, 1975 by the LANDSAT 2 (ERTS B) satellite.

Prints and transparencies of LANDSAT images are available for all of Canada, and are referred to by the orbital track number and the picture centre number. The study area occupied the bottom half of track 36, picture centre 22, and the top half of track 36, picture centre 23. Black and white prints and transparencies for each of the four channels were obtained for these frames.

The location of picture centres for LANDSAT scenes is arbitrary, since the data produced along any orbital track is continuous. Therefore it was possible to order a computer compatible tape (CCT) of the LANDSAT 2 imagery for the exact area required. These tapes are available through the Canadian Centre for Remote Sensing in Ottawa (CCRS,1974). LANDSAT data tapes may also be ordered by listing the NASA image number, in this case 2186 16575.

The tape ordered was a "new format" CCT which has had radiometric corrections applied by CCRS. The radiance levels were linear, 8 bit numbers derived from the original 6 bit compressed logarithmic intensities received by the detectors (Schubert, 1976, pp. 53-55.). Radiance values on the new tape varied from 0 to 255 for each wavelength band.

Geographically corrected CCT´s, in which the pixel coordinates are re-arranged to produce images with a conventional north-south orientation, were not available at the time the study was undertaken. This procedure, while enabling the production of computer display maps with the same orientation as conventional maps, would not have an effect on the classification results.

The imagery chosen was single date, as overlay techniques to combine multidate imagery were not readily available. The use of overlay techniques required the careful matching of geometrically corrected images, so that data from different dates were not improperly assigned to adjacent, potentially contrasting pixels. Thie (1976, pp. 58-63), using the in-house computer facilities of CCRS, indicated that the impact of substitution of a winter channel for one summer channel had a considerable affect on classification results, although classification accuracy may be increased or lowered for particular classes, depending on the vegetative cover type.

Since only single date imagery was available for this study, a mid summer date was chosen. At that time, vegetative response was uniformly near optimum values, and results obtained were more consistent for extrapolation to other areas and dates.

4.3 FIELD INVESTIGATIONS

Fieldwork was carried out during late July 1975, 1976, and 1977, for a total of four weeks. Access to the area was by motor vehicle, so that field investigations were limited to areas reasonably close to roads and forestry cutlines. Sites were described and sampled in order to provide training and test areas for the computer classification methods.

Ground truth data were recorded for all training sites accessible to the author. Point-Quarter measurements were made of the tree strata, where feasible. This consisted of ten stops in a predetermined rectangular pattern, from which points the distance, circumference, and species of the nearest tree in each of the four quadrants were recorded. A computer program was later implemented to analyze the data obtained from this plotless sampling technique. Several ecological parameters, such as the relative density, dominance, and frequency were calculated for each tree species in the site. These data were later used to compare sites in different training classes, and to correlate spectral responses with vegetation. In addition to this, visual estimates were made of the tree coverage. This included the range in height of the tree species present and an estimate of the crown closure.

The understory coverage was also estimated for the various cover types representing more than 5% of the surface area. These cover types were mainly plant species, although in some instances rock, pine needles, fallen trees, etc. were noted as significant cover types. It was felt that for a study based upon spectral reflectance, that this would be a more relevent assessment of the vegetation than a floristic listing of all the species present at each site. Photographs of these sites were taken using a 35 mm camera, to provide an overall view of the site as well as close-ups of the ground cover.

Soil profiles were examined within each site, and the soils were classified according to the most recent edition of The Canadian System of Soil Classification (Canada Soil Survey Committee, 1978, revised). The percentages of the various soil series or series complexes were then determined for each site, using Manitoba Soil Survey field legends established for these areas.

4.4 LABORATORY INVESTIGATION

It was the objective of this study to evaluate not only the benefits of automated computer methods of processing LANDSAT data, but also to do so using readily available "in house" digital computer facilities.

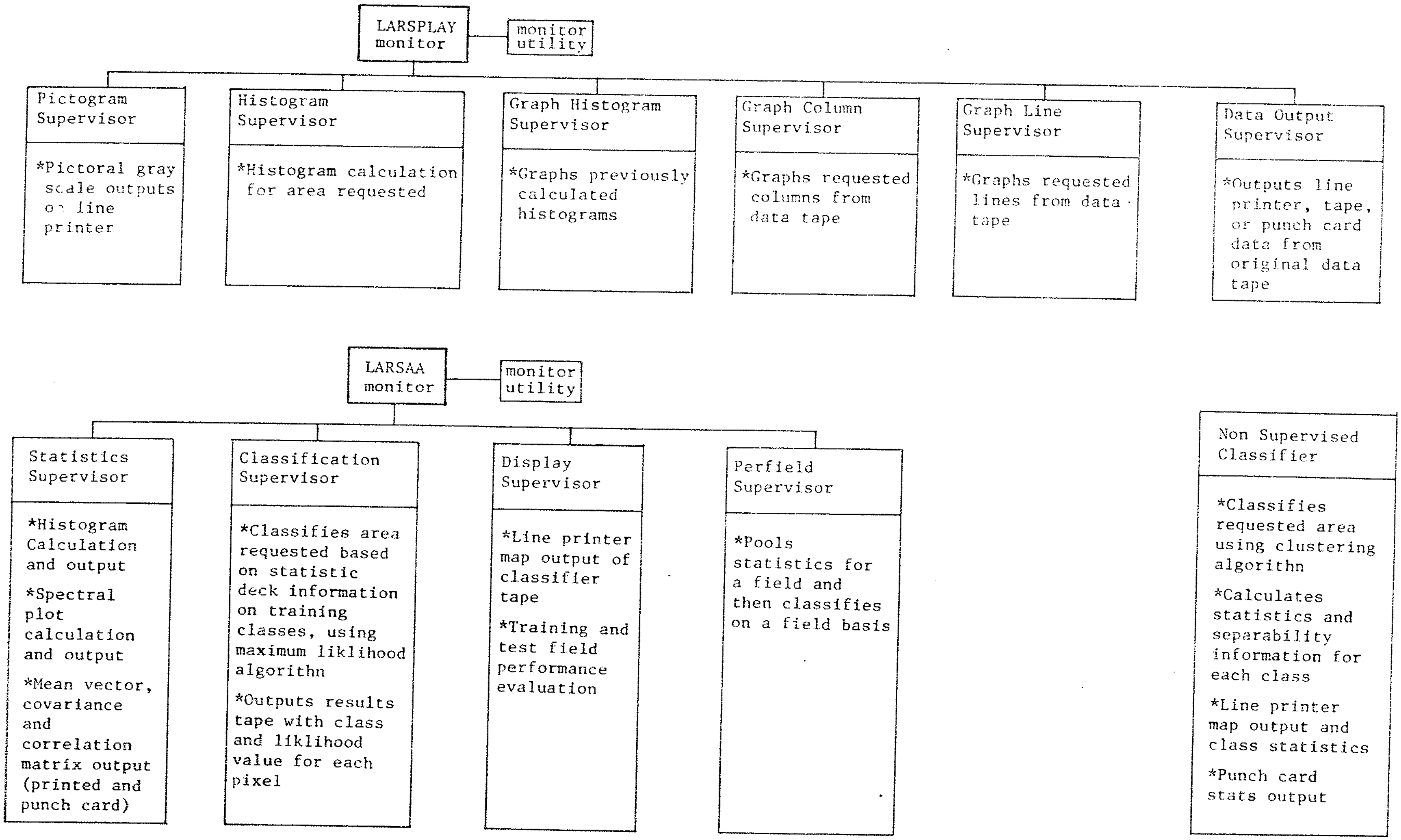
With this objective in mind, LARSYS, a large computer software package, was obtained. A computer tape copy of LARSYS Version 2 was obtained in 1975 from Dr. Wacker, Professor of Electrical Engineering at the University of Saskatchewan. Updated versions of this program (LARSYS Version 3.1) are also available commercially(1).

The LARSYS Version 2 is a large FORTRAN software package, consisting of four monitors, NSCLASS, REFORMAT, LARSPLAY, and LARSAA, each containing a number of related programs, as shown in Figure 3. These programs were designed for specific routine data processing tasks required for both the supervised and non-supervised methods of analysis of multi-spectral scanner data. All programs were accessed through the LARSYS monitor and supervisor control cards, and the commands available for each supervisor program all followed similar formats. Description of the format and specific program examples are provided in Appendix A.

LARS Version 2 was originally conceived and written to handle digital aircraft scanner data. This means that certain headers related to aircraft flight lines, such as flight line number, altitude and ground heading were generated. It also incorporates several processing algorithims, such as data calibration coding and the feature selection processor, which were not relevant when using four channel LANDSAT MSS

(1) Computer Software Management and Information Center. University of Georgia. Suite 112, Barrow Hall, Athens, Georgia 30602.

Figure 3.
LARS PROGRAM STRUCTURE (Version 2)



data.

LARSYS programs were also initially designed to operate interactively from the console, with the user being able to monitor the job output and request changes in the supervisor processing. All programs and data were stored online, so that IBM job control language (JCL) was minimized.

When implemented at the University of Manitoba, LARSYS programs were stored on disk and the input data were stored on magnetic tape. The control and data cards were stored in files using MANTES, the University of Manitoba text editing system (Ferch et al., 1976). LARSYS jobs were run in batch mode using the IBM 370/168 computer system of the University of Manitoba.

The original 800 BPI LANDSAT data tape was reformatted using a supervisor program in order to make the data compatible with the LARSYS input format. This data was re-recorded on a 6250 BPI data tape. The reformatted data contained row and column designators, so that the position of any point in the image has a unique address. The first pixel in the top lefthand corner of the image was designated as being in row 1, column 1.

4.4.1 Supervised Classification

In order to perform a supervised classification, the following steps were followed;

1. Selection of training areas for all classes.
2. Location of training areas on data tape
3. Generation of statistics deck.

4. Classification of map area.

5. Display of classified map area.

6. Repetition of steps 1 to 5 to refine results.

Each of these steps was handled by a separate program. For each LARS supervisor used in the supervised classification, the operation and output of the program is described, and examples of the input commands are listed in Appendix A.

4.4.1.1 Selection of Training Areas

The first and most critical step in a supervised classification technique is the selection of proper training areas for all classes.

Potential sites were first evaluated by photo interpretation techniques. Available ground truth information, including drill logs from Manitoba Hydro powerline construction projects, data from Canada Land Inventory maps and sites, and Manitoba Soil Survey information were all utilized.

In order to produce optimum classification and mapping results, the size and type of land units must be compatible with the LANDSAT data collection and automatic classifier procedures. The classifier program performs a pixel-by-pixel classification, with each pixel approximately 58m X 77m in size. Therefore simple landscape units with pixel sized or larger dimensions were chosen as appropriate training areas. These are equivalent to phases of biophysical ecosites (Canada Commitee on Ecological Land Classification, 1979), or soil mapping units consisting of closely related soil series.

Larger, heterogeneous map units representing combinations of land types (biophysical land systems or complexes of soil associations), while desirable for conventional reconnaissance level mapping purposes, contain pixels with widely divergent spectral responses. These would not be recognized as larger, spectrally unique entities by one step, pixel-by pixel classifiers.

Sites were selected according to the following criteria:

1. All sites had uniform soil conditions throughout their specified areas.
2. All sites had uniform vegetation conditions. Vegetation on each site was typical of other areas with similar soil types. In most cases this represented climax or near-climax vegetation. For areas where exposed bedrock and a shallow till veneer over bedrock predominated, forest fires were frequent in occurrence, and vegetation was predominantly dense stands of 40-50 year old jack pine (Thie,1972). In response to these conditions, training and test sites which represented both of these conditions were designated.
3. Training and test sites were selected for each of the major soil types expected to be encountered within the map area.
4. Where possible, preference was given to sites which were accessible to the author. Other sites were selected only for those soil classes which represented important soils groups, and for which reliable Canada Land Inventory or Manitoba Soil Survey data on the soils and and vegetation were available.

5. Training sites preferably had a size of 6 pixels or more in a N-S direction, in order to account for variations in the six LANDSAT detectors in each band.

6. All sites covered an area of at least 9 pixels (approximately 4 hectares) in size and were in positions which were easy to locate with reference to nearby features (Ryerson,1977).

Based on these criteria, approximately 90 ground truth sites were delineated on the air photos as potential training fields. Half of these were subsequently rejected or modified due to unsuitable soil or vegetation conditions, or due to undesirable spectral characteristics encountered during the classification procedures.

A summary of the sites selected as supervised training and test fields are shown in Appendix B.

4.4.1.2 Production of Grayscale Maps

In order to determine the location of potential training and test area pixels on the Landsat data tape, alphanumeric printouts were generated using the LARSPLAY pictogram processor. This program used different symbols to represent each pixel, based upon their recorded brightness levels in one particular wavelength band. These printouts, actually a crude form of grayscale map, contained line and column coordinates so that once the areas of interest are located, they could be referenced by these coordinates for subsequent analysis.

The LARSYS Version 2 software package allowed for the production of grayscale maps using a standard computer line printer as an output device, through the LARSPLAY monitor programs. Determination of the exact coordinates for the training and test areas on the data tape was critical for supervised classification, and results were therefore highly dependent on the proper transfer of area coordinates from the airphotos to the grayscale map images.

LARSPLAY grayscale maps used standard line printer alphanumeric symbols to represent brightness values of each pixel chosen for display, as shown in Figure 4. Since LANDSAT pixels were rectangular, representing approximately 77 m in a north-south direction and 58 m in an east-west direction, a line printer output of 10 characters per inch and 8 lines per inch was used to minimize scale distortions. This resulted in a scale of 1:22,800 in an east-west direction and 1:24,200 in a north-south direction. By printing only every second pixel on every second line ("2x2") an output scale of approximately 1:46,000 was achieved. Although this entailed a loss of resolution, it did provide a product that was easier to relate to the 1:78,000 scale aerial photography.

A determination of the most suitable band for grayscale map production was accomplished by visual analysis of various printouts and single band black and white LANDSAT prints and transparencies. The band 4 (500-600nm) and band 5 (600-700nm) images showed little contrast between various forested areas and other surface features, such as water bodies, although cleared areas such as roads were clearly distinguished by their higher reflectance. Band 6 (700-800nm) and 7(800-1100nm) data were very similar, with all water bodies showing up as prominant dark areas. Contrast between various vegetated areas was also more pronounced. This increased contrast was confirmed by histo-

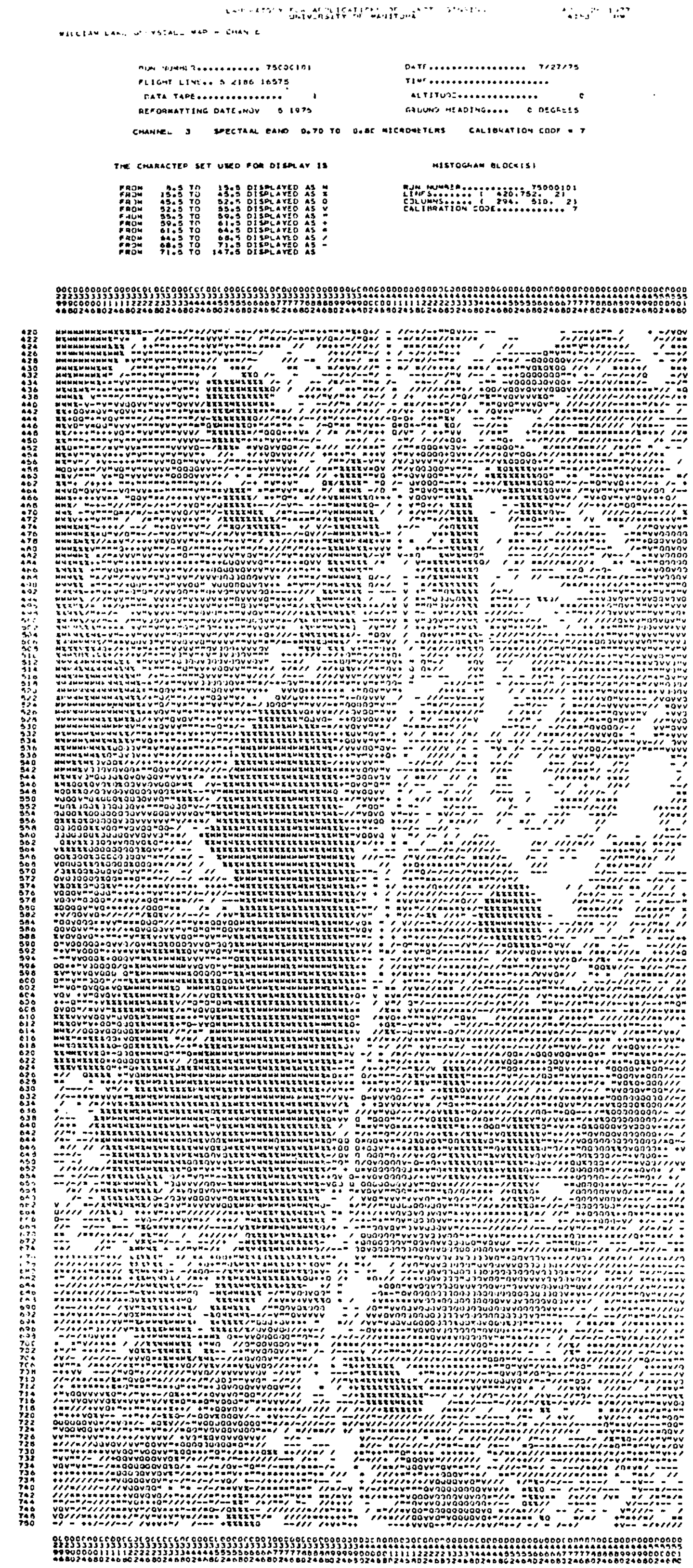


Figure 4: Example of a LARSPLAY grayscale map.

gram outputs for a selected area, which showed a much wider distribution of brightness values for bands 6 and 7. As a result of these studies, band 6 data was chosen for all subsequent grayscale map production. Similar conclusions have been noted by other investigators, and are the basis for the choice of band 6 imagery for the production of "Quicklook" images (CCRS,1974).

When the default options of the LARSPLAY grayscale map program were employed, a histogram of the image brightness for the area requested is produced, and the resulting curve is divided into ten equal area partitions or "bins" (Phillips and Simmons, 1969). These are then assigned equally active standard symbols (M$XZ*I/=-) to represent pixels from lowest reflectance (M) to highest (blank). The choice of ten grayscale levels was retained as a satisfactory compromise, as fewer levels did not provide enough detail, and there was not enough difference in contrast between the alphanumeric symbols to provide more grayscale levels than this. In an attempt to improve on the default set of symbols, a Fortran program was used to produce blocks of alphanumeric symbols. After comparison of many different combinations, a set of revised grayscale symbols (M%QV"+=/-) was adopted. This provided only a marginal improvement. The lack of an overprint capability, which would have permitted a wider range of tonal variations, was the main limitation to the use of the LARSPLAY program.

An alternate program developed by J.G. Mills (1976) was then employed to produce grayscale maps using a Versatec plotter as an output device. This method used small, contiguous dot cell matrices instead of alphanumeric symbols, thereby providing finer detail and a much wider range of tonal variations. Data tape column and row coordinates were also generated along the sides of the images, using the same dot cell matrix. An example of this type of grayscale map output is shown in Figure 5. LARSPLAY histogram "bin" values obtained from the same area were input manually and used for all subsequent Versatec plotter grayscale map areas.

By varying the size of the dot cell matrix, two different scales of output were obtainable; 1:160,000 ("normal"), and 1:79,000 ("zoom option"). The latter output was nearly equivalent in scale to the aerial photography, and provided an excellent product for obtaining data tape coordinates for all training and test sites.

4.4.1.3 Generation of Statistics Deck

The statistics processor of the LARSAA program was employed to calculate reflectance data and statistics for all pixels within the various training areas. These actually consisted of mean relative spectral values and covariance matrices of each training area.

In order for a final classification scheme to be successful, the classes of interest had to be spectally separable. Which of the training classes have uniquely separable spectral plots cannot be readily ascertained beforehand, and therefore various types of statistical outputs were employed to analyze the data. These included histograms of individual training fields and groups of training fields which were designated to specific training classes. Tables showing the means, standard deviations, and correlation matrices of the various channels were also generated for each training area. Coincident

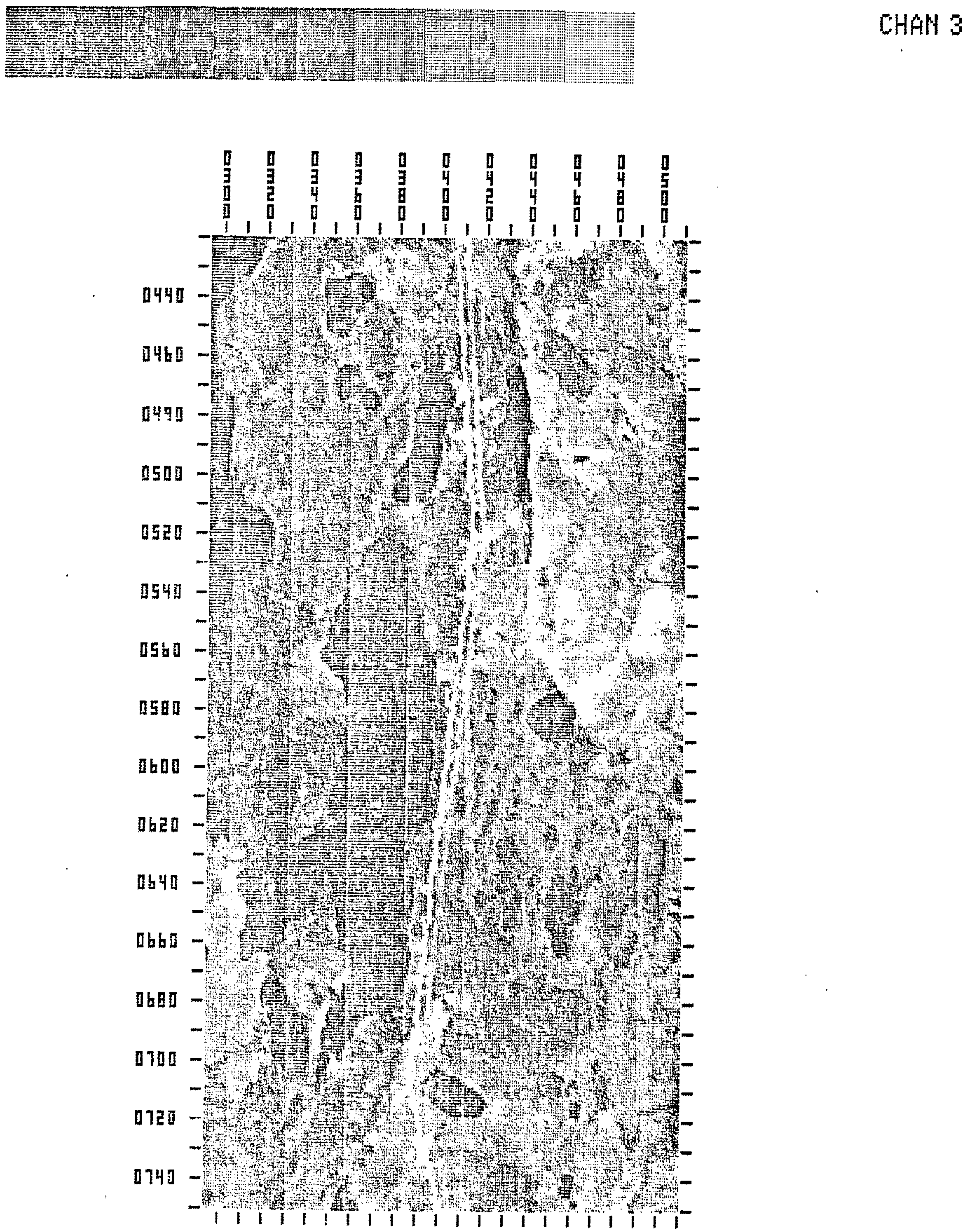


Figure 5: Example of 1:160,000 scale grayscale map output produced by the Versatec plotter program.

spectral plots, showing the plus and minus one standard deviation reflectance values plotted in linear form for each channel provided a particularly useful means of visually comparing different classes.

Once classes had been evaluated and compared, a statistics deck containing reflectance information for all classes was generated and used for classification purposes.

4.4.1.4 Classification and Map Display

Most automatic classification techniques treat the multispectral scanner channels as axes in an n-dimensional feature space. Regions are then plotted for each class, based upon the reflectance data contained in the statistics deck.

Each pixel is assigned a position in this feature space according to its reflectance values in each channel or axis. A decision rule is then implemented to determine to which class the pixel will be assigned.

The two most common decision rules employed by automatic classifiers are the minimum distance decision rule and the maximum liklihood decision rule. Both methods produce similar results (Peet et al., 1975). When reflectance data for a class is obtained by the LARSYSAA statistics processor, a normal curve is fitted to represent the data. Information such as the mean and standard deviation in each dimension is computed and stored in the statistics deck. The classifier considers this as an n-dimensional Gaussian probability function centered on the mean, where the probability is a maximum. Classification proceeds by positioning each pixel in the feature space and calculating the probability values at that position according to the Gaussian probability functions representing each of the classes. The pixel is then assigned to the class having the highest probability value, hence the name maximum liklihood decision rule.

The MLDR classifier involves much computer time and resources to implement, but provides an accurate and flexible means of classification. For example, thresholds can be applied; a pixel can be rejected as unclassified if the probability it belongs to the most likely class is less than a specified value. One of the design requirements of the LARS classifier program was that it must provide the ability to recognize a variety of ground cover types for many different user groups (Hoffer, 1973). Therefore the assumption was made that the reflectance measurements for a group of pixels representing any given class will usually exhibit a normal distribution. Histogram outputs provided for each training class field by the LARSYSAA statistics processor approximate a normal curve in most cases.

The classifier was used to carry out the actual classification on a pixel by pixel basis and the results were stored on magnetic tape.

The display processor was then employed to read the results from the classifier output tape and then to apply various options to analyze and display the results on a line printer. The basic output was an alphanumeric map-like printout, with various symbols used to represent the classes to which the pixels have been assigned. These maps were then compared with conventional soil maps and aerial photographs to determine qualitatively the accuracy of the classification results.

Several methods of enhancing the legibility of the final automated classification maps were also investigated.

The display processor outlined training and test fields on the output maps and produced quantitative classification results in tabular form. The training field performance was a useful indicator of training class separability, while the test field results indicated the reliability and extensability of the classification results (Schubert, 1976).

At this point in the procedure, a repetition of the supervised classification steps is usually necessary in order to refine the results. Several interactions of training, displaying, classifying, and analysing the training statistics are usually required before an optimum set of classes evolves.

4.4.1.5 Development of Final Training Classes

Initial classification results were very poor. The first statistics deck contained one or more training fields established for all significant classes of soil conditions expected to be encountered in the study area. It was found that although many training fields had spectral signatures that were somewhat divergent, most of them had considerable overlap with competing classes. This resulted in unacceptable training and test field performance, as well as display maps with a poor correlation with known soil conditions.

In order to improve results, training sites with a wide range of spectral overlap with other classes were rejected. Meaningful soils groups, however, often encompassed a range of vegetative conditions which resulted in different spectral signatures. These training fields were considered as separate classes, and were grouped together only during the final display process, using a common symbol for each group. For example, several mineral soil types occurred in both burned and unburned areas. The burned and unburned training fields obviously had different vegetative and spectral signature conditions, and were therefore treated separately for classification purposes. These were grouped together with a common soils group in the final map display.

It was also found that strongly contrasting soil types often had similar vegetative cover, resulting in similar spectral signatures. To reduce misclassification, these different soil types had to be listed as constituents in a much broader soils group than was originally intended. Where such soil types were unacceptably different, the type representing the lesser area was dropped to minimize the extent of the misclassification.

A large number of major and minor revisions of training classes and class groupings were incorporated into the statistics deck as a result of analysis of the various statistics processor outputs, classification results, and map display. This cyclical process of evaluation and modification was repeated many times in an effort to improve classification results. In all, major revision attempts were incorporated into 8 successive versions of the statistics deck before a final training set evolved.

4.4.2 Unsupervised Classification

In order to perform an unsupervised classification, the following steps were followed;

1. Selection of a representative strip of map area.
2. Cluster analysis of pixels within the representative area.
3. Generation of statistics deck.
4. Classification of map area.
5. Display of classified map area.
6. Final display with class symbol revisions.

4.4.2.1 Area Selection and Cluster Analysis

The initial step in an unsupervised classification was the selection of a suitable area for cluster analysis. The following constraints were imposed on the area selected;

1. Due to the nature of the LARS NSCLASS clustering algorithm, the maximum number of pixels that can be classified is 35500/(N+1), where N is the number of channels selected (Wacker and Simmons, 1970). The maximum number of classes that can be specified is 40.
2. The area was a representative subset of the entire map area.
3. The area chosen was accessible for subsequent ground truth checking, or located within areas covered by existing ground truth and photointerpretive data. This facilitated an assessment of the cluster classification results.

The second step involved the use of the clustering algorithm, in this case the NSCLASS supervisor from the LARS computer software package. Options available to the user included the area to be classified, the channels of data to be considered, and the number of classes and degree of separability required. The program clustered the pixels in the data set accordingly, selecting the most uniquely separable groups of pixel reflectance values which occurred in the n-dimensional feature space, calculating their mean position and separability from other clusters. A mathematical description of the clustering algorithm employed in unsupervised classification was provided by Swain (1972).

The clustering procedure involved a great deal of computer time and resources, and therefore the number of pixels was limited to a small subset of the entire data set (Swain, 1972). This limit was approximately 8000 pixels, compared with the 7 1/2 million pixels contained in an entire LANDSAT frame.

It was anticipated that band 4 would make an insignificant contribution to total class separability during the initial clustering procedure. This was based on supervised performance experience and confirmed by the coincident spectral plot for the unsupervised classes, which indicated considerable overlap in spectral signature for vegetated soils classes in band 4. The use of the remaining three bands only allowed for the use of a larger representative cluster sample size. The total number of pixels chosen was 7937.

The output was a line printer map using alphanumeric symbols to represent the clusters to which the pixels were assigned. In addition, the number of points belonging to each cluster in the area and cluster separability information was provided for each class.

4.4.2.2 Refinement of Unsupervised Methodology.

Selection of the area for cluster analysis was recognized as critical to the further success of the method. Therefore, a preliminary knowledge of the map area conditions was a basic prerequisite step. This was provided by the information obtained prior to implementation of the supervised classification procedure.

Normally, additional fieldwork is necessary to identify the various classes represented in the pictoral display printouts. Since additional fieldwork was not feasible during the course of this study, areas were chosen so that classes could be identified from existing ground truth information.

Because of the wide range of physiographic, soils, and vegetation conditions encountered over the map area, and the restriction of the cluster sample size, a combination of four separate areas transecting the widest possible range of conditions was chosen. These were located along the William River in the northeastern portion of the map area; along P.T.H. 6 in the central region; and in two areas of the The Pas Moraine, in the southwestern and southeastern portions of the map area. These areas were located on the data tape in a similar manner to supervised training areas, utilizing Versatec plotter grayscale map coordinates.

The most separable classes resulting from a clustering procedure are rarely those of primary interest to the user, particularly so in the case where discrimination of classes with subtle differences in vegetation types was anticipated. Therefore the maximum number of classes allowable (40) was requested. These cluster classes were later attributed to various unique map unit groups.

The NSCLAS program provides a number of output formats which indicate cluster identity, including cluster spectral coordinates, class separability information, and pictoral outputs of the clustered area.

Mean and variance spectral data for the 40 cluster classes are illustrated in Appendix B.

Clusters were not correlated with unique soils classes at this stage. Several clusters were identified as representing different cloud conditions, and were consolidated into two classes. This resulted in the reduction of the number of unique classes to 37.

4.4.2.3 Generation of an Unsupervised Statistics Deck

Uniform areas from the unsupervised classifier output map were selected for each of the cluster classes. This insured that each ground cover class with a unique spectral signature was represented as a separate class within the nonsupervised statistics deck.

A statistics deck was then compiled by delineating uniform training areas for each cluster on the NSCLAS pictoral maps. Training fields for each class contained only pixels for that particular cluster class. The statistics deck contained spectral reflectance data for all classes in all four LANDSAT bands. Pixels from a single cluster class in a very limited area were occasionally found to have a single digital reflectance value in a particular LANDSAT band. This condition was encountered for 3 cluster classes and would not permit the proper function of the maximum liklihood decision rule classifier during further processing. As a result, several training fields, representing a total of at least 15 pixels, were delineated for each cluster class in order to provide a suitable range of reflectance values.

The unsupervised statistics deck was then used for classification and initial display of portions of the map area. These pictoral displays were compared with photointerpretive evaluations and known soil conditions in order to identify the classes. Various types of output, including histograms, coincident spectral plots and feature space location of each class were generated.

4.4.2.4 Classification and Display of Map Area

Classification and display steps are identical to those previously described for the supervised method. The same LARSYS programs and MLDR classifier were employed.

4.4.2.5 Final Display of Map Area

During the unsupervised classification procedure, the identity of the cluster classes was not known. Using the display of the map area with computer assigned cluster class symbols the classes were identified and grouped into meaningful units, based on comparison with ground cover data and photointerpretation of the same map area.

Spectral information obtained for each class from the LARSAA statistics processors also provide valuable information.

The final step in the unsupervised method was a display of the map area using connotative, user assigned symbols to represent classes or groups of classes. Test area performance was also calculated, in a similar manner as for the supervised classification method.

Chapter V

RESULTS AND DISCUSSION

5.1 SUPERVISED CLASSIFICATION PERFORMANCE

5.1.1 Final Training Class Description

The final supervised classification legend consisted of 14 spectrally separable groups. These included 10 soils groups (4 mineral and 6 organic), 2 water groups, and groups for areas covered by cloud and cloud shadows. The final statistics deck contained reflectance data from 31 separate training fields. Data from one or more similar fields were grouped into a total of 21 spectrally unique training classes.

Names for training groups, classes, and fields were derived from abbreviations of soil names or material types they constitute, so that they were as connotative as possible.

5.1.1.1 Separable Mineral Soil Groups

The mineral soil groups could be separated into only four significant mapping groups, as indicated in Table 1. These groups were designated as Till (deep, imperfect to well drained mineral soils), Till/R (shallow veneer of till over bedrock), Rock (limestone bedrock outcrop), and Dering (poorly drained till soils).

The Till group incorporated a variety of mineral soil types whose training fields exhibited similar spectral signatures, as illustrated

Table 1. Mineral Soil Groups Separable by Automatic Supervised Classification.

Map Symbol	Group Name	Training Class Name	Training Field Name	Soil Series	Parent Material	Drainage	Dominant Vegetation
A	Till	AT2 Chitek ATB	AT2-1 CI-1 ATB-1	Degraded Eutric Brunisol	Extremely calcareous loam textured glacial till.	Imperfect	Black spruce & jackpine with an understory of feathermosses.
							Burned - regrowth of jackpine and ericaceous shrubs.
		ALLUV	ALLUV-1	Cumulic Regosol	Very fine sandy loam alluvial deposits.	Imperfect	Black spruce and white spruce with a ground cover of feathermosses.
		KI	KI-1	Orthic Gray Luvisol	15 to 90 cm mod. to strongly calc., fine textured lacustrine deposits over ext. calc. loamy till.	Imperfect to good	Black spruce with some balsam fir.
D	Dering	Dering	AT3-1	Carbonated Rego Humic Gleysol, peaty phase	15 to 40 cm peat over ext. calc. loamy till.	Poor	Black spruce with a ground cover of sphagnum & feath-mosses.
L	Till/R	R6LI4	R6LI4-1	60% Rock Outcrop 40% Degraded Eutric Brunisol, Lithic Phase	60% limestone bedrock. 40% 15-25 cm ext. calc. loamy till over lime-stone bedrock.	Good	Jackpine with an understory of lichens and pine needles.
		CRXLI	CRXLI	Degraded Eutric Brunisol, Lithic Phase	50% very coarse gravel beach deposits. 50% 15-25 cm ext. calc. loamy till over lime-stone bedrock.	Good	Jackpine with an understory of juniper, lichens & pine needles.
		CRXLIB	CRXLIB-1				Burned - scattered regrowth of jackpine & shrubs.
R	Rock	R9LI1	R9LI1-1	90% Rock Outcrop 10% Degraded Eutric Brunisol, Lithic Phase	90% limestone bedrock. 10% 15-25 cm ext. calc. loamy till over lime-stone bedrock.	Good	Jackpine & black spruce with a ground cover of lichens, juniper, and bedrock.
		R	R-1				Burned-scattered regrowth of jackpine and shrubs on bedrock.

in Table 1. This included soils developed on deep, loamy regional till (training fields AT2-1 and CI-1), sandy loam textured alluvial deposits (training field ALLUV-1), and lacustrine clay veneers over glacial till (training field KI-1). These soil materials all supported mixed stands of jack pine and spruce, with crown closures of about 70 percent. Since these soil types developed on contrasting materials which were not separable, it represented a serious limitation of the supervised classification method.

In order to overcome the problem of misclassification of burned areas, a separate class ("ATB") was established to represent this condition. This class, consisting of training field ATB-1 (Figure 6), had, as expected, a distinctly different spectral signature from other classes in the group. This site had been burned approximately 15 years previously and supported a regrowth of jack pine 1 to 3 meters in height, with a crown closure estimated at about 15 percent. The ground cover was composed of fallen jack pine (Pinus banksiana), mosses, and numerous ericaceous shrubs and plants, including bearberry (Arctostaphylus uva-ursi), saskatoon (Amelanchier alnifolia), strawberry (Fragaria virginiana), potentilla (Potentilla fruiticosa), twin flower (Linnaea borealis), and bunchberry (Cornus canadensis). The soil was a uniform, well drained Eluviated Eutric Brunisol developed on extremely calcareous regional till. Additional ground truth information for selected sites has been listed in Appendix C, while an analysis of the vegetation data obtained for these sites is described in Section 5.2 .

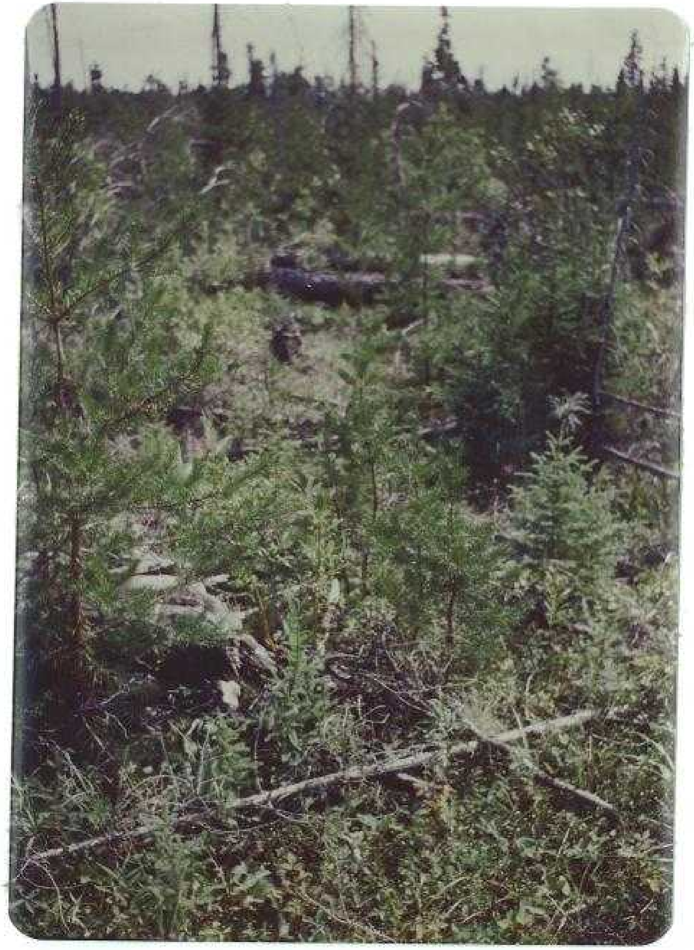


Figure 6: Training field ATB-1.

This site represents well drained till soils with a regeneration of vegetative cover.

Figure 7: Training field AT3-1.

This site represents poorly drained till soils of the Dering class.

The second mineral soil mapping group found to be spectrally separable was the Dering group, consisting of poorly drained, Rego Humic Gleysol, carbonated, peaty phase soils. Vegetative cover was open black spruce with some balsam fir and cedar, and a ground cover of Sphagnum, feathermoss, and ericaceous shrubs. This class was represented by a single training site (Figure 7). No other poorly drained mineral soil types were found which occupied uniform areas large enough to be reliably used as training fields.

The Till/R group consisted of three classes representing a soil condition with a co-dominant mixture of either limestone bedrock or fractured waterworked cobbly material grading into consolidated bedrock, and a shallow veneer of glacial till overlying the bedrock. Such soil complexes are very common in the Moose Lake Plain physiographic area, where they occupy large uniform areas suitable for training and test site delineation. Two normal training classes were chosen (fields R6LI4-1 and CRXLI-1, Figure 8), as well as a training class representing similar soils under burned conditions (field CRXLIB-1, Figure 9).

The fourth group was comprised of areas with a continuous exposure of limestone bedrock at the surface (Figure 10). Vegetation in these areas consisted of very open stands of jack pine with an understory of juniper, lichens, and pine needles. A burned class (Figure 11) was also included in this group.

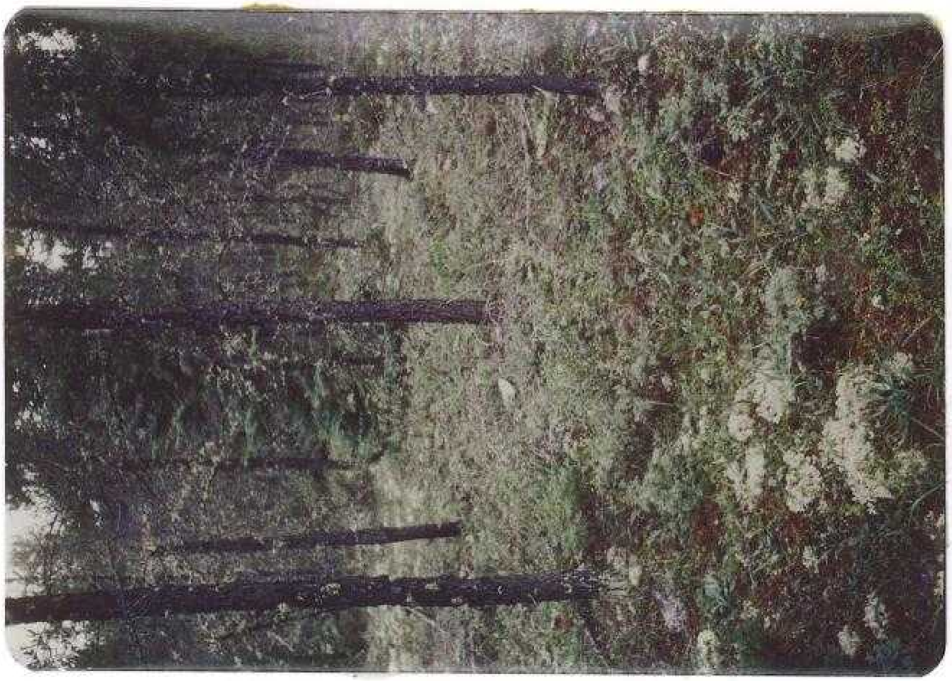


Figure 8: Training field CRXLI-1, Till/R group.
This site shows the typical open jack pine forest cover of soil areas with a combination of fragmented limestone bedrock and shallow till veneer soils.

Figure 9: Training field CRXLIB-1, Till/R group.
This site shows the regeneration of open jack pine and ground cover vegetation in burned areas where the soil consists of a combination of fragmented limestone bedrock and shallow till veneer soils.

Figure 10: Training field R9LI1-1, Rock soil mapping group.
This area is dominantly exposed limestone bedrock with minor inclusions of shallow glacial till veneer. Vegetation consists of a very open stand of jack pine with juniper, lichen, and pine needle ground cover.

Figure 11: Training field R-1, Rock soil mapping group.
This figure illustrates the predominance of exposed limestone bedrock, with a very sparse regrowth of jack pine following a recent fire.

5.1.1.2 Separable Organic Soil Mapping Groups

Organic soils were separated into 6 significant mapping groups, as indicated in Table 2.

Three deep organic soil groups with more than 160 cm of peat were discriminated. The first of these was the Stead group (Figure 12), representing very poorly drained Typic Mesisol soils developed on moderately decomposed fen peat. Vegetation was mainly sedges, reeds, and aquatic mosses, with open water at the surface in some localities.

The second organic soils group, termed Katimik (Figure 13), is similar to the Stead group except for the presence of a thin 15 to 65 cm surface layer of fibric Sphagnum moss peat overlying mesic fen peat. This was associated with a major change in vegetation type, consisting of thin stands of black spruce and tamarack, with an understory of Sphagnum moss, sedges, and ericaceous shrubs. Stead and Katimik soil map units were set up to recognize the extensive flatlying or very gently sloping areas of deep, uniform fen peat deposits known to occur in the study area, particularly in the Grand Rapids Lowland and Hargrave Lowland physiographic subsections.

The third deep organic soil type was designated the "WHX" group, illustrated in Figure 14. This represents organic soil areas composed of a thick (65 to 160 cm) layer of fibric Sphagnum moss peat overlying moderately decomposed forest or fen peat. The predominance of Sphagnum moss and associated ericaceous shrubs resulted in a very hummocky micro topography and an irregular distribution of stunted black spruce. Soil subgroups in this mapping group included Mesic Fibrisols, Typic Fibrisols, and Fibric Mesisols.

Table 2. Organic Soil Groups Separable by Automatic Supervised Classification.

Map Symbol	Group Name	Training Class Name	Training Field Name	Soil Series	Parent Material	Dominant Vegetation
●	Stead	Stead	STD1 MCX1	Typic Mesisol (>160 cm peat)	More than 160 cm of mesic fen peat with less than 15 cm fibric sphagnum peat on the surface.	Sedges, mosses, reeds with scattered tamarack and swamp birch.
—	Katimik	Katimik	KT-1 KT-3	Typic Mesisol, Fibric Mesisol (>160 cm peat)	15-60 cm fibric sphagnum peat overlying mesic fen peat.	Scattered thin stands of stunted black spruce and some tamarack with an understory of sphagnum moss.
=	WHX	WHX	WHX-1	Mesic Fibrisol (>160 cm peat)	60 to 120 cm fibric sphagnum peat over mesic forest or fen peat.	Stunted black spruce and tamarack, with an understory of sphagnum moss and ericaceous shrubs.
● ●	Crane	Crane	CR-1 CR-3	Terric Mesisol (<160 cm peat)	40 to 160 cm of mesic fen peat with less than 15 cm fibric sphagnum peat on the surface.	Sedges, mosses, reeds and grasses, with a few scattered tamarack and swamp birch.
<	Orok	Orok	ORX-1	Terric Mesisol, Terric Fibric Mesisol	50% less than 15 cm fibric sphagnum peat over mesic forest peat. 50% 15 to 60 cm fibric sphagnum peat over mesic forest peat.	Stunted black spruce and tamarack with an understory of sphagnum, reeds, and ericaceous shrubs.
>	KXLLX	KXLLX	KXLLX-1	Terric Mesisol, Terric Fibric Mesisol, Terric Mesic Fibrisol (<160 cm peat)	50% 15 to 60 cm fibric sphagnum peat over mesic forest peat. 50% 60 to 120 cm fibric sphagnum peat over mesic forest peat.	Stunted black spruce and tamarack, with an understory of sphagnum moss and ericaceous shrubs.

Figure 12: Training field STD-1, Stead soil mapping group. This site indicates typical sedge, reed, and aquatic moss vegetation associated with deep, very poorly drained fen peat deposits.

Figure 13: Photograph of a soil area typical of the Katimik soil mapping group.
This photograph indicates typical stunted black spruce tree cover, with an understory of Sphagnum, sedges, and ericaceous shrubs. The soil is a Typic Mesisol, sphagnic phase, with a thin layer of fibric Sphagnum moss peat overlying deep mesic fen peat deposits.

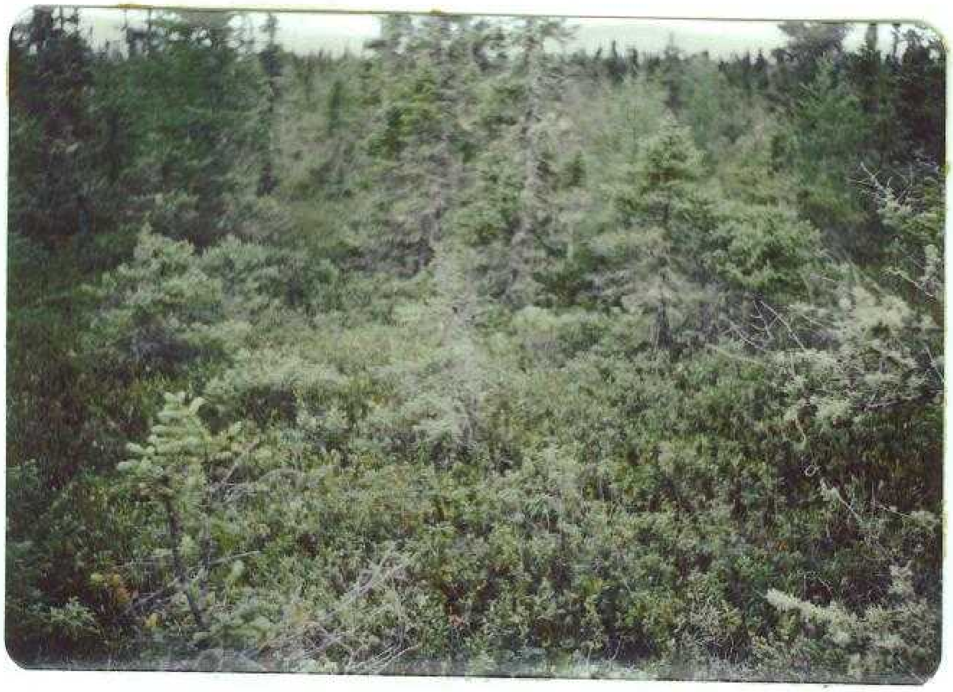


Figure 14: Test field WHX-2, WHX soil mapping group. This site indicates typical vegetative cover on organic soils consisting of a thick layer of fibric Sphagnum moss peat overlying moderately decomposed forest or fen peat.

Figure 15: Training field CR-1, Crane soil mapping group. This site, approximately 8 km southeast of Easterville, is a typical , uniform, flatlying Crane soil area with predominantly sedge vegetation. The soil is classified as a Terric Mesisol, with approximately 75cm of moderately decomposed fen peat overlying loamy regional till.

Three shallow organic soil mapping groups were successfully classified. The first of these was the Crane group (Figure 15), representing Terric Mesisol soils, developed on 40 to 160 cm of mesic fen peat. The underlying mineral material, depending on location, is either loamy, extremely calcareous till or clayey lacustrine sediments. The Crane group is similar in vegetative cover and organic parent material to the Stead group, differing mainly in the depth of the organic material and possibly the duration of the saturated moisture regime.

The second shallow organic soil mapping group was the Orok group, representing areas of shallow (40 to 160cm) mesic forest peat deposits. The underlying mineral material was undifferentiated, ranging from loamy glacial till to clayey to sandy lacustrine sediments. This soil group exhibits discontinuous hummocks of fibric Sphagnum peat occupying approximately 50% of the surface area. Orok soil areas support a dense black spruce and tamarack forest cover, with an understory of ericaceous shrubs and a ground cover of Sphagnum, feathermoss, and reed grasses (Figure 16).

The final organic soil type delineated was the "KXLLX" group. This group consists of similar organic materials as the Orok group, but with a thicker, continuous layer of fibric Sphagnum peat overlying the mesic forest peat. Vegetation is a somewhat more open stand of stunted black spruce with an understory of Sphagnum moss and ericaceous shrubs (Figure 17).

These final two organic soil groups are most prevalent on the level to very gently sloping areas of the The Pas Moraine physiographic subdivision.

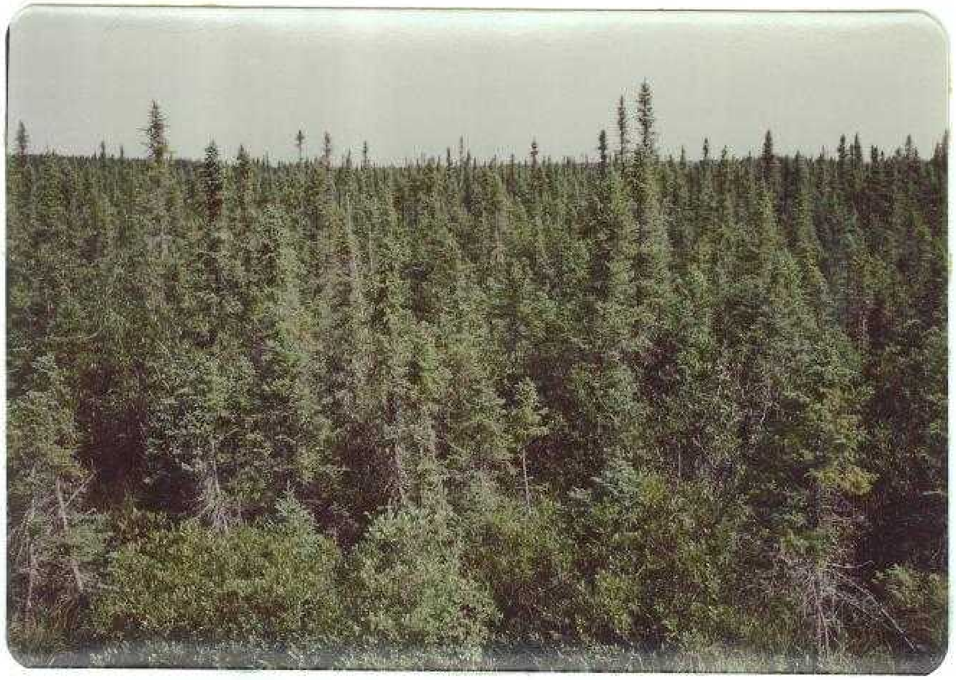


Figure 16: Training field ORX-1, Orok soil mapping group. General view of Orok training area southwest of Little Limestone Lake, illustrating typical dense stands of black spruce and tamarack.

Figure 17: Training field KXLLX-1, KXLLX soil mapping group. This view indicates typical open black spruce and tamarack vegetation of the KXLLX training site, located on Long Point.

5.1.1.3 Separable Nonsoil Mapping Groups

Several groups were also established to recognize nonsoil areas. Water bodies were also recognized as a separate mapping group. In order to test the usefulness of LANDSAT data for distinguishing different water body types, two separate training classes were distinguished. The first class ("WATER") had training areas established on William Lake, Cedar Lake, and the Grand Rapids reservoir. This class was chosen to represent deep, clear water bodies. The second class ("MWATER") had training areas located on Eating Point Lake, immediately northwest of Grand Rapids; Limestone Bay, on the northwesternmost corner of Lake Winnipeg; and Little Limestone Lake. This class represents water areas which had higher reflectance values in aerial photography and LANDSAT band 4 and 5 imagery.

LANDSAT imagery covering an entire 185 km2 area was rarely completely cloud free. The presence of cloud or cloud shadows resulted in the misclassification of the underlying soil areas into the closest, but likely incorrect soils group. Therefore training groups were established for both cloud and cloud shadows in order to recognize and exclude these areas from soils classification.

5.1.2 <u>Quantitative Classification Results</u>

5.1.2.1 Coincident Spectral Plots

The coincident spectral plots shown in Figures 18 and 19 indicate graphically the range of spectral intensities in each band (mean plus or minus one standard deviation) for all 21 final training classes. The spectral intensities are represented by digital CCT values from 0 (darkest) to 255 (brightest).

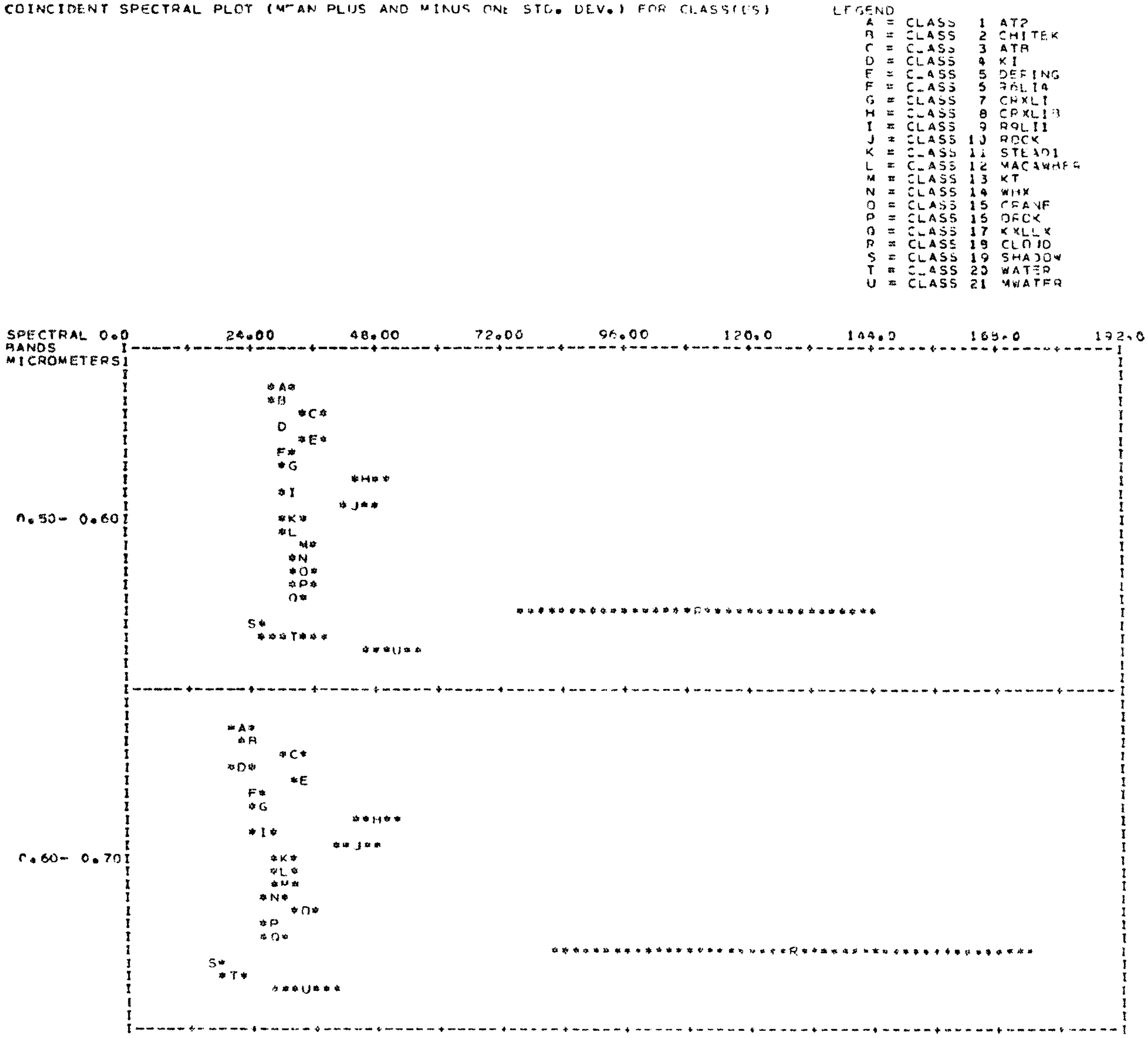


Figure 18: Coincident spectral plot for supervised training classes in bands 4 and 5.

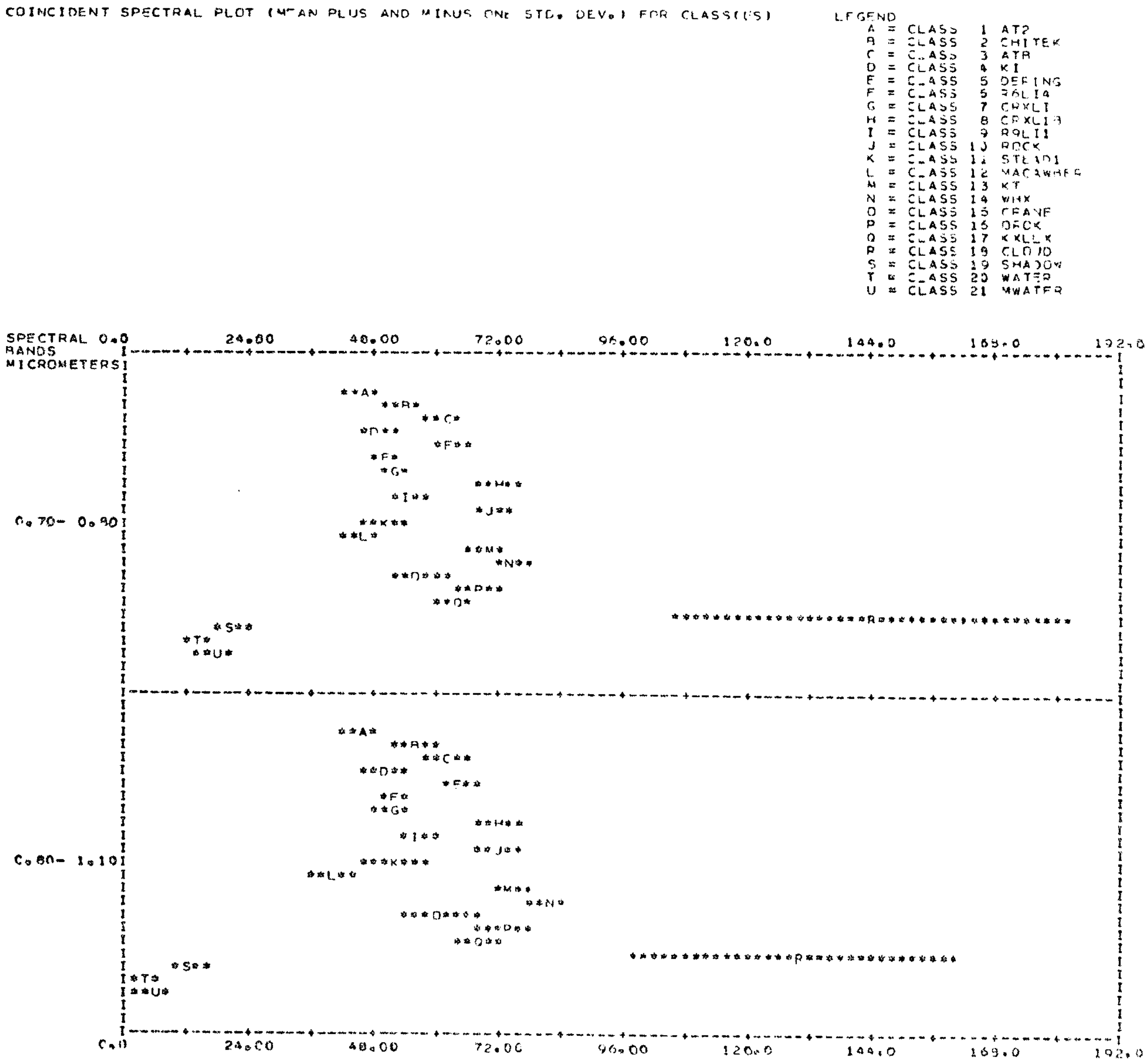


Figure 19: Coincident spectral plot for supervised training classes in bands 6 and 7.

Several general obervations were readily apparent. The cloud class was very bright in all 4 bands, with a wide range of spectral values.

The two water classes were spectrally distinct in the 500-600 nm (green) and 600-700 nm (red) bands, where the MWATER class had significantly higher reflectance values. Both classes overlapped the range of soils class reflectance values in these bands. The two water classes are progressively much darker than vegetated soils classes in bands 6 and 7. These results were in accordance with standard LANDSAT imagery, in which water bodies appeared very dark in bands 6 and 7.

The class representing cloud shadows was also similar to soils classes in bands 4 and 5, and had considerably lower reflectance values in the near infrared bands 6 and 7, though they were not as dark as the water classes. As a result, shoreline areas where pixels were "contaminated" with both land and water contributions to the spectral reflectance were frequently classified as cloud shadow.

The soils classes with various vegetative covers all fell within a fairly narrow range of spectral intensities in each of the four bands. The slightly higher reflectance values in band 4 (green) than in band 5 (red), and the much higher values in bands 6 and 7 (near infrared) are characteristic of vegetated surfaces. This similarity of spectral signatures from all vegetative types, regardless of structure or underlying soil conditions, resulted in considerable potential for overlap and misclassification between competing soil groups. This factor accentuated the need for careful selection of training fields and classes and both complicated and limited the selection of a final supervised classification legend.

5.1.2.2 Training Field Performance

For classification purposes, threshold percentages were arbitrarily set at 5.0% for all soils classes and 0.1% for nonsoil classes. Thresholds indicate the degree of similarity a pixel must have to the nearest class before classification is accepted; therefore pixels were rejected from soils classes if there was less than a 5% likelihood they belonged to the most probable soils class. A wider range of values was permitted for nonsoil classes, as cloud and shadow areas were characterized by a wide range of reflectance values.

Training field performance for the final set of supervised training fields are indicated in the confusion matrix in Table 3. These outputs indicate the type of misclassification errors which occur for each training field as well as the overall classification performance. A total of 1795 out of 2074 training pixels were classified correctly, for an overall training field performance of 86.5%. This figure, a weighted average for all training classes, was based on the number and percentage of pixels identified as belonging to the mapping group of which the training field was a member. For soils mapping and classification purposes the WATER and MWATER classes were grouped together.

Results which included a large number of spectrally distinct nonsoil classes did not provide a true indication of soil mapping performance. For soil training classes only, 1036 out of 1311 pixels were classified correctly, resulting in an overall correct classification of 79.0%.

TABLE 3

CONFUSION MATRIX ILLUSTRATING FINAL SUPERVISED TRAINING FIELD PERFORMANCE

FIELD DESIG.	GROUP	NO OF SAMPS	PCT. CORCT	NUMBER OF SAMPLES CLASSIFIED INTO													
				TILL	TILL/R	ROCK	STEAD	WATER	DERING	KT	WHX	CRANE	OROK	KXLLX	CLOUD	SHADOW	THRSHOLD
AT2-1	TILL	28	96.4	27	1	0	0	0	0	0	0	0	0	0	0	0	0
CI-1	TILL	39	82.1	32	3	3	0	0	0	0	0	0	0	1	0	0	0
ATB-1	TILL	15	66.7	10	0	0	0	0	3	0	0	2	0	0	0	0	0
KI-1	TILL	66	92.4	61	3	1	1	0	0	0	0	0	0	0	0	0	0
AT3-1	DERING	21	85.7	3	0	0	0	0	18	0	0	0	0	0	0	0	0
R6LI4-1	TILL/R	56	89.3	6	50	0	0	0	0	0	0	0	0	0	0	0	0
CRXLI-1	TILL/R	49	85.7	1	42	4	2	0	0	0	0	0	0	0	0	0	0
CRXLIB1	TILL/R	54	74.1	0	40	13	0	0	1	0	0	0	0	0	0	0	0
R9LI1-2	ROCK	73	69.9	11	10	51	0	0	0	0	0	0	0	1	0	0	0
R1	ROCK	45	84.4	0	7	38	0	0	0	0	0	0	0	0	0	0	0
STD1	STEAD	36	83.3	1	0	0	30	0	1	0	0	4	0	0	0	0	0
MCX2	STEAD	99	100.0	0	0	0	99	0	0	0	0	0	0	0	0	0	0
KT-1	KT	304	75.0	6	0	0	0	0	3	228	6	4	33	23	1	0	0
WHX-1	WHX	49	83.7	0	0	0	0	0	0	3	41	0	5	0	0	0	0
CR1	CRANE	77	68.8	5	0	0	17	0	2	0	0	53	0	0	0	0	0
CR-3	CRANE	42	69.0	5	0	0	0	0	5	2	0	29	0	1	0	0	0
ORX-1	OROK	20	60.0	0	0	0	0	0	0	2	1	0	12	5	0	0	0
ORX-2	OROK	18	72.2	0	0	0	0	0	0	0	4	0	13	1	0	0	0
KXLLX-1	KXLLX	220	73.6	9	0	6	0	0	2	7	2	1	31	162	0	0	0
CLOUD1	CLOUD	36	100.0	0	0	0	0	0	0	0	0	0	0	0	36	0	0
CLOUD2	CLOUD	9	100.0	0	0	0	0	0	0	0	0	0	0	0	9	0	0
SHADOW1	SHADOW	27	96.3	0	0	0	0	0	0	0	0	0	0	0	0	26	1
SHADOW2	SHADOW	91	98.9	0	0	0	0	1	0	0	0	0	0	0	0	90	0
H2O-6	WATER	45	97.8	0	0	0	0	44	0	0	0	0	0	0	0	1	0
H2O-4	WATER	60	100.0	0	0	0	0	60	0	0	0	0	0	0	0	0	0
H2O-3	WATER	54	98.1	0	0	0	0	53	0	0	0	0	0	0	0	0	1
H2O-5	WATER	441	100.0	0	0	0	0	441	0	0	0	0	0	0	0	0	0
	TOTAL	2074		177	156	116	149	599	35	242	54	93	94	194	46	117	2

OVERALL PERFORMANCE (1795/2074) = 86.5

5.1.2.3 Training Group Performance

Classification results expressed as training group performance are given in Table 4. Overall performance was 86.5%, with an average group performance of 84.0%. Considering the ten soils groups only, the average group performance was 79.5%, ranging from a high of 95.6% for the Stead group to a low of 65.8% for the Orok group.

5.1.2.4 Test Field Performance

Training field results alone did not provide a true picture of classification performance. When a performance evaluation is made of the same training fields used to derive the initial classification statistics, the results were unrealistically good. The classification statistics were in such cases optimally tailored for application to the same selected areas. Similar findings were reported by Schubert (1976, pp. 101-102).

An analysis of test fields delineated for all of the various classes was also made. These test fields, located in other portions of the map area, provided a more realisic appraisal of supervised classification performance and extensibility over the map area in its entirety. Display maps of large portions of the map area were also produced to evaluate classification results.

Test field results are shown in Table 5. 1602 out of 2809 pixels were identified as belonging to the correct mapping group, resulting in an overall test field performance of 57.0%. For soils classes only, 1024 out of 2192 pixels were correctly identified, resulting in an overall test field performance of 46.8%. This was considerably lower than the training field performance.

TABLE 4

SUPERVISED TRAINING GROUP PERFORMANCE

NUMBER OF SAMPLES CLASSIFIED INTO

	GROUP	NO OF SAMPS	PCT. CORCT	TILL	TILL/R	ROCK	STEAD	WATER	DERING	KT	WHX	CRANE	OROK	KXLLX	CLOUD	SHADOW	THRSHOLD
1	TILL	148	87.8	130	7	4	1	0	3	0	0	2	0	1	0	0	0
2	TILL/R	159	83.0	7	132	17	2	0	1	0	0	0	0	0	0	0	0
3	ROCK	118	75.4	11	17	89	0	0	0	0	0	0	0	1	0	0	0
4	STEAD	135	95.6	1	0	0	129	0	1	0	0	4	0	0	0	0	0
5	WATER	600	99.7	0	0	0	0	598	0	0	0	0	0	0	0	1	1
6	DERING	21	85.7	3	0	0	0	0	18	0	0	0	0	0	0	0	0
7	KT	304	75.0	6	0	0	0	0	3	228	6	4	33	23	1	0	0
8	WHX	49	83.7	0	0	0	0	0	0	3	41	0	5	0	0	0	0
9	CRANE	119	68.9	10	0	0	17	0	7	2	0	82	0	1	0	0	0
10	OROK	38	65.8	0	0	0	0	0	0	2	5	0	25	6	0	0	0
11	KXLLX	220	73.6	9	0	6	0	0	2	7	2	1	31	162	0	0	0
12	CLOUD	45	100.0	0	0	0	0	0	0	0	0	0	0	0	45	0	0
13	SHADOW	118	98.3	0	0	0	0	1	0	0	0	0	0	0	0	116	1
	TOTAL	2074		177	156	116	149	599	35	242	54	93	94	194	46	117	2

OVERALL PERFORMANCE (1795/2074) = 86.5

AVERAGE PERFORMANCE BY CLASS (1092.5/13) = 84.0

TABLE 5

SUPERVISED TEST FIELD PERFORMANCE

FIELD DESIG.	GROUP	NO OF SAMPS	PCT. CORCT	NUMBER OF SAMPLES CLASSIFIED INTO: TILL	TILL/R	ROCK	STEAD	WATER	DERING	KT	WHX	CRANE	OROK	KXLLX	CLOUD	SHADOW	THRSHOLD
TTILL1	TILL	66	93.9	62	2	0	0	0	0	0	0	0	1	1	0	0	0
TTILL2	TILL	56	37.5	21	22	6	3	0	3	0	0	1	0	0	0	0	0
TT/R-1	TILL/R	56	12.5	6	7	41	2	0	0	0	0	0	0	0	0	0	0
TT/R-2	TILL/R	176	27.3	41	48	79	2	0	4	0	0	0	0	2	0	0	0
TT/R-3	TILL/R	88	58.0	37	51	0	0	0	0	0	0	0	0	0	0	0	0
TT/R-4	TILL/R	72	69.4	13	50	9	0	0	0	0	0	0	0	0	0	0	0
TT/R-5	TILL/R	56	80.4	2	45	4	5	0	0	0	0	0	0	0	0	0	0
R9LI1-1	ROCK	42	59.5	7	10	25	0	0	0	0	0	0	0	0	0	0	0
TR-1	ROCK	81	60.5	0	25	49	0	0	0	0	0	2	0	0	5	0	0
TR-2	ROCK	84	35.7	0	52	30	0	0	1	0	0	0	0	0	1	0	0
TDR-1	DERING	55	50.9	18	0	4	1	0	28	1	0	3	0	0	0	0	0
TMCX-1	STEAD	144	48.6	11	4	10	70	0	12	1	0	35	0	1	0	0	0
TSTD-2	STEAD	18	50.0	1	0	2	9	0	2	0	0	1	0	3	0	0	0
TKT-1	KT	90	51.1	1	0	0	0	0	0	46	2	2	25	14	0	0	0
TKT-3	KT	36	38.9	1	0	0	0	0	0	14	2	0	16	3	0	0	0
TRLX-1	KT	156	50.6	17	0	0	0	0	16	79	5	10	12	16	0	0	1
TWHX-2	WHX	35	51.4	0	0	0	0	0	0	7	18	0	7	3	0	0	0
TWHX-3	WHX	170	38.2	1	0	0	0	0	0	65	65	1	17	15	0	0	6
TWHX-4	WHX	84	17.9	1	0	1	0	0	0	35	15	1	20	11	0	0	0
TCR-1	CRANE	90	38.9	13	0	1	6	0	25	0	0	35	0	10	0	0	0
TCR-2	CRANE	49	51.0	6	0	0	5	0	11	0	0	25	0	2	0	0	0
TCR-3	CRANE	49	67.9	9	0	0	2	0	4	1	0	38	0	0	1	0	0
TCR-4	CRANE	60	68.3	1	0	1	12	0	3	1	1	41	0	1	0	0	0
TOROK1	OROK	63	4.8	2	1	18	0	0	1	1	0	0	3	37	0	0	0
TOROK2	OROK	54	40.7	1	0	0	0	0	0	4	3	0	22	24	0	0	0
TOROK3	OROK	135	23.0	23	4	10	0	0	0	0	2	0	31	56	0	0	0
TKXLLX1	KXLLX	120	80.8	10	0	3	0	0	3	0	0	0	7	97	0	0	0
TH2O-1	WATER	90	100.0	0	0	0	0	90	0	0	0	0	0	0	0	0	0
TH2O-2	WATER	195	100.0	0	0	0	0	195	0	0	0	0	0	0	0	0	0
TCLOUD1	CLOUD	209	84.7	0	0	0	0	0	0	0	0	0	0	0	177	0	32
TCLOUD2	CLOUD	60	100.0	0	0	0	0	0	0	0	0	0	0	0	60	0	0
TSHADO1	SHADOW	63	88.9	4	0	0	2	0	0	0	0	0	0	0	0	56	1
	TOTAL	2809		309	321	293	119	285	113	264	112	195	161	296	244	56	41

OVERALL PERFORMANCE (1602/2809) = 57.0

5.1.2.5 Test Group Performance

When the results are summarized as test group performance (Table 6), the overall average for all groups was 60.0%, while soils groups alone achieved an average performance of 50.4%. Here again, test group performance was considerably lower than training group performance.

In addition to the fact that training areas used to derive the classification statistics may have produced unrealistically good results, several other factors may be attributed to the lower test field performance. Training areas represent the best, most uniform soil conditions. Test fields are delineated to represent average soil conditions; no attempt was made to reject or modify test fields to improve results. The identification of training and test areas required a heavy reliance on photointerpretation, with limited field checking and sampling. Soil conditions are rarely completely uniform over large areas.

5.1.2.6 Nature of Misclassification Errors

It was obvious from the use of the supervised automated classification process that a tradeoff existed between the number of training classes established and the classification performance. A very simple legend with a few very general, but spectrally unique, classes could provide good classification results, but the legend would be too broad to be of use for reconnaissance soil mapping purposes. The utility of computer mapping methods must therefore also be evaluated in terms of their capability to provide a mutually exclusive and comprehensive classification of the entire map area. According to current Canadian

TABLE 6

SUPERVISED TEST GROUP PERFORMANCE

NUMBER OF SAMPLES CLASSIFIED INTO

GROUP	NO OF SAMPS	PCT. CORCT	TILL	TILL/R	ROCK	STEAD	WATER	DERING	KT	WHX	CRANE	OROK	KXLLX	CLOUD	SHADOW	THRSHOLD
TILL	122	68.0	83	24	6	3	0	3	0	0	1	1	1	0	0	0
TILL/R	448	44.9	99	201	133	9	0	4	0	0	0	0	2	0	0	0
ROCK	207	50.2	7	87	104	0	0	1	0	0	2	0	0	6	0	0
STEAD	162	48.8	12	4	12	79	0	14	1	0	36	0	4	0	0	0
WATER	285	100.0	0	0	0	0	285	0	0	0	0	0	0	0	0	0
DERING	55	50.9	18	0	4	1	0	28	1	0	3	0	0	0	0	0
KT	282	49.3	19	0	0	0	0	16	139	9	12	53	33	0	0	1
WHX	289	33.9	2	0	1	0	0	0	107	98	2	44	29	0	0	6
CRANE	255	54.5	29	0	2	25	0	43	2	0	139	0	13	1	0	1
OROK	252	22.2	26	5	28	0	0	1	14	5	0	56	117	0	0	0
KXLLX	120	80.8	10	0	3	0	0	3	0	0	0	7	97	0	0	0
CLOUD	269	88.1	0	0	0	0	0	0	0	0	0	0	0	237	0	32
SHADOW	63	88.9	4	0	0	2	0	0	0	0	0	0	0	0	56	1
TOTAL	2809		309	321	293	119	285	113	264	112	195	161	196	244	56	41

OVERALL PERFORMANCE (1602/2809) = 57.0

AVERAGE PERFORMANCE BY CLASS (780.6/13) = 60.0

soil mapping practices, simple map units are allowed to contain up to 15% of unspecified inclusions of dissimilar soil or nonsoil types (Mapping Systems Working Group, 1981, pp. 38,39) Similar, non limiting soil types are permitted to occupy up to 50% of simple map units.

If training and test areas are considered equivalent to simple map units, then the type of misclassification, as well as the correct classification percentages, must be considered. Clearly, misrepresentation of closely related soil group types, frequently possessing similar soil properties, is not as serious a classification error as assignment to a strongly contrasting soil group type.

The confusion matrices provided a means of evaluating the nature of misclassification errors for each class.

Performance statistics for the four mineral soil groups were quite good for unburned conditions. These soil groups were not directly comparable to map units employed for conventional soil maps, where a different range of component soil series or complexes is used to represent map units. The Till group in particular required a very generalized group definition, consisting of a very broad range of mineral parent material types.

In order to make the four mineral soil group separations, several training classes representing soil types other than the Till group had to be rejected as they contained too a wide range of spectral variation which overlapped significantly with other classes. Training fields were initially selected for peat plateaus of frozen organic soils, and for beach ridges, composed of sorted sand and gravel deposits. Peat plateaus were found to have similar spectral signatures to the Till group, while beach ridges overlapped the range of Till, Till/R, and Rock soil group signatures. Training fields for these two classes were eliminated as they would have resulted in large errors of commission throughout the map area, which were not justified considering the small portion of the total map area they were known to represent. The inability to distinguish these two unique soils groups, which are readily separable by conventional aerial photointerpretation, is a serious drawback to the use of the supervised classification method.

The Hargrave Lowland werea, where frozen peat plateaus are an important soil type, represented only a small portion of the total map area. If the distribution of these soils was more extensive, separate sets of training classes might be required for each physiographic area in order to reduce serious misclassification errors.

The use of burn classes to overcome misclassification of burn areas was only partially successful. Burn classes could not be located for the range of successional stages encountered with different soil conditions. As a compromise, areas which supported typical regenerative vegetation following burns 15 to 20 years previously were selected for the Till, Till/R, and Rock soil groups. These had, as expected, quite different spectral signatures from the unburned groups. However, the burn training fields for all three classes had considerable spectral overlap, with the Till/R and Rock burn classes (CRXLIB and ROCK classes, Figures 18 and 19) appearing almost identical. As a result, there was considerable classification error between these groups in burn areas, as revealed in both training and test field performances.

The use of burned and unburned classes did produce more accurate soil maps, particularly in the Moose Lake Plain area where forest fires are a fairly frequent occurrence. Without them, burn areas would have been classified as organic soil areas with a similar sparse tree cover.

A wide range of natural vegetative cover conditions allowed for the separation of more organic soil classes than mineral classes. Also, errors arising from forest fire burns were not a serious problem for organic soil groups. Errors which did occur were mainly between classes having similar types of vegetative cover and soil conditions. For example, considerable misclassification occurred between Crane and Stead soil groups (Tables 4 and 6). These are Terric Mesisol and Typic Mesisol soils developed on similar fen peat materials. These soils supported similar vegetation, the main observable differences being the shorter sedge vegetation and the presence of open surface water in the Stead training areas during the late July imagery aquisition period (Figure 12).

There was also considerable misclassification between the KT, WHX, and KXLLX soil groups, as revealed by the test area statistics. The Orok test areas had the most serious classification errors, with the largest number of pixels assigned to the KXLLX group (Table 5). The Orok group had discontinuous Sphagnum hummocks overlying moderately decomposed forest peat. The KXLLX group was characterized by a continuous cover of Sphagnum overlying moderately decomposed forest peat. Therefore these two soil groups are quite similar. Based on test field performance, these two soil groups should likely be merged.

More significant misclassification error occurred between mineral and organic soil groups, although the actual percentage errors were fairly low.

Many Stead areas were actually patterned fens, with transverse treed ridges ("strangs"), separated by wetter areas of sedge vegetation ("flarks"). The treed areas were occasionally misclassified as Till/R or Rock.

Some test areas of the Crane soils group (TCR-1, TCR-2, TCR-3, Table 5) had a swamp-like vegetative cover of dense shrubs and cedar, instead of the open sedge vegetation of the training areas. This resulted in considerable misclassification of portions of such areas as Dering or Till, due to the similarity in spectral signature with the Till burn class.

Another limitation of the supervised classification technique for mapping organic soils was that the underlying mineral parent material could not be determined. For example, Terric Mesisols underlain by extremely calcareous, loamy glacial till were recognized as the Crane series, a distinct mapping entity in a conventional map legend. Terric Mesisol soils underlain by lacustrine clay, bedrock, or sand deposits were assigned different soil series and map unit designations. Although these differences were not always apparent from small scale aerial photointerpretation, they could usually be inferred from the landform, topographic position, or ground truth information obtained from similar nearby sites. This limitation did not apply to deep organic soil types, as the underlying mineral parent material did not affect the soil series designation.

5.1.2.7 Channel Selection

The amount of computer processing time, and hence the cost of computer classification, was dependent upon the number of classes in the statistics deck and the square of the number of channels considered (Eppler,1975).

In an effort to reduce classification costs, the deletion of one channel was considered. The spectral intensities of band 4 (green light) exhibited a narrow range, with considerable overlap for all vegetated soils classes, as shown in Figure 18. This indicated that band 4 contributed little to classification separability. This was confirmed by classifying the same training and test areas using all four channels (Tables 4 and 6) with results obtained using only three channels (Tables 7 and 8). Individual fields and classes exhibited slight decreases or increases in classification performance. Overall training group performance was 86.5% using all four channels, and 85.6% when band 4 was omitted. Overall test group performance was 57.0% using all channels, and 56.0% using bands 5,6 and 7 only.

It was anticipated that the slight decrease of 0.9% in overall training performance and 1.0% in test performance resulting from the deletion of band 4 data would be compensated for by a considerable saving in computer costs. A comparison of job statistics was later done for the same area classified using 4 and 3 channels of data respectively. Central processing unit (CPU) time was reduced by 1/3, although the number of input/output transactions (I/O counts) remained the same. Due to the algorithim used in computing costs, which included such constant factors as the number of lines printed and data tapes mounted, the resulting cost saving was slightly over 15%.

Table 7: Supervised training group performance, using LANDSAT bands 5,6, and 7.

NUMBER OF SAMPLES CLASSIFIED INTO

	GROUP	NO OF SAMPS	PCT. CORCT	TILL	TILL/R	ROCK	STEAD	WATER	DERING	KT	WHX	CRANE	OROK	KXLLX	CLOUD	SHADOW	THRSHOLD
1	TILL	148	87.8	130	5	6	2	0	2	0	0	1	0	2	0	0	0
2	TILL/R	159	79.2	8	126	22	2	0	1	0	0	0	0	0	0	0	0
3	ROCK	118	72.9	10	19	86	0	0	0	0	0	0	0	3	0	0	0
4	STEAD	135	96.3	1	0	0	130	0	1	0	0	3	0	0	0	0	0
5	WATER	600	99.8	0	0	0	0	599	0	0	0	0	0	0	0	0	1
6	DERING	21	61.9	7	0	0	0	0	13	0	0	1	0	0	0	0	0
7	KT	304	74.7	0	0	0	0	0	7	227	8	3	31	28	0	0	0
8	WHX	49	85.7	0	0	0	0	0	0	3	42	0	4	0	0	0	0
9	CRANE	119	63.9	9	0	2	16	0	12	3	0	76	0	1	0	0	0
10	OROK	38	63.2	0	0	0	0	0	0	2	5	0	24	7	0	0	0
11	KXLLX	220	69.1	7	0	6	0	0	4	16	0	1	34	152	0	0	0
12	CLOUD	117	99.1	0	1	0	0	0	0	0	0	0	0	0	116	0	0
13	SHADOW	118	97.5	0	0	0	0	1	0	0	0	0	0	0	0	115	2
	TOTAL	2146		172	151	122	150	600	40	251	55	85	93	193	116	115	3

OVERALL PERFORMANCE(1836/ 2146) = 85.6

AVERAGE PERFORMANCE BY CLASS(1051.1/13) = 80.9

TABLE 8

Supervised test group performance, using LANDSAT bands 5,6, and 7.

	GROUP	NO OF SAMPS	PCT. CORCT	TILL	TILL/R	ROCK	STEAD	WATER	DERING	KT	WHX	CRANE	OROK	KXLLX	CLOUD	SHADOW	THRSHOLD
				NUMBER OF SAMPLES CLASSIFIED INTO													
1	TILL	122	71.3	87	21	8	2	0	2	0	0	0	0	2	0	0	0
2	TILL/R	448	46.0	79	206	151	8	0	2	0	0	0	0	2	0	0	0
3	ROCK	207	54.6	4	72	113	0	0	1	0	0	1	0	1	15	0	0
4	STEAD	162	48.1	27	5	13	78	0	7	1	0	25	0	6	0	0	0
5	WATER	285	100.0	0	0	0	0	285	0	0	0	0	0	0	0	0	0
6	DERING	55	49.1	20	0	4	0	0	27	1	0	3	0	0	0	0	0
7	KT	282	43.3	16	0	1	0	0	19	122	10	9	52	52	0	0	1
8	WHX	289	26.3	0	0	1	0	0	2	117	76	3	55	29	0	0	6
9	CRANE	255	48.2	46	0	2	32	0	36	4	0	123	0	11	1	0	0
10	OROK	252	20.6	25	5	28	0	0	0	18	3	0	52	121	0	0	0
11	KXLLX	120	85.8	3	0	3	0	0	6	0	0	0	5	103	0	0	0
12	CLOUD	269	90.3	0	0	0	0	0	0	0	0	0	0	0	243	0	26
13	SHADOW	63	90.5	3	0	0	2	0	0	0	0	0	0	0	0	57	1
	TOTAL	2809		310	309	324	122	285	102	263	89	164	164	327	259	57	34

OVERALL PERFORMANCE(1572/ 2809) = 56.0

AVERAGE PERFORMANCE BY CLASS(774.2/13) = 59.6

Classification using 3 channel data was conducted for most subsequent printouts, particularly the large classification and display maps covering the entire map area which were produced for comparison purposes for both the supervised and unsupervised methods (Maps 1 and 2, Appendix D).

5.2 VEGETATION ANALYSIS

5.2.1 Qualitative Analysis

Vegetation conditions for all training and test sites were noted during the course of the field investigations. This included a listing of major tree species, their height ranges, and estimated crown closure. The understory coverage was also noted for the various cover types. A listing of LANDSAT spectral response values for representative training sites is provided in Table 9.

As previously noted in Section 5.1.2.1, all soils classes with vegetative cover exhibited a similar, characteristic spectral signature. Specific vegetative differences were difficult to correlate with spectral responses, as they represented minor variations in the same characteristic signature. Nevertheless, several observations were apparent.

The TILL group, represented here by the CI-1 training field data, had the highest crown closure estimates and yet had the lowest spectral response values in bands 4 and 5. This was attributed to the shadow effect produced by the dense coniferous forest stand.

The Till/R and ROCK groups had a sparser tree cover and a higher percentage of unvegetated ground cover, which yielded a lower spectral

TABLE 9

Landsat Reflectance Values and Vegetative Cover Estimates for Selected Supervised Training Sites

Supervised Training Area			Landsat Spectral Response (0-255)				Tree Cover				Principle Understory Constituents	
Group	Class	Field	Band 4	Band 5	Band 6	Band 7	Species	(%)	Height	Crown Closure	Species or Ground Cover	(%)
Till	CI	CI-1	29.7	23.1	53.6	56.3	Picea mariana Pinus banksiana	80% 20%	8-10m 12-14m	70%	Feathermoss Ericaceous shrubs	85% 15%
Till/R	CRXLI	CRXLI-1	31.3	25.7	51.4	51.0	Pinus banksiana Picea mariana	90% 5%	6-8m 2-3m	40%	Unvegetated (pine needles) Cladonia Bearberry Juniper Rock	20% 20% 20% 10% 5%
Till/R	R6LI4	R6LI4-1	30.1	24.8	50.1	51.5	Pinus banksiana Picea mariana	95% 5%	6-7m 3-5m	30%	Cladonia unvegetated (pine needles) Bearberry, twinflower Juniper Rock	40% 30% 20% 5% 5%
Rock	R9LI1	R9LI1-1	31.4	25.6	54.8	56.8	Picea mariana Pinus banksiana	60% 40%	3-8m 6-8m	30%	Cladonia Rock Juniper Bearberry	35% 30% 20% 15%
Orok	ORX	ORX-2	33.4	27.2	68.1	73.7	Larix larcina Picea mariana	90% 10%	2-4m 2m, some 6m	20%	Betula papyrifera Feathermoss Carex ericaceous shrubs	25% 25% 15% 10%
KXLLX	KXLLX	KXLLX-1	32.4	27.9	63.5	68.1	Picea mariana Larix larcina	80% 20%	6-7m	25%	Sphagnum Feathermoss Ledum groenlandicum Chamaedaphne	50% 20% 40% 10%
WHX	WHX	WHX-1	33.6	28.2	74.6	81.4	Picea mariana Larix laricina	85% 15%	1-6m 2-3m	15%	Chamaedaphne Ledum groenlandicum Feathermoss Sphagnum	30% 30% 10% 5%
Stead	Stead	STD-1	32.1	30.4	50.3	51.4	-	-	-	-	Carex, buckbean open water Drepanocladus	80% 10% 10%
Crane	Crane	CR-1	34.2	34.5	56.8	60.9	-	-	-	-	Carex Drepanocladus Buckbean, equisitum	80% 10% 10%

response, particularly in the near infrared bands 6 and 7, where response was more directly related to live vegetative cover.

Most organic soil classes had slightly higher spectral response values in all four bands than mineral soil classes. This was attributed to the lack of shadows due to the relatively short, stunted tree cover, and the abundant vegetative ground cover of mosses and ericaceous shrubs.

An exception appeared to be the deep, mesic fen soils of the STEAD group, which had lower spectral response values in bands 6 and 7, comparable to those of mineral soil groups. This was due to the contribution of areas of open water, which had a very low spectral response in the near infrared wavelengths. This similarity of response, despite the extreme differences in vegetative cover, accounted for the test field misclassification of STEAD and mineral soil classes (Table 5). The presence of variable amounts of open water in STEAD areas greatly influenced the spectral response of pixels in the group. This resulted in difficulty in accurately mapping these soil areas by automated means, despite their unique open vegetative cover and ease of identification by conventional airphoto interpretation techniques. Similar results were noted by Thie (1976, pp. 63.);

> A slight change in the water surface may change the pixel value as measured by satellite. This may cause considerable difficulty in the "signature" classification of these wetlands. In this study, the sedge dominated areas and patterned fen areas are consistently poorly classified; whereas the more homogeneous areas such as peat polygons and stone fields performed considerably better.

5.2.2 Quantitative Analysis

It was initially felt that vegetative spectral response is mainly a function of forest cover structure and species distribution for the majority of supervised training sites in the Boreal Forest environment. In addition to data provided by qualitative descriptions, a plotless sampling technique was used to analyze vegetative conditions for a range of supervised training sites. This technique was the most convenient method for sampling vegetative communities in which shrub or tree size woody plants of similar morphology were dominant. For each training site, ten stops were selected in a predetermined rectangular pattern, from which points the distance, circumference, and species of the nearest tree in each of the four quadrants were recorded. This data is listed in Appendix C.

A program for the analysis of data generated by the point-quarter method was obtained from Prof. J. M. Stewart, of the Botany Dept. of the University of Manitoba. This Fortran program required as input for each tree species in each study area, the number of individuals, the sum of their measured basal areas, the number of points they occur in, and the mean distance from the sample point. Output consisted of average dominance, density, relative density, relative dominance, frequency, relative frequency, and importance value calculations for the vegetative stand at each site. These parameters are all standard measurements of species abundance in woodland stands (Kershaw, 1973, pp. 198-200), and are illustrated for the selected training sites in Table 10.

Average dominance values are a measure of the sum of the basal area for each species divided by the number of individuals of that species. Relative density is the number of individuals of a species encountered divided by the number of quadrants sampled (40). Frequency is the number of sample points at which a species occurs divided by the total number of sample points (10). Relative dominance and relative frequency represent the dominance and frequency values obtained for a given species expressed as a percentage of the total dominance or frequency of all species. The importance value is a sum of the relative frequency, relative dominance, and relative density, and ranges from 0 to 300. It is a measure of the overall contribution of the species to the plant community.

All of the vegetative parameters served to characterize the plant communities, and their differences indicated the influence of microclimate, geography, drainage, vegetative succession, and soil conditions between the different training sites.

Neither the density, dominance, frequency, nor their combined importance value provided a suitable measure that may be directly related to canopy reflectance, and therefore to spectral signatures. The density calculation referred to the number of trees per unit area, without regard to their size or basal area. Dominance referred to the size of the individuals. Therefore a new term, relative areal coverage, was derived from the data in an attempt to more closely relate to the actual percentage cover. This was calculated by multiplying the density value obtained for each species in an area by the sum of its basal areas. The sum of these values for all tree species encountered

TABLE 10

Vegetation Parameters for Selected Supervised Training Sites.

Supervised Training Area			Species	# of Individuals (Total=40)	Avg. Dom. Value	Density	Relative Density (%)	Dominance	Relative Dominance (%)	Frequency	Relative Frequency (%)	Importance Value (Total =300)	Crown Closure (Visual estimate)	Relative Areal Coverage (all species)
Group	Class	Field												
Till	CI	CI-1	Picea mariana	29	57.29	41.62	72.50	2384.39	54.46	1.00	55.56	182.52		
			Pinus banksiana	10	131.79	14.35	25.00	1891.46	43.20	0.70	38.89	107.09		
			Populus balsamifera	1	71.10	1.44	2.50	102.05	2.33	0.10	5.56	10.39		
						57.41		4377.89		1.80			70%	88,157
Till/R	CRXLI	CRXLI-1	Pinus banksiana	37	90.60	107.35	92.50	9726.22	97.14	1.00	76.92	266.57		
			Picea mariana	3	32.86	8.70	7.50	286.02	2.86	0.30	23.08	33.43		
						116.06		10012.24		1.30			40%	360,719
Till/R	R6LI4	R6LI4-1	Pinus banksiana	35	77.87	86.40	87.50	6727.18	87.65	1.00	71.43	246.58		
			Picea mariana	5	76.80	12.34	12.50	947.90	12.35	0.40	28.57	53.42		
						98.74		7675.08		1.40			30%	240,204
Rock	R9LI1	R9LI1-1	Picea mariana	26	27.30	78.67	65.00	2147.84	41.43	0.90	60.00	166.43		
			Pinus banksiana	14	71.69	42.36	35.00	3036.95	58.57	0.60	40.00	133.57		
						121.04		5184.79		1.50			30%	109,024
Orok	ORX	ORX-2	Larix laricina	29	26.45	40.11	72.50	1060.79	72.26	1.00	62.50	207.26		
			Picea mariana	11	26.77	15.21	27.50	407.32	27.74	0.60	37.50	92.74		
						55.32		1468.11		1.60			20%	35,246
KXLLX	KXLLX	KXLLX-1	Picea mariana	26	36.20	84.93	65.00	3074.37	75.80	1.00	62.50	203.30		
			Larix laricina	14	21.46	45.73	35.00	981.32	24.20	0.60	37.50	96.70		
						130.66		4055.69		1.60			25%	55,108
WHX	WHX	WHX-1	Picea mariana	34	16.72	124.77	85.00	2085.82	88.04	1.00	62.50	235.54		
			Larix laricina	6	12.86	22.02	15.00	283.23	11.96	0.60	37.50	64.46		
						146.79		2369.05		1.60			15%	22,146

was used to express relative areal coverage for each representative training area in Table 10.

Most of the vegetation statistics calculated in Table 10 confirm in quantitative terms what had been apparent from visual observations. Black spruce was the dominant tree species in the TILL site, while jack pine was dominant in the TILL/R and ROCK training areas where forest fires have been a more frequent occurrence. Stunted black spruce and tamarack were the most important tree species in organic soil sites, with a higher relative dominance of black spruce on the KXLLX and WHX sites, where the surface cover of Sphagnum moss peat is progressively deeper.

The relative areal coverage values did not correlate well with the visual crown closure estimates. This was attributed to several factors. The basal area figures used in subsequent dominance and relative areal coverage calculations represented the area covered by the tree trunk at a height of 1 m above the ground. This did not provide the assumed simple linear correlation with the areal coverage of the vegetative canopy for trees of different ages, species, densities, and different site conditions. For example, the highest areal coverage and dominance values were obtained for the two TILL/R training areas. These sites had a dense regeneration of jack pine with a relatively narrow and open canopy. The TILL site had a much higher estimated crown closure, yet had much lower relative areal coverage values. This was attributed to the more mature stand of predominantly spruce trees, which provided a much more complete vegetative cover. The calculated density and relative areal coverage values clearly were not representative of crown closure values, and were therefore not a useful predictor of spectral signature and automated classification performance.

5.3 UNSUPERVISED CLASSIFICATION PERFORMANCE

5.3.1 Final Training Class Description.

An unsupervised classification of the Grand Rapids area was conducted as described in Section 4.4.2 . Many unsupervised cluster classes could not be attributed to a single unique soil condition in all areas. For example, several cluster classes were identified with both organic and burned mineral soil types in different localities. Soil types and their final display symbols were assigned so that errors of omission and commission were minimized.

Various statistical outputs were used to aid in the identification of the cluster classes. The most useful of these were the coincident spectral plots illustrated in Figures 20 and 21.

Of the 37 cluster classes, 4 were attributed to nonsoil conditions. Two of these represented cloud classes of different brightness, and were designated by a blank symbol on the final output maps. Urban areas, highways, and other cleared areas were also classified in these groups. A third class represented areas of cloud shadow and marginal water conditions, and was also assigned a blank symbol. The fourth class represented water and was designated by the symbol "W".

The remaining 33 cluster classes were attributed to 10 soil map unit types. Four of these represented mineral soil conditions and six represented organic soil conditions. Descriptions of these map unit

COINCIDENT SPECTRAL PLOT (MEAN PLUS AND MINUS ONE STD. DEV.) FOR CLASS(ES)

LEGEND
A = CLASS 1 12
B = CLASS 2 236
C = CLASS 3 4
D = CLASS 4 5
E = CLASS 5 78
F = CLASS 6 9
G = CLASS 7 A
H = CLASS 8 B
I = CLASS 9 C
J = CLASS 10 D
K = CLASS 11 E
L = CLASS 12 F
M = CLASS 13 G
N = CLASS 14 H
O = CLASS 15 I
P = CLASS 16 J
Q = CLASS 17 K
R = CLASS 18 L
S = CLASS 19 M
T = CLASS 20 N
U = CLASS 21 O
V = CLASS 22 P
W = CLASS 23 Q
X = CLASS 24 R
Y = CLASS 25 S
Z = CLASS 26 T
$ = CLASS 27 U
+ = CLASS 28 V
= = CLASS 29 W
/ = CLASS 30 X
A = CLASS 31 Y
B = CLASS 32 Z
C = CLASS 33 STAR
D = CLASS 34 /
E = CLASS 35 MINUS
F = CLASS 36 .
G = CLASS 37 BLANK

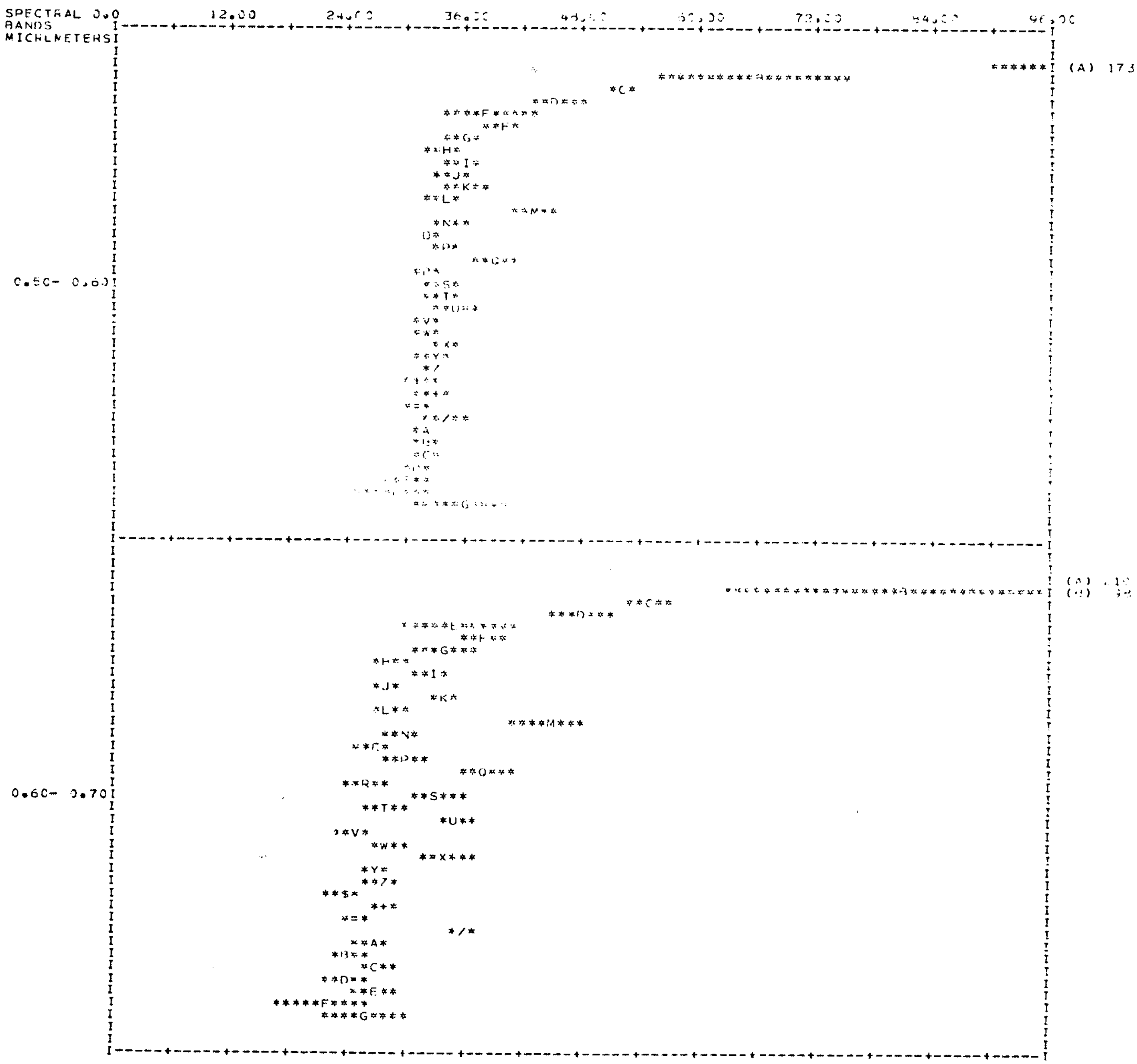


Figure 20: Coincident spectral plot for unsupervised training classes in bands 4 and 5.

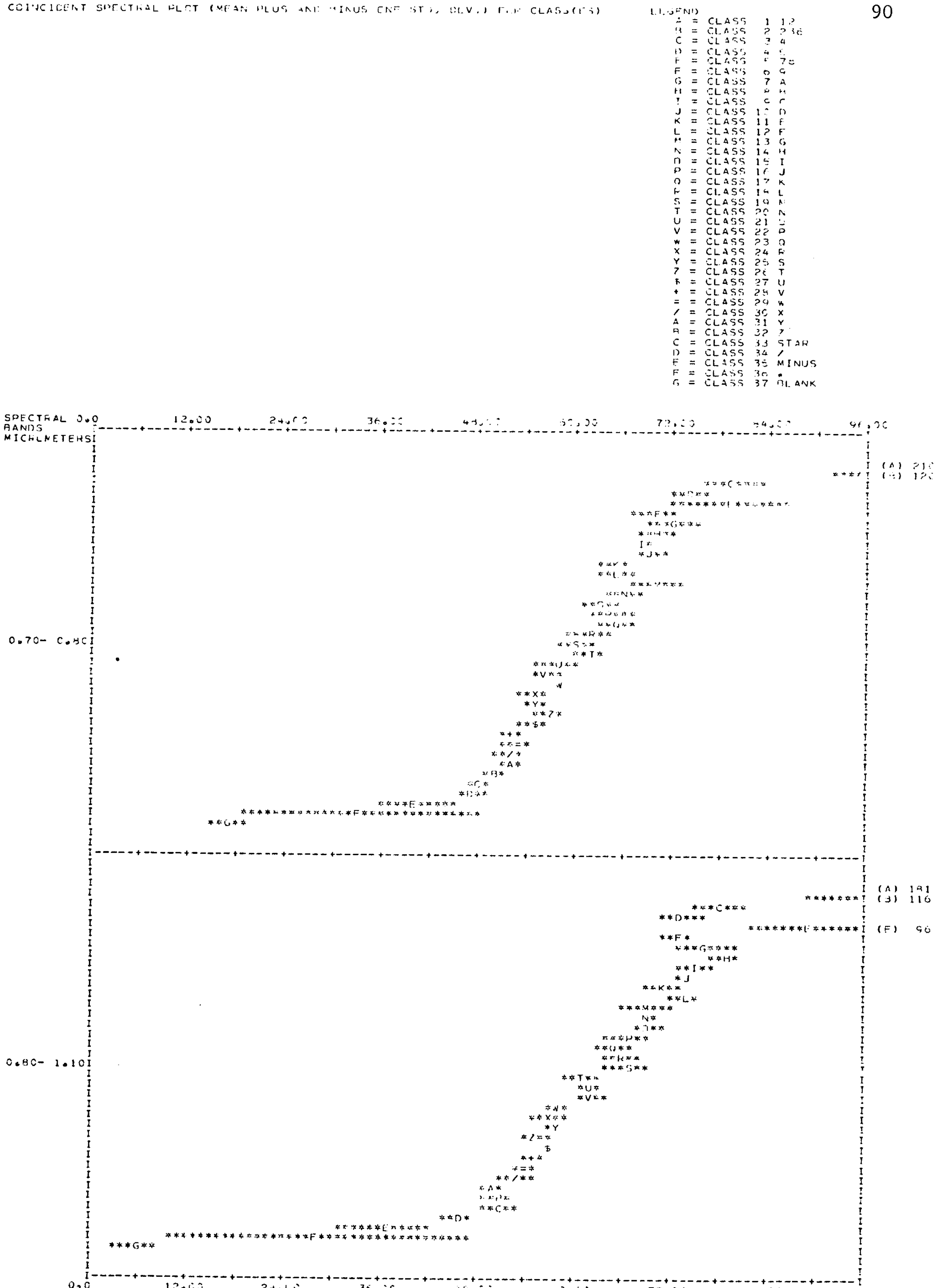


Figure 21: Coincident spectral plot for unsupervised training classes in bands 6 and 7.

types are given in Table 11. Alphanumeric symbols assigned to soil groups were selected to be as connotative as possible and to correlate with symbols used for similar map unit types separable by the supervised method. Alphabetic symbols were used for mineral soil map units; non-alphabetic symbols were used to represent organic map units.

The 4 mineral soil groups were similar in definition to those separable by the supervised method. Four of the organic soil mapping groups ("STEAD", "KT", "CRANE", and "WHX") were also basically equivalent to those groups assigned similar names and symbols using the supervised method.

The unsupervised "OROK-KX" group was comparable to a combination of the supervised "OROK" and "KXLLX" groups. These supervised groups represented closely related soil conditions of Sphagnum peat overlying shallow accumulations of mesic forest peat, which resulted in considerable overlap and misclassification between them. Four unsupervised cluster classes were attributed to a combination of these conditions and were assigned to the unsupervised "OROK-KX" group.

The "HALCROW" group consists of shallow fen peat soils with a 15 to 65 cm layer of Sphagnum moss peat on the surface. Vegetation consisted of an open stand of stunted black spruce and tamarack, with a ground cover of Sphagnum, sedges, and ericaceous shrubs. Eastern white cedar (<u>Thuja occidentalis</u>) also commonly occurs on this and other poorly drained soil types in the The Pas Moraine area. The "HALCROW" group was not considered of sufficient areal extent to warrant selection as a training group for supervised classification, but

Table 11

Soil Mapping Groups Separable by Unsupervised Classification.

Map Symbol	Soil Group[1]	Parent Material	Soil Profile Type[2]	Drainage	Vegetation
A	Till	Extremely calcareous loamy glacial till* Clay veneer over extremely calcareous, loamy glacial till.	Eluviated Eutric Brunisol* Gleyed Eluviated Eutric Brunisol Orthic Gray Luvisol Gleyed Gray Luvisol	Well to imperfect	Black spruce, jack pine, white spruce, with an understory of feathermoss and ericaceous shrubs.
D	Dering	15 to 40 cm of mesic peat overlying extremely calcareous loamy glacial till.	Rego Humic Gleysol, carbonated, peaty phase.	Poor	Black spruce with a ground cover of Sphagnum and feathermoss.
L	Till/R	Approx. 50% dolomite bedrock outcrop and 50% 10-25 cm of extremely calcareous loamy till over dolomite bedrock.	Eluviated Eutric Brunisol	Well	Jack pine with a ground cover of juniper, lichens and pine needles.
R	Rock	Dolomite bedrock outcrops with minor areas of extremely calcareous loamy till over bedrock.		Well	Jack pine and black spruce with a ground cover of lichens, juniper and exposed bedrock.
•	Stead	Deep ($>$160 cm) mesic fen peat with little or no ($<$15 cm) fibric Sphagnum moss peat on the surface.	Typic Mesisol	Very poor	Sedges, mosses and reeds with scattered tamarack and swamp birch.
-	Katimik	Deep ($>$160 cm) mesic fen peat with a thin (15 to 65 cm) fibric Sphagnum peat surface layer.	Typic Mesisol, sphagnic phase.	Poor to very poor	Scattered thin stands of stunted black spruce and some tamarack with an understory of Sphagnum moss and ericaceous shrubs.
=	WHX	Deep ($>$160 cm) organic soils composed of 65 to 160 cm of fibric Sphagnum peat overlying mesic forest or fen peat.	Mesic Fibrisol* Typic Fibrisol Fibric Mesisol	Poor to very poor	Stunted black spruce with an understory of Sphagnum moss and ericaceous shrubs.
:	Crane	Shallow (40-160 cm) mesic fen peat with little or no ($<$15 cm) fibric Sphagnum moss peat on the surface.	Terric Mesisol	Very poor to poor	Sedges, mosses, reeds and grasses, with a few scattered tamarack and swamp birch.
;	Halcrow	Shallow (40-160 cm) mesic fen peat with a thin (15-65 cm) surface layer of fibric Sphagnum moss peat.	Terric Mesisol, sphagnic phase	Very poor to poor	Stunted black spruce and tamarack with an understory of Sphagnum, sedges, reeds, and ericaceous shrubs.
>	OROK-KX	Shallow (40-160 cm) organic soils with a 0 to 160 cm surface layer of fibric Sphagnum moss peat overlying mesic forest peat.	Terric Mesisol, sphagnic phase* Terric Mesisol Terric Fibric Mesisol Terric Mesic Fibrisol Terric Fibrisol	Poor to very poor	Stunted black spruce and tamarack with an understory of Sphagnum moss and ericaceous shrubs.
W	Water	Water			
	Cloud	Clouds			
	Shadow	Cloud Shadows			

* Indicates dominant parent material or soil series.

1. Groups may contain several training fields and classes with different spectral characteristics.

2. Soil classification according to the Canadian System of Soil Classification (revised, 1978). Canada Soil Survey Committee. Agriculture Canada, Ottawa.

was the single best soils group that could be attributed to two unsupervised cluster classes.

5.3.2 Quantitative Classification Results

The nature of the unsupervised method precluded the use of training fields to evaluate classification success. Quantitative results were therefore restricted to test field performance evaluations. The same test fields used in supervised classification were used for those map unit groups found to be common to both methods. New test fields were located for those classes unique to the unsupervised method. A list of the unsupervised test fields and their coordinates is provided in Appendix B. No attempt was made to influence performance results by subsequent modification of the test field population.

5.3.2.1 Test Field and Group Performance

Unsupervised classification test field performance is indicated by the confusion matrix in Table 12. A total of 1672 out of 2924 pixels were classified correctly, for an overall performance of 57.2%. This figure is potentially misleading due to disparities in sample size and the inclusion of nonsoil classes; performance for the soils test fields alone was only 42.8%. These results are summarized for each mapping group in Table 13.

5.3.2.2 Nature of Misclassification Errors

As with the supervised classification results, other factors must be evaluated in conjunction with the final test group performance val-

Table 12: Unsupervised test field performance.

FIELD DESIG.	GROUP	NO OF SAMPS	PCT. CORCT	NUMBER OF SAMPLES CLASSIFIED INTO: CLOUD	ROCK	TILL/R	TILL	STEAD	KT	DERING	CRANE	HALCROW	ORCK-KX	WHX	SHADOW	WATER
TTILL1	TILL	65	69.7	0	0	10	47	5	0	1	0	0	2	0	2	0
TTILL2	TILL	56	37.5	1	2	20	21	4	0	4	2	2	0	0	0	0
TT/R-1	TILL/R	56	30.4	0	27	17	7	0	0	5	0	0	0	0	0	0
TT/R-2	TILL/R	176	50.0	0	47	88	26	3	0	12	0	0	0	0	0	0
TT/R-3	TILL/R	88	30.7	0	0	27	49	11	0	0	0	0	0	0	1	0
TT/R-4	TILL/R	72	69.4	0	4	50	10	8	0	0	0	0	0	0	0	0
TT/R-5	TILL/R	56	57.1	1	0	32	5	18	0	0	0	0	0	0	0	0
RALI1-1	ROCK	42	40.5	0	17	18	4	1	0	1	0	0	1	0	0	0
TR-1	ROCK	81	75.3	15	61	4	0	0	1	0	0	0	0	0	0	0
TR-2	ROCK	84	70.2	2	59	23	0	0	0	0	0	0	0	0	0	0
TDR-1	DERING	55	16.4	0	2	9	0	0	1	9	5	15	14	0	0	0
TMCX-1	STEAD	144	23.6	3	14	13	6	34	1	14	54	4	1	0	0	0
TSTD-2	STEAD	18	11.1	0	0	5	1	2	0	4	1	1	4	0	0	0
TKT-1	KT	90	53.3	0	0	1	0	0	48	0	0	5	19	17	0	0
TKT-3	KT	36	66.7	0	0	0	0	0	24	0	0	1	4	7	0	0
TRLX-1	KT	156	36.5	0	4	5	0	0	57	0	0	54	21	15	0	0
TWHX-2	WHX	35	40.0	0	0	5	0	0	12	0	0	0	4	14	0	0
TWHX-3	WHX	170	20.6	0	0	41	0	0	76	0	0	5	13	35	0	0
TWHX-4	WHX	84	34.5	0	1	3	0	0	37	2	0	1	11	29	0	0
TCR-1	CRANE	90	18.9	0	0	1	0	0	1	13	17	41	17	0	0	0
TCR-2	CRANE	49	69.4	0	0	1	0	0	0	9	34	3	2	0	0	0
TCR-3	CRANE	56	71.4	1	0	6	0	0	0	0	40	9	0	0	0	0
TCR-4	CRANE	60	68.3	0	0	2	0	1	1	0	41	14	1	0	0	0
THL-1	HALCROW	35	71.4	0	0	0	0	0	8	0	0	25	2	0	0	0
THL-2	HALCROW	45	6.7	0	5	4	0	0	0	16	1	3	16	0	0	0
THL-3	HALCROW	35	45.7	0	1	9	0	0	6	0	0	16	3	0	0	0
TORCK1	ORCK-KX	63	34.9	0	7	7	1	0	1	25	0	0	22	0	0	0
TORCK2	ORCK-KX	54	66.7	0	0	3	0	0	10	3	0	0	36	2	0	0
TORCK3	ORCK-KX	135	47.4	0	6	12	13	2	27	8	0	0	64	3	0	0
TKXLLX1	ORCK-KX	120	76.7	0	0	3	0	0	5	12	0	8	92	0	0	0
TH2O-1	WATER	90	98.9	0	0	0	0	0	0	0	0	0	0	0	1	89
TH2O-2	WATER	195	100.0	0	0	0	0	0	0	0	0	0	0	0	0	195
TCLOUD1	CLOUD	209	99.5	208	1	0	0	0	0	0	0	0	0	0	0	0
TCLOUD2	CLOUD	60	100.0	60	0	0	0	0	0	0	0	0	0	0	0	0
TSHAD01	SHADOW	63	95.2	0	0	0	2	1	0	0	0	0	0	0	60	0
	TOTAL	2924		291	258	419	191	90	316	138	195	207	343	122	64	284

OVERALL PERFORMANCE(1672/ 2924) = 57.2

Table 13: Unsupervised test group performance.

	GROUP	NO OF SAMPS	PCT. CORCT	NUMBER OF SAMPLES CLASSIFIED INTO CLOUD	ROCK	TILL/R	TILL	STEAD	KT	DERING	CRANE	HALCROW	OROK-KX	WHX	SHADOW	WATER
1	CLOUD	269	99.6	268	1	0	0	0	0	0	0	0	0	0	0	0
2	ROCK	207	66.2	17	137	45	4	1	1	1	0	0	1	0	0	0
3	TILL/R	448	47.8	1	78	214	97	40	0	17	0	0	0	0	1	0
4	TILL	122	54.9	1	2	30	67	9	0	5	2	2	2	0	2	0
5	STEAD	162	22.2	3	14	18	7	36	1	18	55	5	5	0	0	0
6	KT	282	45.7	0	4	6	0	0	129	0	0	60	44	39	0	0
7	DERING	55	16.4	0	2	9	0	0	1	9	5	15	14	0	0	0
8	CRANE	255	51.8	1	0	10	0	1	2	22	132	67	20	0	0	0
9	HALCROW	115	38.3	0	6	13	0	0	14	16	1	44	21	0	0	0
10	OROK-KX	372	57.5	0	13	25	14	2	43	48	0	8	214	5	0	0
11	WHX	289	27.0	0	1	49	0	0	125	2	0	6	28	78	0	0
12	SHADOW	63	95.2	0	0	0	2	1	0	0	0	0	0	0	60	0
13	WATER	285	99.6	0	0	0	0	0	0	0	0	0	0	0	1	284
	TOTAL	2924		291	258	419	191	90	316	138	195	207	349	122	64	284

OVERALL PERFORMANCE(1672/ 2924) = 57.2

AVERAGE PERFORMANCE BY CLASS(722.3/13) = 55.6

ues. The nature of the misclassification errors and the ability of the legend to provide a comprehensive and mutually exclusive classification of the range of soils conditions in the entire map area were also important factors.

The nonsoil mapping classes; cloud, cloud shadow, and water all had well defined cluster classes and therefore provided very high test group performance results (Table 13), ranging from 95.2% to 99.6%.

Misclassification errors for the TILL, TILL/R, and ROCK groups were mainly confined to alternate members of these three classes with the most similar soil conditions. For example, TILL was most frequently misclassified as the TILL/R group; ROCK was most often misclassified as TILL/R; and TILL/R test areas were misclassified as both ROCK and TILL.

Test field performance for other soils groups were generally lower, and often resulted in a wider range of misclassification errors.

The KT group, representing Typic Mesisol, sphagnic phase soils, was most frequently misclassified (60 out of 282 pixels) as HALCROW, which represents Terric Mesisol, sphagnic phase soils developed on the same sequence of organic materials. The HALCROW group was also the major source of classification error for the CRANE group, representing a total of 67 out of 255 pixels in CRANE test areas. These two soil groups were also closely related, as indicated in Table 11.

The OROK-KX group had the highest classification success of all organic soil groups, 57.5% (Table 13). This group incorporated 4 unsupervised cluster classes, and represented a range of soil conditions designated by two separate groups in the previous supervised classification. Errors of commission however, lowered the classification success of other unsupervised soil map unit types, particularly the KT, DERING, and HALCROW groups.

The STEAD, WHX, and DERING groups had the poorest performance, all of them being less than 30% correctly classified. This was generally attributed to a lack of correlation between cluster classes and unique vegetative and soils conditions. The two clusters which were most frequently associated with DERING group on the initial display print-outs, for example, also included some areas that corresponded to OROK-KX, HALCROW, or regenerating areas of the TILL soil group. The DERING group was retained primarily because of its anticipated large areal extent within the map area and the difficulty of conceptually combining this group with other map unit types with which major confusion errors occurred. Otherwise this group could be considered, along with raised lacustrine beach ridges and frozen organic peat plateaus, as not representing unique cluster classes of LANDSAT spectral data, and therefore not mappable as discrete units using the unsupervised method.

Combining similar soil mapping groups with poor performance results would have increased overall classification performance considerably, although this would have entailed reduction of the final classification legend into fewer, more generalized soil mapping groups. For example, combining the STEAD and CRANE groups and the WHX and KT groups would have resulted in a combined classification performance of 53.7% for the STEAD-CRANE group and 65.0% for the WHX-KT group. This would have increased the overall unsupervised soils group classification from 42.8% to 50.0%, although the number of separable soils classes would decrease from 10 to 8.

5.4 COMPARISON OF SUPERVISED, UNSUPERVISED, AND CONVENTIONAL MAPPING TECHNIQUES.

5.4.1 Supervised Versus Unsupervised Classification.

A comparison of mapping group performance results for test areas is provided in Table 14. The same test areas were used for those soil mapping groups that were common to both methods. Test areas were chosen to represent the full range of vegetative ground truth conditions encountered for each group, and therefore individual test field performances varied markedly. No test fields were rejected or modified to improve results as it was felt that classification performance for this set of test fields was typical of the map area as a whole.

Although the supervised classification yielded better results for several groups, notably the TILL, DERING, and STEAD groups, other results were quite comparable. The final legends in both instances were restricted to approximately 10 soil mapping groups. Similar tradeoffs between classification performance and the number of discrete map unit types were encountered for both automated methods.

Additional insight into supervised and unsupervised performance was provided by display maps such as Maps 1 and 2, in Appendix D.

Nonsoil conditions representing cloud, cloud shadow, and water were accurately distinguished by both methods. Using the unsupervised method, only a single water class was separable, while the supervised method permitted two water classes to be distinguished.

Table 14. Comparison of Supervised and Unsupervised Soil Mapping Group Performance.

Mapping Group	Number of Pixels	Classification Performance[1] Supervised Method	Unsupervised Method
Till	122	71.3	54.9
Till/R	448	46.0	47.8
Rock	207	54.6	66.2
Dering	55	49.1	16.4
Stead	162	48.1	22.2
Katimik	282	43.3	45.7
WHX	289	26.3	27.0
Crane	255	48.2	51.8
Halcrow[2]	115	-	38.3
Orok-KXLLX[3]	372	75.5	57.5
Water	285	100.0	99.6
Cloud	269	90.3	99.6
Shadow	63	90.5	95.2
All Classes	2809	56.0	57.2
Soils Groups only[4]		49.3	42.8

1. Performance indicates the percentage of pixels of each test area classified as belonging to the correct soil mapping group, using channels 2,3 and 4 of Landsat data.
   One or more test areas were used for each soil group. The test fields are listed in Appendix B.

2. This group was not separable by supervised classification.

3. These two groups were not separable by unsupervised classification. Supervised classification performance is the value obtained if the two groups were merged, as recommended due to their poor individual performance.

4. These are the values obtained for the 10 non-merged soils classes distinguishable by each method. Results are not strictly comparable due to differences in mapping group legends.
   Merger of closely related soil mapping groups with poor performance would improve overall results substantially for both methods.

Both the supervised and unsupervised legends were relatively comprehensive for organic soil conditions, with the exception of their inability to distinguish organic peat plateaus from mineral soil conditions with similar tree cover. Misclassification of portions of patterned fens or other sparsely treed organic soil types as completely inappropriate ROCK or TILL/R mineral soil types was an occasional, though persistent problem for both methods.

The range of mineral soil conditions encountered in the map area was represented by only 4 separable soil mapping groups for either method. Differences in parent material types for well drained, deep mineral soils could not be reliably distinguished.

The potential for misclassification imposed by various regenerative vegetation conditions were only partially overcome by these automated methods. This was attempted by assignment of cluster classes to these conditions with the unsupervised method, and by selection of training fields and classes using the supervised approach. The choice of the Grand Rapids study area, with it´s extensive fire history, proved to be an unusually severe test for both methods. Although not readily apparent from group performance statistics, qualitative appraisal of the final display map reveals that the unsupervised method had less burned mineral soil areas misclassified as organic soil types. This was offset by the greater misclassification of known organic soil areas as mineral soil.

Despite the similarity in results, both automated methods involved different sampling strategies. These differences in approach suggest that under certain mapping constraints and requirements, the use of a particular automated method may be more appropriate.

The supervised method required the critical selection of training areas for all potential mapping conditions. This demanded considerable initial ground truth and photointerpretive input. A process of refinement of results was then performed which was both time consuming and made extensive use of computer resources. The supervised method offered the advantage of direct selection of classes that had only slight spectral differences, whereas this was not possible using unsupervised cluster classes. The main advantage of the supervised approach would be in mapping large areas once a suitable set of training field statistics is devised. For example, if adjacent map sheets with comparable soils conditions were required to be mapped, and LANDSAT data with similar atmospheric and seasonal conditions were available, then the use of the supervised method would be appropriate.

The unsupervised method illustrated quickly, with little user interaction time, the location of the most spectrally distinct cluster classes in the area. However, relating cluster classes to known ground truth conditions and consolidating them into practical mapping groups was a difficult, time consuming task requiring considerable ground truth checking in conjunction with airphoto interpretation. The use of the unsupervised approach would be more feasible where no preliminary ground truth was available. A final unsupervised classification map could then be produced by aquiring ground truth information in selected cluster class areas. Alternatively, an initial cluster map could be used as a guide to sampling strategy for a conventional mapping program.

The application of supervised and unsupervised mapping methods has been succinctly expressed by Thie (1976, pp.55) as follows;

> In other words, unsupervised classification shows quickly what is sp ctrally separable, but classes may not be useful. The supervised classification attempts to provide directly what is needed, but this may prove to be spectrally unseparable.

The main limitaion to both automated methods for soils mapping is twofold. Firstly, there was a poor correlation between natural vegetative conditions and soils types appropriate to reconnaissance scale mapping. Secondly, there was only limited discrimination of spectral signatures of different vegetative conditions imposed by the LANDSAT MSS resolution and the availability of only 4 very broad wavelength bands.

5.4.2 Automated Methods Versus Conventional Mapping Techniques.

Conventional reconnaissance soil mapping techniques required the aquisition of ground truth information throughout the map area and extensive reliance on photointerpretation techniques to delineate and label map units.

The differences between automated and conventional approaches are indicated by the final soils maps and legends produced by each method and provided in Appendix D.

In contrast to the 8 to 10 soil mapping groups provided by automated techniques, conventional methods resulted in the recognition of 57 map unit components. These represented discrete soil conditions, normally soil series, series phases, or complexes of related soil series. These were used singly or in a multitude of combinations to describe conditions within particular map unit areas. A legend in which the various map unit components are described separately is termed an uncontrolled legend (Mapping Systems Working Group, 1981, p. 52). Alternate legend types considered appropriate for conventional 1:125,000 scale reconnaissance soils mapping involve the use of a controlled or closed legend. By these latter approaches, a limited number of map unit types, generally 50 to 100, are used, with the dominant and significant soil types within each being described in the legend.

Conventional methods clearly resulted in much more detailed and accurate descriptions of soil conditions within the map area. This would be true regardless of the type of conventional legend format employed. An appreciation of the differences in conventional maps and those produced by automated means can be seen by comparing Figures 22 and 23.

Figure 22 illustrates conventional airphoto mapping techniques. The various elements of airphoto interpretation, particularly landform, vegetation, tone, texture, and cultural features such as gravel pits and patterns of development were all employed. When used in combination with ancillary knowledge such as geologic and hydrologic conditions in the area, and adequate ground truth information, the result was an acceptably accurate soils map.

Figure 23 shows a soil map of the same area as produced by the automated supervised technique. Water bodies were accurately distinguished, although the resolution did not permit proper recognition of water bodies that were smaller than several pixels in size. The pattern of mineral and organic soil group areas generally corresponded

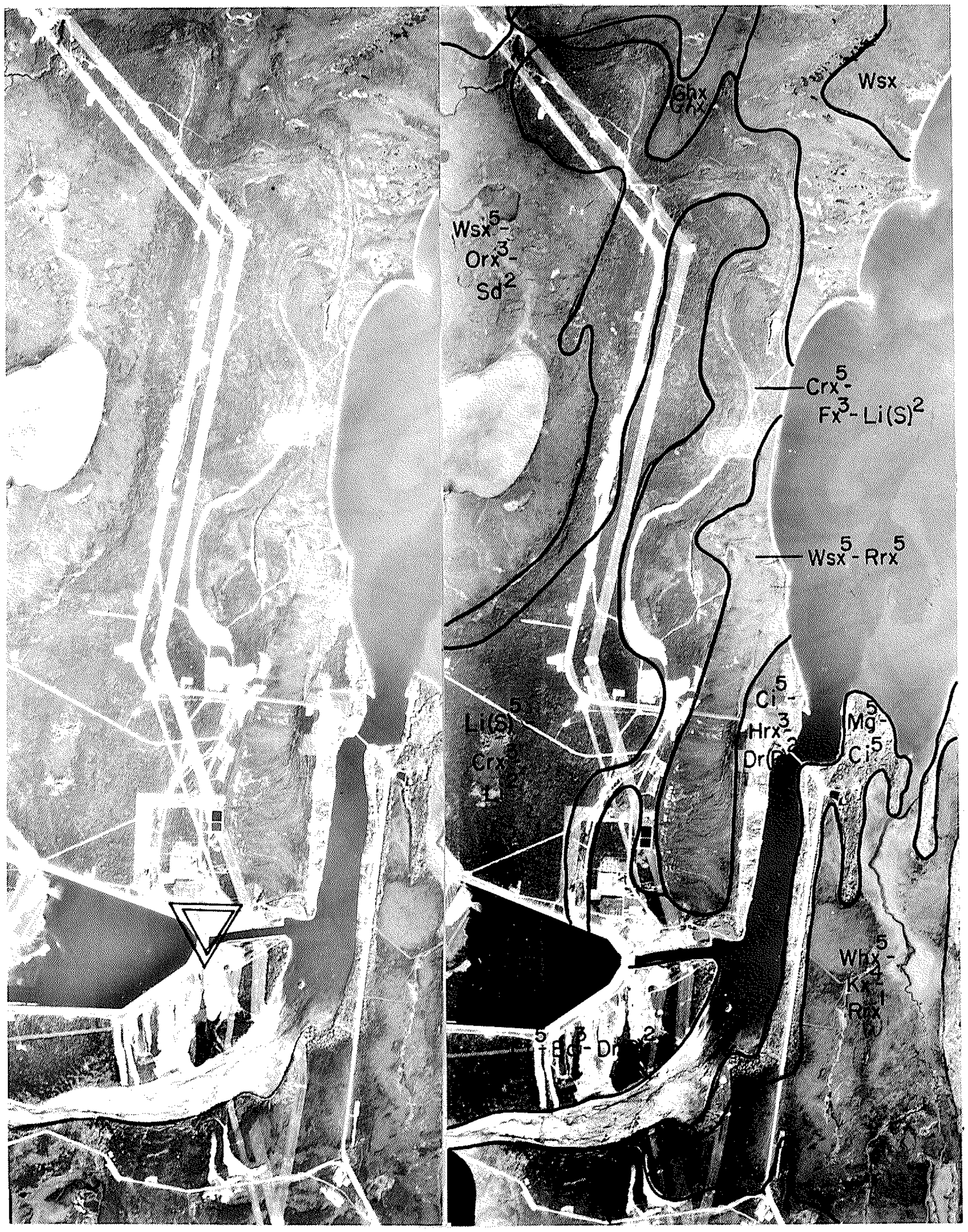


Figure 22: Airphoto Stereopair Illustrating Conventional Mapping Techniques. This stereopair shows the Grand Rapids townsite area, with conventional soil mapping boundaries and symbols delineated. Soil mapping symbols are defined in Map 3, Appendix D. Note the reservoir impounding water for the hydroelectric generating station and the dry riverbed of the Saskatchewan River channel, now used as a spillway. Depressional areas with organic soils are readily distinguished from upland areas of mineral soil types.

Figure 23: Supervised soils map of a portion of the Grand Rapids area. This illustrates the same area as the previous airphoto pair, as mapped by automated classification methods.

well with the same areas identified by aerial photointerpretation (Figure 22, areas 4 and 5). However, variations in vegetative cover due to natural and man made alterations resulted in the classification of some pixels as organic soil types within known mineral soil areas. Sand and gravel deposits indicated by the easily recognizable elevated beach ridges on the east side of the bedrock escarpment were indistinguishable by automated methods.

Cleared areas, such as excavations, highways, building sites, and the exposed riverbed had high reflectance values and were classified as either burned areas of the ROCK class, or as the CLOUD class. While a separate class or classes could have been devised for these disturbed conditions, it would have been immaterial for soils mapping purposes. The labelling of clouds, cloud shadows, along with actual urban or cleared land as unclassified areas prevented their assignment into incorrect soils classes. Nevertheless, it represented a significant limitation in the use of automated methods for mapping large areas. Conventional maps must represent the entire map area, and the human interpreter unconsciously ignores or makes use of the presence of cleared or burn area features in the classification process.

Automated computer mapping techniques did offer several distinct advantages. Once a reliable set of classification statistics was established, large areas can be mapped very quickly, with uniform reliability. The use of computer methods allowed an area calculation for each class by means of a count of the pixels classified into each soil mapping group. In addition, single factor or interpretive maps could be easily and inexpensively produced. This is accomplished by reassignment of symbols for each class in the final display output program.

Time and cost estimates for automated and conventional mapping techniques could only be approximated. The conventional reconnaissance map requires a minimum of 80 days for a 2 man field party, and an additional 40 days of photointerpretive work, correlation, legend building and map editing. Automated methods still require considerable fieldwork, estimated at about 20 days for a comprehensive supervised legend and 10 days for identification of unsupervised cluster classes. These methods still rely on airphoto interpretation to identify and select training and cluster classes. A considerable amount of user time was required to carry out the computer classification procedures, as well as the actual computational costs associated with running the programs. The cost of running a classification program for an entire NTS mapsheet area using 3 channels of LANDSAT data was approximately $220 for 21 classes (as used in the supervised method) and $450 for 37 classes (as used in unsupervised classification, with an initial and final display). These estimates did not include the time and costs associated with creating a satisfactory set of classification statistics, which could easily surpass the final classification and display costs. The initial cyclical steps required to refine the results using the supervised approach would decrease the difference between the two methods. Commercial data processing rates were anticipated to be approximately 3 times the university rates quoted here, to which must be added the $200 cost of aquiring each frame of LANDSAT digital imagery.

An additional significant, though often overlooked factor in favour of the use of conventional methods was the ancillary information obtained during the mapping process. This includes not only data from a large number of soil inspections, but also insight and hypotheses concerning surficial geology, hydrology, and soil, vegetation, and climatic relationships throughout the map area. This information is normally expressed in the soils report which accompanies the map. Automated map production does not provide the report writer with such information. This factor, as well as the superiority of the conventional soils map product, clearly outweighs the substantial savings in fieldwork and mapping time provided by the present automated soils mapping techniques.

5.4.2.1 The Potential of Future Automated Analysis Enhancements for Soils Mapping.

Numerous methods of improving the accuracy of automated mapping techniques are under active development. These include (1) the overlaying of multidate imagery, (2) spatial analysis programs which can analyze the pattern of spectral information inherent in the imagery, and (3) the provision of future satellite mounted MSS to cover a wider range of spectral bands in more selective portions of the electromagnetic spectrum. The overlaying of multidate imagery is now feasible as a result of the introduction of geometrically corrected LANDSAT imagery available through the CCRS digital image correction system (CCRS, 1981, No. 2, pp 8-9). Spatial analysis techniques are still in their infancy, and no improved satellite MSS system has yet been flown to replace the current LANDSAT series.

Investigation of these enhancements was beyond the scope of the present study. It is anticipated that all of these factors would improve automated classification performance, although the limitations inherent in the methodology would still rule out their acceptance as a viable means of producing reconnaissance level soils maps.

Soil mapping requires the recognition of static, indirectly observable surface and subsurface conditions, to which all conventional ground truth information and photointerpretive elements provide a meaningful contribution. Analysis of reflective spectral information on a pixel-by-pixel basis, although providing another dimension in interpretive capabilities, was not in itself sufficient to map indirect soil features. Automated spatial analysis techniques applied to this data could only crudely approximate human photointerpretive skills. The dependence of automated techniques on the limited correlation between vegetative conditions and significant soils differences would remain a serious "weak link" in the mapping process. Recognition of spectrally distinct, directly observable features of the earth's surface, such as vegetation classes, water bodies, or snow and ice conditions is a much more straightforward and potentially successful process. Mapping of such classes, particularly when required on a changing temporal basis, is a more appropriate application of current automated methods for analyzing LANDSAT data.

5.5 AUTOMATED MAP PRODUCTION ENHANCEMENTS.

5.5.1 Standard Line Printer Outputs.

The standard line printer output provided a spatial display of alphanumeric symbols which are assigned to represent the classification of each pixel at its assigned map position. The standard output scale of 1:22,000 was too large to conveniently represent reconnaissance scale soils maps. These maps have been traditionally produced at much smaller scales, which were appropriate for the level of inspection and generalization. The small scale map also provided a synoptic view of soil conditions throughout the entire study area. Automated map output scales were adjusted by printing only a subset of the available pixels, although this utilized only a portion of the classification results and entailed a corresponding loss of resolution. The printout maps were also reduced by conventional photomechanical means to provide a suitable scale. Reduction of standard 1:46,000 scale printouts of every second pixel in every second row to 1:125,000 scale are illustrated by Maps 1 and 2 in Appendix D. This appeared to be the practical limit of legible map displays, while still providing a single output map to represent an area the size of a conventional reconnaissance soils map.

The final automated map product is a mosaic of individual classification results. This product was often difficult to interprete or evaluate as no grouping of areas of similar soil conditions was performed. Selection of a connotative set of alphanumeric symbols for soil and nonsoil classes which utilize the full range of grayscale values available provided a partial solution. Pixel areas were also coloured over manually, either directly on the printouts or by using overlays. This resulted in a much more recognizable visual map display of soil conditions, although it was a very laborious and time consuming process.

5.5.2 Alternatve Map Enhancement Procedures.

5.5.2.1 Colour Display Map Production.

An alternate approach was developed by the author to provide the benefits of a colour enhanced map product (Figure 24). The steps involved are outlined in Figure 25. Three separate alphanumeric printout maps were produced of the same area, in which only mineral, organic, and water mapping groups respectively were displayed, with all other groups assigned blank symbols. These were then transferred to mylar bases at a reduced 1:125,000 scale. Single colour images were then produced using a Thermofax copier machine, with the mineral, organic, and water display maps produced in red, green, and blue respectively. These transparencies were overlayed and photographed with a large format camera to produce a colour negative. Colour prints of the map area were then produced, of which Figure 24 is an example. Mineral soil areas (red), organic soil areas (green), and water bodies (blue) were readily distinguished, yet the original alphanumeric mapping group symbols were still retained. Training areas and pixel coordinate symbols were common to all three maps and therefore appear black when the images are superimposed. Areas unclassified on all images showed up as white. These typically related to either shoreline conditions or cleared areas of high reflectance such as P.T.H. 6 and the parallel hydro line right of way which bisected the area.

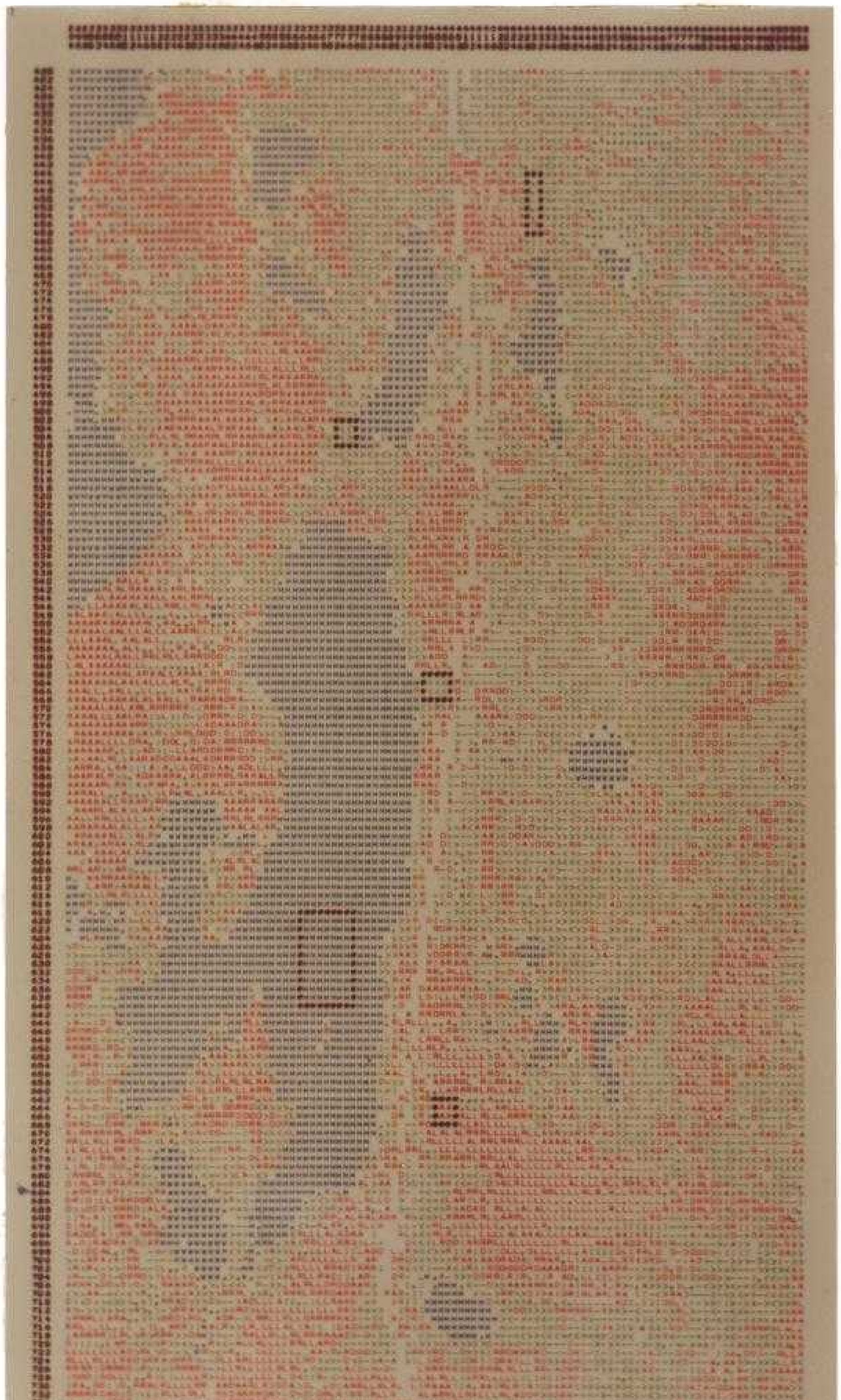
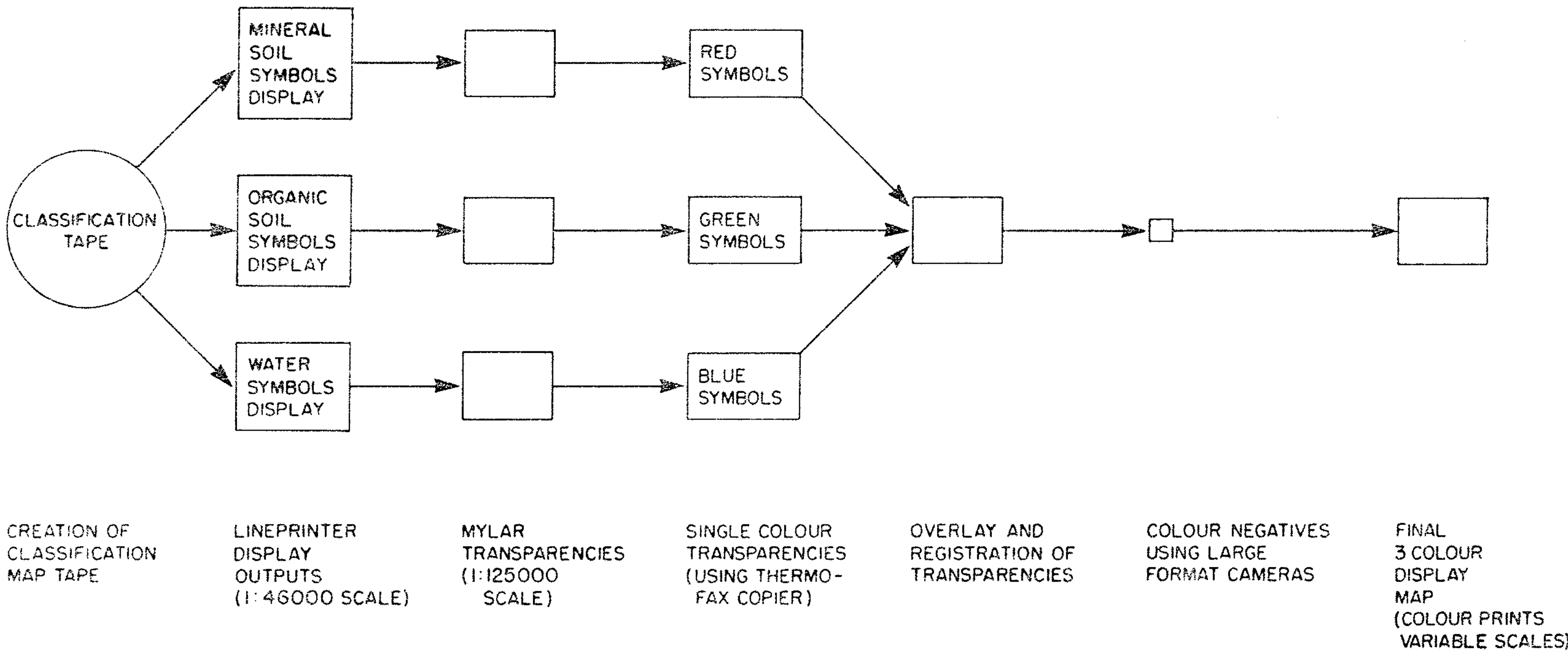


Figure 24: Colour display map of the Little Limestone Lake area. This represents a colour enhanced version of a supervised display map. All alphanumeric symbols representing mineral soil groups are in red, organic soil groups are green, and water classes are blue. The legend and map area are a subset of the supervised map of the Grand Rapids area (Map 1, Appendix D). Black symbols designate training areas. The white line representing unclassified pixels bisecting the map is P.T.H. 6.

Figure 25: Steps involved in colour display map production process.



For the 370 square kilometer study area, it is estimated that the cost for computer map display, reduction of the original 52 cm X 28 cm grayscale map, and preparation of colour transparencies prior to photography was approximately 15 dollars for each separate colour required. For the three colour image produced at the scale illustrated, the production cost is approximately 50 dollars, or slightly less than 15 cents per square kilometer.

5.5.2.2 Software Map Production Enhancements.

Most currently available automated classification methods, including those used in this study, employ a pixel by pixel classifier. The final display map appeared as a mosaic of individual classification results for small areas, which is in many ways analagous to a display of soil sample site information. Conventional soil maps are more than a display of site specific classifications; they are a portrayal of meaningful units within the continuum of natural soil distribution in the landscape. Creation of these areas, termed map units, can be regarded as either a process of subdivision or agglomeration (MSWG, 1981). The resulting map units may represent similar or uniformly variable patterns of soil conditions. They serve as a means of portraying the distribution of soils in the landscape and provide management units for various interpretive uses of soil information.

Present automated methods fail to perform this mapping function. In order to produce similar units for automated soils maps, additional steps would have to be performed, utilizing one of the following approaches;

1. Classification results could be consolidated following pixel by pixel classification. Contiguous pixels with the same classification results could be grouped into larger, uniform areas. Criteria could be developed to accept a certain number of dissimilar pixels as either recognized or unrecognized inclusions. This could be accomplished by manual means, involving the outlining of uniform areas on a transparent overlay, or by development of software to produce a computer output map with map unit designations. "Smoothing" or "noise reduction" programs have already been developed which remove uniquely classified pixel results from otherwise uniform areas. These programs represent an initial step in this direction.
2. The spectral data could be manipulated prior to classification. Spectral information could be initially averaged over blocks of pixels, so that a single average set of reflectance values would represent the entire block.

   This approach was attempted by reformatting the LANDSAT data set into blocks of 12 by 16 pixels, with a single averaged set of reflectance values for each block. Attempts to produce meaningful classification results with this data set were frustrated by the arbitrary block boundaries. Most blocks contained a range of reflectance conditions, resulting in average values which were unrepresentative of any constituent pixels. A nonsupervised cluster analysis of block reflectance values did not provide a satisfactory correlation with soil mapping classes. In addition, resolution was considerably reduced, with objects smaller than several blocks in size being unrecognized or misclassified. Map units, even if successful, would have remained as blocks of standard dimensions.

Alternatively, a "perfield" classifier could be employed to provide one classification for an entire block of pixel values. This type of classifier has been developed by the Laboratory for Applications of Remote Sensing at Purdue University for classifying fields of agricultural crops.

The main problem with both of these approaches is the determination of the proper field or block dimensions. Block sizes may be derivable from boundary recognition programs, which key on significant reflectance value changes in the data set (LARS, 1970, pp. 38). For agricultural crops the field size and boundary conditions are obvious. For other applications, such as mapping soils under Boreal Forest conditions, the more subtle changes in reflectance values would make adequate boundary detection a difficult process.

All programs utilizing either prior or post classification enhancements to produce map unit groupings would not distinguish between random misclassification errors or legitimate variability in the mapping classes. Random misclassification errors are those resulting from the presence of small "impurities" within pixel areas which contribute to the overall signature. Therefore current automated procedures are not capable of creating map units which correspond to those delineated by conventional mapping techniques.

Chapter VI

CONCLUSIONS

This study provided an evaluation of automated mapping techniques utilizing LANDSAT data for reconnaissance level soils mapping in a typical Boreal Forest environment of central Manitoba. The LARS Version 2 programs used in this research could not be employed interactively using CRT displays and cursors, but required operation in a batch mode, using a standard line printer for initial output and display. Although these procedures were more cumbersome to use in this format, the results achieved were typical of other current automated analysis systems.

Supervised classification resulted in the recognition of 14 classes, including cloud, cloud shadow, 2 water classes, and 10 soil mapping groups. Overall training group classification was 86.5%, with a figure of 79.5% achieved when the soils groups alone were considered. Test field results, which provide a more realistic appraisal of classification performance and extensability, yielded an overall performance of 60.0%, with soils groups alone achieving only 50.4%

Deletion of the band 4 data during the classification procedure decreased training group results by 0.9% and test group results by 1.0%. This indicated that under these mapping conditions band 4 contributed little to class separability.

Unsupervised classification, utilizing a clustering algorithm, resulted in the delineation of 13 significant mapping groups, representing clouds, cloud shadows, water, and 10 significant soil mapping groups. Overall test field performance was 57.2%, while for soils groups alone the performance was only 42.8%

Despite the differences in the two automated classification methods, results in both cases were remarkably similar, both in terms of the type and number of classes recognized and the nature of the classification problems encountered. Both methods allowed the successful recognition of 8 to 10 soil mapping groups, depending on the acceptability criteria applied. Both methods were employed rigourously in order to determine their ultimate classification potential for soils mapping with a single image LANDSAT data base. It is unlikely that a greater number of meaningful soil mapping groups could be reliably distinguished from this approach, particularly in a routine mapping procedure where time and ground truth would be more limited. In both cases, a tradeoff existed between the number of classes established and classification success. Combining similar soil mapping groups with poor performance results would have increased overall performance considerably, although this would have reduced the final classification legends into fewer, more generalized soil mapping groups.

The major limitations to the number of soils classes that could be reliably distinguished and mapped by current automated means were threefold.

The poor correlation between soil conditions and unique vegetative cover was the primary factor. Similarities in the natural vegetative cover of significantly different soils groups were a major problem, resulting in the inability to distinguish reliably between different mineral soil parent materials, and between these materials and frozen organic peat plateaus with a similar, densely forested vegetative cover. Disturbance of natural vegetation by clearing or fire created additional problems that could only be partially offset by the assignment of training classes to represent these conditions. The presence of open water in shoreline areas and on the surface of fens, and the presence of cloud and cloud shadow in some areas also influenced the spectral signatured and interferes with classification success.

The correlation between vegetative conditions and spectral response values in the four bands of the LANDSAT single image data base represented the second "weak link" in the mapping process. Merging of the data set with additional ancillary data, such as topographic or alternate remote sensing information, was beyond the scope of the present study.

A third limiting factor was the function of the automated classifier, which analyzed spectral information on a pixel-by-pixel basis, and ignored important spatial relationships inherent in the data base.

Benefits from the use of automated mapping techniques included the potential saving in sampling and mapping time over conventional techniques, the uniformity of classification results, and ease of subsequent manipulation of the final map product.

In contrast to the 8 to 10 soil mapping groups provided by automated techniques, conventional methods resulted in the recognition of 57 map unit components. Conventional methods utilized airphoto interpretation in combination with ground truth in key preselected areas.

Photointerpretation techniques allowed the use of tone, texture, relief, landform, drainage, vegetation, and land use information inherent in the photographs for soil mapping purposes. For example, certain soil and parent material types could be mapped by their distinctive landform shapes, such as beach ridges or peat plateaus. These were not readily identifiable by automated means. In addition, a skillful photointerpreter can readily combine ground truth information and ancillary knowledge of soils, vegetative, geologic, and hydrological conditions during the mapping process.

Despite efforts to utilize current automated classification methods to their ultimate potential, the separable map unit types proved to be too few in number and too general to provide a practical alternative to conventional methodology. Numerous efforts were made to optimize the automated computer maps into a more satisfactory and legible format, although the results were not comparable to current conventional map displays. In order to portray the distribution of soil types as manageable units, the map must divide the natural landscape into map units representing areas of similar, or at least uniformly variable soil conditions. Present automated methods fail to perform this soil mapping function.

Soil mapping requires the recognition of static, indirectly observable surface and subsurface conditions. The dependence of automated mapping techniques in a Boreal Forest environment was limited by the correlation between detectable vegetative differences and significant soil conditions. Despite the anticipated advances in data aquisition and automated classification in the future, this factor will remain a major obstacle to the use of automated classification methods for reconnaissance level soil mapping purposes.

Recognition of spectrally distinct, directly observable features of the earth's surface by automated means is a much more straightforword and potentially successful process. Mapping of such features, particularly when required on a changing temporal basis, is a more appropriate application of current automated methods for analyzing LANDSAT data.

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Appendix A

LARS COMPUTER PROGRAMS

A.1 INTRODUCTION

The research at the Laboratory for Applications of Remote Sensing is intended to serve many applications and analysis purposes. The LARSYS software system has been established to tie these programs together.

The control structure of the system is composed of a monitor and distinct processing phases, with each processing phase directed by it´s own supervisor.

This multi-phase structure minimizes the amount of core memory occupied at any one time by the program instructions in order to maximize the amount of memory available for data.

The program consists of three levels; the monitor, the supervisor, and data cards.

The principle responsibility of the monitors is to recognize and interpret monitor control cards which describe the jobs to be done and request the loading of the supervisor phases to execute those jobs. It handles only variables which are used throughout the system.

The main function of the supervisor is to recognize and interpret supervisor control cards and to coordinate and direct the processors under it´s control in order to execute the analysis requested. Control usually alternates between the supervisor and the processors. Each supervisor handles only variables which are applicable to it´s processors.

Data sets are stored on intermediate storage devices such as tapes or discs for use in various supervisor subroutines. This further maximizes the amount of usable core.

A.2 LARS PROGRAM FORMAT

All control cards have the following format;

1. They have a key word starting in column one, followed by at least one blank, and then any control parameters relative to the key word.
2. A key word contains at least four non-blank characters, the first of which must be non-numeric.
3. A control parameter may be a word or value which may be followed by parentheses which enclose value(s) which may be numeric or literal.
   a) All control parameters and values within parentheses must be separated by commas.
   b) All control parameters consist of one or more non-blank characters, the first of which must be non-numeric.
   c) A value may be numeric or literal. The forms- 3*1, 3*1.0, and 3*A - are all permissable to show multiple values.

Specific control cards formats are as follows;

1. A monitor control deck begins with a monitor control card. The key word must start with a "$".
2. The deck must end with a card containing "$END" starting in column one.

3. The supervisor control deck begins with supervisor control cards. This supervisor control deck is an entity in itself.
4. No data cards may appear within a supervisor control deck.
5. The deck must end with a card containing "END" starting in column one.
6. Statistics decks generated by LARSYS supervisors have a specific structure.
7. Input data decks supplied by the user (LARS-12 cards) must follow a specific format.
8. The data deck must end with a card containing "*END" starting in column one.

An example of the hierarchy and order of control cards is as follows;

```
Monitor Control Cards
Supervisor Control Cards
END  (end of supervisor processing)
Data Cards
*END  (end of data)
$END  (end of monitor processing)
```

A.3 EXAMPLES OF AUTOMATED CLASSIFICATION PROGRAMS

A.3.1 Larsplay Pictogram Program Example

```
//XXXXTERM JOB ´0989,XXX,,T=75,I=79,LP=88,R=200´,W.FRASER
/*TSO  XXXX
/*D6250  XXXX03  (BIN 958)
//JOBLIB DD DSN=MILLS.#0261.ERTSYS.LOAD,DISP=SHR
//SPLA EXEC PGM=SPLAY,REGION=200K
//FT01F001 DD UNIT=SYSDA,SPACE=(TRK,(5,2))
//FT05F001 DD DDNAME=SYSIN
//FT06F001 DD SYSOUT=(1,,0321)      PRINTER
//FT07F001 DD SYSOUT=B      PUNCH
//FT11F001 DD UNIT=D6250,DCB=(DEN=4,BUFNO=0),VOL=SER=XXXX03,
//  DSN=GRAND,LABEL=(2,SL,,IN),DISP=SHR      INPUT TAPE
//FT15F001 DD SYSOUT=A        MESSAGE DATA SET
//SYSIN DD *
$COMM WILLIAM LAKE GREYSCALE MAP - CHAN 6
$PIC
OPTIONS SYM(M,%,Q,V,",+,=,/,-, )
BLOCK RUN(75000101),LINE(0420,750,2),COL(294,510,2)
CHANNEL 3
END                                                              00000190
$END                                                             00000200
$EXIT                                                            00000205
/*
```

A.3.2 Versatec Plotter Display Map Program Example

This example provides a map display of the same area as the LARSPLAY Pictogram program. The first data card specifies the bin edges for the 10 grayscale levels.

```
//XXXXTERM JOB '0989,XXX,,T=15,L=1,R=150,I=15',W.FRASER
/*MESSAGE PLEASE PLOT 4 COPIES
/*TSO  XXXX
/*TAPE  VPLOT
/*D6250  XXXX03  (BIN 958)
//JOBLIB DD DSN=MILLS.#0261.ERTSYS.LOAD,DISP=SHR
//  EXEC PGM=$FAX,REGION=150K
//FT05F001 DD DDNAME=SYSIN
//FT06F001 DD SYSOUT=A
//FT11F001 DD UNIT=D6250,VOL=SER=XXXX03,DSN=GRAND,
//  LABEL=(2,SL,,IN),DISP=SHR     LARS INPUT TAPE
//VPLOT DD UNIT=D800,VOL=SER=VPLOT,LABEL=(,SL),
//  DSN=VPLOT,DISP=(NEW,KEEP)    PLOT TAPE
//SYSIN DD *
15.5 45.5 52.5 55.5 59.5 61.5 64.5 68.5 71.5 202.5
3
420 750
294 510
/*
```

A.3.3 LARSAA Training Fields Statistics Deck Program Example

```
//XXXXTERM JOB ´0989,XXX,,T=08,L=10,I=10,LP=88,CO=2,R=256´,W.FRASER
/*TSO  XXXX
/*MESSAGE PLEASE INTERPRET CARDS
/*D6250 XXXX03  (BIN 958)
//JOBLIB DD DSN=MILLS.#0261.ERTSYS.LOAD,DISP=SHR
//SYSA EXEC PGM=LARSAA,REGION=256K
//FT02F001 DD UNIT=SYSDA,                       SAVTAP
//   SPACE=(TRK,(5,2)),DCB=(RECFM=F,LRECL=130,BLKSIZE=130)
//FT03F001 DD UNIT=SYSDA,SPACE=(TRK,(6,2)),       SCRTCH
//   DCB=(RECFM=F,LRECL=440,BLKSIZE=440)
//FT05F001 DD DDNAME=SYSIN
//FT06F001 DD SYSOUT=(1,,0221)                   PRINTER
//FT07F001 DD SYSOUT=B                   PUNCH
//FT11F001 DD UNIT=D6250,VOL=SER=XXXX03,DISP=OLD,
//   DSN=GRAND,LABEL=(2,SL)           DATAPE
//FT15F001 DD SYSOUT=A,DCB=RECFM=UA             MESSAGE DATA SET
//SYSIN DD *
$COMM IMPROVED CLASS Y FOR STATDECK A
$STAT
OPTIONS MAXCL(05),HIST(F,C),SPECTRL(F,C),CORRE(C)
PUNCH  BCD
CHANNEL 1,2,3,4
SIZE  SPCINT(1)
END
CLASS 12
75000101  12-1        1772 1782    2  310  314    212       CLOUD ON MORAINE
CLASS 236
75000101  236-1        584  596    1  404  404    1236
75000101  236-2        806  814    1  422  422    1236
*END
$END
$EXIT
/*
```

A.3.4 LARSAA Classification Program Example

```
//XXXXTERM JOB '0989,XXX,,T=75,L=09,I=65,LP=68,CO=2,R=256',W.FRASER
/*TSO  XXXX
/*D6250 XXXX03  (BIN 958)
/*D6250  001734-WR
//JOBLIB DD DSN=MILLS.#0261.ERTSYS.LOAD,DISP=SHR
//SYSA EXEC PGM=LARSAA,REGION=256K
//FT02F001 DD UNIT=SYSDA,                    SAVTAP
//  SPACE=(TRK,(5,2)),DCB=(RECFM=F,LRECL=130,BLKSIZE=130)
//FT03F001 DD UNIT=SYSDA,SPACE=(TRK,(6,2)),     SCRTCH
//  DCB=(RECFM=F,LRECL=440,BLKSIZE=440)
//FT05F001 DD DDNAME=SYSIN
//FT06F001 DD SYSOUT=A                 PRINTER
//FT07F001 DD SYSOUT=B                 PUNCH
//FT10F001 DD UNIT=D6250,VOL=SER=001734,LABEL=(01,SL),
//  DCB=(RECFM=VS,LRECL=1600,BLKSIZE=1604,BUFNO=1),
//  DSN=MAP,DISP=(NEW,KEEP)            MAPTAP
//FT11F001 DD UNIT=D6250,VOL=SER=XXXX03,DISP=OLD,
//  DSN=GRAND,LABEL=(2,SL)          DATAPE
//FT15F001 DD SYSOUT=A,DCB=RECFM=UA          MESSAGE DATA SET
//SYSIN DD *
$COMM FILE 01 $CLASS OF A AREAS,CHAN 2,3,4-DECK8
$INIT  TAPE(001)
$CLASS
SERIAL 0301600101
DECK
CHANNEL 2,3,4
END
MODULE STATISTICS DECK FOR AIRANAL          0                                  1
CLASS AT2                                                                      2
75000101  AT2-1      1609 1612    1  884   890    1AT2     E OF MORRISON       3
CLASS CHITEK                                                                   4
75000101  CI-1       1715 1727    1  957   959    1CHITEK  NR EAST. RD.        5
   21 CLASS    29 FIELD     4 CHANNELS                                        52
CHAN  1 WAVELENGTH 0.50- 0.60 CODE  7 CO   2.00 C1  63.00 C2   0.0            53
CHAN  2 WAVELENGTH 0.60- 0.70 CODE  7 CO   2.00 C1  63.00 C2   0.0            54
CHAN  3 WAVELENGTH 0.70- 0.80 CODE  7 CO   2.00 C1  63.00 C2   0.0            55
CHAN  4 WAVELENGTH 0.80- 1.10 CODE  7 CO   2.00 C1  63.00 C2   0.0            56
NO. PTS.        28        39
MN 0.2971428E 02 0.2260713E 02 0.4564285E 02 0.4517856E 02                    60
MN 0.2974358E 02 0.2312820E 02 0.5364102E 02 0.5628204E 02                    61
CV 0.2063492E 01-0.5291004E-02 0.3136243E 01-0.2169312E 00 0.1298942E 01      81
CV 0.9275132E 01 0.2751322E 00-0.1494709E 00 0.4695766E 01 0.8448412E 01      82
*END                                                                         123
RUN(75000101),LINE(0246,288,2),COL(936,976,2)
RUN(75000101),LINE(0304,344,2),COL(810,850,2)
*END
$END
$EXIT
/*
```

A.3.5 LARSAA Display Program Example

```
//XXXXTERM JOB ´0989,XXX,,T=4M,L=20,I=60,LP=88,CO=3,R=256´,W.FRASER
/*TSO XXXX
/*D6250 001734
//JOBLIB DD DSN=MILLS.#0261.ERTSYS.LOAD,DISP=SHR
//SYSA EXEC PGM=LARSAA,REGION=256K
//FT02F001 DD UNIT=SYSDA,                    SAVTAP
//  SPACE=(TRK,(5,2)),DCB=(RECFM=F,LRECL=130,BLKSIZE=130)
//FT03F001 DD UNIT=SYSDA,SPACE=(TRK,(6,2)),     SCRTCH
//  DCB=(RECFM=F,LRECL=440,BLKSIZE=440)
//FT05F001 DD DDNAME=SYSIN
//FT06F001 DD SYSOUT=(1,,0321)          PRINTER
//FT07F001 DD SYSOUT=B                  PUNCH
//FT10F001 DD UNIT=D6250,VOL=SER=001734,LABEL=(07,SL),
//  DCB=(RECFM=VS,LRECL=1600,BLKSIZE=1604,BUFNO=1),
//  DSN=MAP,DISP=(OLD,KEEP)             MAPTAP
//FT15F001 DD SYSOUT=A,DCB=RECFM=UA          MESSAGE DATA SET
//SYSIN DD *
$COMM FILE 07 TRIAL DISPLAY TO TEST SYMBOLS - DECK A
$DISPLAY
SERIAL 0301600101
OPTIONS  OUTLINE(TRAIN)
TABLES TEST(F,C,P)
SYMBOLS :,:,R,R,L,R,-,=,-,-,;,-,L,>,>,>,L,>,;,D
SYMBOLS :,L,D,:,R,R,A,L,L,:,L,L,.,A,.,:,W
THRESHOLD 37*0.1
GROUP CLOUD(01/1,2/)
GROUP ROCK(02/3,4,6,25,26/)
GROUP TILL/R(03/5,13,17,22,28,29,31,32/)
GROUP TILL(04/27,34/)
GROUP STEAD(05/33,35/)
GROUP KT(06/7,9,10,12/)
GROUP DERING(07/20,23/)
GROUP CRANE(08/21,24,30/)
GROUP HALCROW(09/11,19/)
GROUP OROK-KX(10/14,15,16,18/)
BLOCK RUN(75000101),LINES(420,750,2),COL(294,510,2)
END
TEST 12
75000101  TAREA      0001 1898    1 0001 1337    1WATER   CALC CLASS AREAS
*END
$END
$EXIT
/*
```

A.3.6 LARSAA Nonsupervised Classifier Program Example

```
//XXXXTERM JOB ´0989,XXX,,T=80,I=29,LP=88,CO=2,R=256´,W.FRASER
/*TSO XXXX
/*D6250 XXXX03  (BIN 958)
//JOBLIB DD DSN=MILLS.#0261.NSCLAS.LOAD,DISP=SHR
//NSCL EXEC PGM=NSCLAS,REGION=200K
//FT01F001 DD UNIT=SYSDA,SPACE=(TRK,(5,2)),  SAVTAP
//    DCB=(RECFM=VBS,LRECL=5000,BLKSIZE=5008)
//FT05F001 DD DDNAME=SYSIN
//FT06F001 DD SYSOUT=(1,,0221)                 PRINTER
//FT07F001 DD SYSOUT=B                 PUNCH
//FT11F001 DD UNIT=D6250,DCB=(DEN=4,BUFNO=1),VOL=SER=XXXX03,
//  DSN=GRAND,LABEL=(2,SL),DISP=SHR      INPUT TAPE
//FT15F001 DD SYSOUT=A             MESSAGE DATA SET
//SYSIN DD *
OPTIONS  MAXCLAS(05),THRES(0.1)
CHAN 2,3,4
END
75000101  TEST        282  572    6  682  700    6ERTS
*END
$END
/*
```

Appendix B

TRAINING AND TEST FIELD DATA

SAVED TRAINING FIELDS

	RUN NUMBER	FIELD DESIG.	FIRST LINE	LAST LINE	LINE INT.	FIRST COLUMN	LAST COLUMN	COLUMN INT.	FIELD TYPE	OTHER INFORMATION	CLASSIFY CLASS	DISPLAY CLASS
1	75000101	AT2-1	1609	1612	1	884	890	1	AT2	E OF MORRISON	AT2	TILL
2	75000101	CI-1	1715	1727	1	957	959	1	CHITEK	NR EAST. RD.	CHITEK	TILL
3	75000101	ATB-1	664	666	1	403	407	1	ATB	CLEARED,BURNED	ATB	TILL
4	75000101	KI-1	924	934	2	759	764	2	KI	KINWOW	KI	TILL
5	75000101	AT3-1	1748	1750	1	312	319	1	DERING	DER ON HLT P.D	DERING	DERING
6	75000101	R6LI4-1	1113	1116	1	490	503	1	R6LI4	W.OF BUFFALO	R6LI4	TILL/R
7	75000101	CRXLI1	834	840	1	412	418	1	CRXLI	S. OF BIG BUR	CRXLI	TILL/R
8	75000101	CRXLIB1	822	830	1	410	415	1	CRXLIB	S. PART OF BI	CRXLIB	TILL/R
9	75000101	R9LI1-2	1416	1426	1	696	700	1	R9LI1	W. OF G.R.	R9LI1	ROCK
10	75000101	R1	772	776	1	397	405	1	ROCK	BURNED OVER L	ROCK	ROCK
11	75000101	STD1	446	457	1	429	431	1	STEAD1	MESIC FEN	STEAD1	STEAD
12	75000101	MCX2	1674	1682	1	346	356	1	MACAWBER	TYP.M.-NO TREE	MACAWBER	STEAD
13	75000101	KT-1	707	722	2	644	662	2	KT	KATIMIK	KT	KT
14	75000101	WHX-1	1294	1300	1	718	724	1	WHX	W OF EATING P	WHX	WHX
15	75000101	CR1	1666	1672	1	290	300	1	CRANE	TERRIC MESISOL	CRANE	CRANE
16	75000101	CR-3	1604	1610	1	307	312	1	CRANE	4MI. E. OF EAS	CRANE	CRANE
17	75000101	ORX-1	503	507	1	373	376	1	OROK	WM. L. RD	OROK	OROK
18	75000101	ORX-2	564	566	1	400	405	1	OROK	SPHAG/MESIC F	OROK	OROK
19	75000101	KXLLX-1	1690	1700	1	1172	1191	1	KXLLX	LONG PT. RD.	KXLLX	KXLLX
20	75000101	CLOUD1	849	852	1	497	505	1	CLOUD		CLOUD	CLOUD
21	75000101	CLOUD2	1786	1794	1	344	352	1	CLOUD		CLOUD	CLOUD
22	75000101	SHADOW1	838	840	1	473	481	1	SHADOW	SHADOW OF CL	SHADOW	SHADOW
23	75000101	SHADOW2	324	330	1	716	728	1	SHADOW	E.OF WM. R.	SHADOW	SHADOW
24	75000101	H2O-1	590	614	4	234	268	4	WATER	WILLIAM LAKE	WATER	WATER
25	75000101	H2O-6	1674	1678	1	216	226	1	MWATER	NR. EASTERVIL	WATER	WATER
26	75000101	H2O-4	1440	1450	2	618	636	2	WATER	RESEVIOR	WATER	WATER
27	75000101	H2O-3	1374	1394	2	660	677	2	MWATER	EATING PT. L.	MWATER	WATER
28	75000101	H2O-5	415	435	2	779	790	4	MWATER	LIMESTONE BAY	MWATER	WATER
29	75000101	H2O-2	620	638	2	364	376	2	WATER	LITTLE LIMEST	MWATER	WATER

SAVED TEST FIELDS

	RUN NUMBER	FIELD DESIG.	FIRST LINE	LAST LINE	LINE INT.	FIRST COLUMN	LAST COLUMN	COLUMN INT.	FIELD TYPE	OTHER INFORMATION	DISPLAY CLASS
1	75000101	TTILL1	1593	1603	1	848	853	1	TILL	E OF MORRISON L.	TILL
2	75000101	TTILL2	1665	1671	1	264	271	1	TILL	SE.OFEASTERVILLE	TILL
3	75000101	TT/R-1	1475	1481	1	772	779	1	TILL/R	S.OF G.R.	TILL/R
4	75000101	TT/R-2	1568	1578	1	485	500	1	TILL/R	L2#19 SW.OF GR.	TILL/R
5	75000101	TT/R-3	1119	1126	1	470	480	1	TILL/R	W. OF R6LIA	TILL/R
6	75000101	TT/R-4	900	908	1	403	410	1	TILL/R	FORMER AT/R-1	TILL/R
7	75000101	TT/R-5	678	690	2	428	442	2	TILL/R	L7#41E.OF LST.L.	TILL/R
8	75000101	R9LI1-1	1245	1250	1	526	532	1	ROCK	NR.CROSS L.	ROCK
9	75000101	TR-1	1566	1574	1	308	316	1	ROCK	4MI.E.OF EASTER.	ROCK
10	75000101	TR-2	785	798	1	316	321	1	ROCK	3MI.W.OF HWY6	ROCK
11	75000101	TDR-1	1747	1751	1	345	355	1	DERING	E.OF AT3-1	DERING
12	75000101	TMCK-1	1695	1710	1	422	430	1	MACAWBER	BY MCX. TA.2	STEAD
13	75000101	TSTD-2	606	611	1	408	410	1	STEAD	E. OF LST.L.	STEAD
14	75000101	TKT-1	710	718	1	719	728	1	KT	KATIMIK	KT
15	75000101	TKT-3	513	523	2	677	688	2	KT	L8#139 NR.LST.BA	KT
16	75000101	TRLX-1	386	397	1	688	700	1	KT	NR. LST. BAY	KT
17	75000101	TWHX-2	1426	1432	1	764	768	1	WHX	E. OF G.RAPIDS	WHX
18	75000101	TWHX-3	662	671	1	663	679	1	WHX	L7#39 N.OF KT-1	WHX
19	75000101	TWHX-4	750	756	1	592	603	1	WHX	L7#40	WHX
20	75000101	TCR-1	1644	1658	1	935	940	1	CRANE		CRANE
21	75000101	TCR-2	1739	1745	1	584	590	1	CRANE		CRANE
22	75000101	TCR-3	1698	1705	1	278	284	1	CRANE		CRANE
23	75000101	TCR-4	1544	1553	1	1119	1124	1	CRANE	L.POINT.N.SIDE	CRANE
24	75000101	TOROK1	799	805	1	631	639	1	OROK	L6#79NR.L.WPG	OROK
25	75000101	TOROK2	512	520	1	383	398	1	OROK	BY OROK-1	OROK
26	75000101	TOROK3	410	424	1	415	423	1	OROK	WM.R.&HWY6	OROK
27	75000101	TKXLLX1	1613	1632	1	1262	1267	1	KXLLX	LONG PT.RD.	KXLLX
28	75000101	TH2O-1	1366	1382	1	744	762	1	WATER	GR.RAPIDS	WATER
29	75000101	TH2O-2	445	459	2	718	730	2	WATER	LST.BAY	WATER
30	75000101	TCLOUD1	335	345	2	740	758	2	CLOUD	E.OF WM.R.	CLOUD
31	75000101	TCLOUD2	1775	1784	1	307	312	2	CLOUD	EAST.RD.	CLOUD
32	75000101	TSHAD01	1768	1774	2	337	345	2	SHADOW	EAST.RD.	SHADOW

Appendix C

VEGETATION ANALYSIS

Ground Truth Site Data - Grand Rapids

Site Name: Ci	Picture #	Object
Photo Number: [illegible] A22427-17	9	ground cover (feathermoss)
Location: on south side of highway	10	bush from road south side [illegible]
east of Beaverdam Lake	11	" " north side

Point- Quarter Data

Quadrant [species/Distance/circumference]

Site#	Quadrant 1	Quadrant 2	Quadrant 3	Quadrant 4
1	bS/203.7cm/27.9cm	JP/162.5cm/26.0cm	bS/154.9cm/36.8cm	JP/167.6cm/3[illegible]cm
2	bS/177.7cm/27.9	bS/101.6cm/12.7	bS/63.5cm/29.2	JP/177.8cm/35.6
3	bS/81.3cm/24.8	JP/121.9cm/41.9	bS/185.4cm/19.1	JP/81.3cm/33.5
4	bS/78.7cm/12.7	bS/182.9cm/36.8	bS/142.3cm/26.7	[illegible]/248.[illegible]cm/71.1
5	bS/66.1cm/33.0	bS/195.6cm/25.4	bS/167.6cm/34.5	bS/43.[illegible]/24.1
6	bS/66.1cm/14.6	JP/83.8cm/45.7	bS/50.8cm/27.3	bS/127.[illegible]/23.5
7	bS/188.0cm/19.7	JP/342.9cm/53.3	bS/137.2cm/33.[illegible]	JP/91.4cm/41.7
8	bS/213.5cm/31.8	bS/106.7cm/26.7	bS/157.5cm/36.8	JP/34.6[illegible]/31.8
9	bS/73.7cm/28.6	bS/106.7cm/15.2	bS/195.6cm/24.8	bS/11[illegible]/21.[illegible]
10	bS/30.5cm/24.8	bS/195.6cm/31.8	bS/75.7[illegible]/21.0	JP/15[illegible]/5[illegible]
11				
12				
13				
14				
15				

Estimated Tree Coverage: 80% Black spruce (25-30')
20% Jack pine (35-40')

crown closure ~ 70% some open spaces

Estimated Understory Coverage
Feathermoss (Hylocomium) 85%
potentilla, fragaria, bunchberry, rubus 15%

Soil Series Description.
Chitek

8cm LFH
15cm water-worked sand & gravel
HCT.

Ground Truth Site Data - Grand Rapids

	Picture #	Object
Site Name: CRX LI - 1 Photo Number: new line 6 A22477-81 Location: ½ mile west of Hwy 6; wooded area just south of Big Burn	27, 28	ground cover vegetation in [illegible]

Point- Quarter Data

Quadrant [species/Distance/circumference]

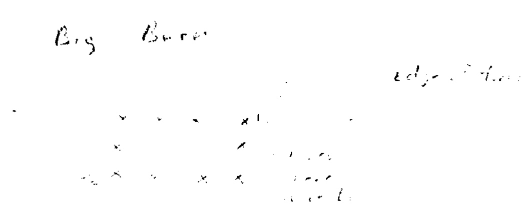
Site#	Quadrant 1	Quadrant 2	Quadrant 3	Quadrant 4
1	JP/175.3cm/30.5cm	JP/165.1cm/25.4cm	JP/228.6cm/33.7	JP/162.5cm/25.6cm
2	JP/210.8cm/45.7cm	JP/421.6cm/43.2cm	JP/218.5cm/33.0	BS/66.1cm/17.8
3	JP/139.7cm/33.0cm	JP/172.8cm/21.0cm	JP/243.8cm/28.6	JP/426.7cm/52.1
4	JP/317.5cm/27.9cm	JP/203.3cm/41.3cm	JP/182.9cm/29.8cm	JP/439.4cm/43.2
5	JP/457.2cm/41.3cm	JP/312.4cm/22.9cm	JP/274.3cm/24.1cm	JP/61.0cm/41.9
6	JP/61.0cm/28.6cm	JP/165.1cm/35.6cm	BS/284.6cm/28.6cm	JP/208.3cm/[illegible]
7	JP/177.8cm/30.5cm	JP/299.7cm/33.0cm	JP/121.9cm/33.0cm	BS/78.7cm/10.2
8	JP/233.7cm/33.0cm	JP/426.7cm/40.0cm	JP/193.0cm/30.5	JP/124.6cm/31.1
9	JP/66.1cm/24.1cm	JP/236.2cm/45.7cm	JP/106.7cm/30.5	JP/403.9cm/36.2
10	JP/48.2cm/35.6cm	JP/142.3cm/14.0cm	JP/160.0cm/17.8cm	JP/314.9cm/22.9
11				
12				
13				
14				
15				

Estimated Tree Coverage: 95% J Pine 20-25'
5% black spruce 5-10'

Crown closure 35-45%

Estimated Understory Coverage: Rock ≤ 5%
open (pine needles) 20%
Cladonia 20%
bearberry 15-20%
Juniper 5-10%

Soil Series Description.
$Crx^5 - Li^5$



Ground Truth Site Data - Grand Rapids

Site Name: R6LI4 - 1 Photo Number: new line 5 A22444-32 Location: on cut line West of Buffalo L. 1¼ miles west of HWY 6	Picture #	Object
	#35 roll 4	road looking NE
	# 36 roll 4	road looking SW
	# 1 roll 5	vegetation (Cladonia, rock + pine needles)

Point- Quarter Data

Quadrant [species/Distance/circumference]

Site#	Quadrant 1	Quadrant 2	Quadrant 3	Quadrant 4
1	JP/132.1cm / 33.7cm	JP/ 177.8cm / 30.5cm	JP/ 61.0cm / 24.1cm	JP/231.1cm / 28.6cm
2	JP/ 91.4cm / 24.1	JP/149.9cm / 24.1cm	JP/ 61.0cm / 23.5	JP/ 142.3cm / 12.3
3	JP/ 142.3cm / 34.3	JP/ 157.5cm / 22.9	JP / 190.5cm / 30.5	JP/193.0cm / 33.[illegible]
4	JP/287.6cm / 45.7	bS/170.2cm / 19.1	JP/200.7cm / 40.6	JP/426.7cm / 36.8
5	JP/294.7cm / 30.5	JP/ 170.2cm / 14.6	JP/ 114.3cm / 33.0	JP/55.9cm / 3[illegible]
6	JP/20[illegible]cm / 21.0	JP/ 284.5cm / 41.9	JP/ 195.6cm / 30.5	JP/ 91.4cm / 19.[illegible]
7	JP/ 193.0cm / 41.9	JP/ 287.0cm / 41.9	JP/ 322.6cm / 36.8	JP/401.3cm / 15.7
8	bS/ 243.8cm / 56.5	bS/264.2cm / 30.5	JP/127.0cm / 33.7	JP/ 378.[illegible] / 27.[illegible]
9	JP/ 144.8cm / 34.3	JP/292.1cm / 26.7	bS/ 91.4cm / 13.7	JP/22[illegible] / 3[illegible]
10	JP/142.3cm / 22.9	JP/223.5cm / 24.8	bS/254.0cm / 12.7	JP/129.7cm / 4[illegible]
11				
12				
13				
14				
15				

Estimated Tree Coverage: 95-100% Jack Pine (20-22' high)
crown closure - 50%

Estimated Understory Coverage:
Cladonia 40%
Juniper 5%
bear berry + twin flower 20%
dried pine needles 30%
rock 5%

Soil Series Description.
good uniform $R^6 - Li(s)^4$

Ground Truth Site Data - Grand Rapids

Site Name: OK2 → Orx(2) Photo Number: New Line 8 A 22427 - 137 Location: W. of Hwy 6 - between Hwy & Little Limestone Lake	Picture # 10, 11 roll 4	Object T.A. (north ½) as viewed from truck on Hwy.

Point-Quarter Data

Quadrant [species/Distance/circumference]

Site#	Quadrant 1	Quadrant 2	Quadrant 3	Quadrant 4
1	bS/167.6cm/11.4cm	bS/170.2cm/19.1cm	Tam/124.4cm/30.5cm	bS/121.9cm/15.9cm
2	Tam/244.1cm/26.0cm	Tam/55.9cm/12.1cm	Tam/195.6cm/18.7cm	Tam/139.7cm/11.4
3	Tam/262.0cm/12.7cm	Tam/381.0cm/17.5cm	Tam/121.9cm/22.2cm	bS/119.4cm/16.5cm
4	Tam/483.5cm/14.6cm	bS/208.3cm/15.2cm	bS/350.5cm/30.5cm	Tam/116.8cm/15.2cm
5	Tam/145.0cm/27.9cm	Tam/30.5cm/12.1cm	bS/76.2cm/17.1cm	bS/167.6cm/22.9cm
6	Tam/106.9cm/14.6cm	bS/253.9cm/19.1cm	bS/144.8cm/13.3cm	Tam/231.1cm/23.5cm
7	Tam/208.2cm/25.4cm	Tam/294.7cm/23.5cm	Tam/165.1cm/10.8cm	Tam/264.2cm/21.3cm
8	Tam/142.3cm/17.8cm	Tam/73.7cm/13.0cm	bS/142.3cm/12.7cm	Tam/99.1cm/19.4cm
9	Tam/244.0cm/11.4cm	Tam/312.4cm/14.0cm	Tam/396.2cm/15.2cm	Tam/66.1cm/11.1cm
10	Tam/76.3cm/19.4cm	Tam/106.7cm/11.4cm	Tam/248.9cm/16.8cm	Tam/284.6cm/14.6cm
11				
12				
13				
14				
15				

Estimated Tree Coverage: 90% Tamarack 6-12'
10% black Spruce (mostly <6', but some 20')

Crown Closure ≈ 20% (15-25%)

Estimated Understory Coverage:
swamp birch 25% (3-5')
Carex grass 10-15%
Ledum + bog rosemary 10%
Sphag + feathermoss (dom.) 25%

Soil Series Description.
Orok ? - Ox ?

Ground Truth Site Data - Grand Rapids

Site Name: KXLLX-1 Photo Number: A 22423 - 213 Location: on Long Point 1 mile SW of tower	Picture #	Object
	3, 4	general ([illegible])
	5, 6	vegetation [illegible]

Point-Quarter Data

Quadrant [species/Distance/circumference]

Site#	Quadrant 1	Quadrant 2	Quadrant 3	Quadrant 4
1	Tam/ 381.0/ 33.0cm	Tam/ 167.6cm/ 27.9cm	Tam/ 177.8cm/ 11.4cm	bS/ 279.4cm/ 15.2cm
2	bS/ 91.4cm/ 20.3cm	bS/ 200.7cm/ 22.9	bS/ 91.4cm/ 30.5	bS/ 264.2cm/ 11.4
3	bS/ 30.5cm/ 11.4	bS/ 121.9cm/ 26.7	bS/ 43.2cm/ 10.2	bS/ 61.0cm/ 26.7
4	bS/ 299.7cm/ 27.9	bS/ 99.1cm/ 17.8	bS/ 248.9cm/ 25.4	bS/ 340.4cm/ 29.2
5	Tam/ 160.0cm/ 15.2	bS/ 182.9cm/ 16.5	Tam/ 105.1cm/ 17.8	Tam/ 200.7cm/ 10.2
6	Tam/ 200.7cm/ 11.4	Tam/ 190.5cm/ 15.2	bS/ 309.9cm/ 12.7	Tam/ 139.7cm/ 10.2
7	Tam/ 190.5cm/ 12.7	Tam/ 243.8cm/ 12.7	Tam/ 121.9cm/ 11.4	bS/ 309.9cm/ 25.4
8	bS/ 180.4cm/ 17.8	Tam/ 266.7cm/ 10.2	bS/ 76.2cm/ 17.8	bS/ 228.6/ 10.2
9	bS/ 38.1cm/ 11.4	Tam/ 45.7cm/ 10.2	bS/ 177.8cm/ 24.1	bS/ 172.0cm/ [illegible]
10	bS/ 63.5cm/ 33.0	bS/ 101.6cm/ 29.2	bS/ 61.0cm/ 17.8	bS/ 144.8cm/ 19.[illegible]
11				
12				
13				
14				
15				

Estimated Tree Coverage: Tam 20% up to 12'
black spruce 80% 18-20' mature height
crown closure 25%

Estimated Understory Coverage: + a few small cedar + swamp birch
Sphagnum 50%
feathermoss 20%
Ledum 30-40%
leatherleaf (chamaedaphne) 10%

Soil Series Description.
good KXLLX complex
HCT at 5'+ depth (152 cm)

Ground Truth Site Data - Grand Rapids

Site Name: P9 L3 1-1 Photo Number: new line 4 A22422-73 Location: on Cross Lake Road	Picture #	Object
	4, 5	
	6	overall view from across road

Point- Quarter Data

Quadrant [species/Distance/circumference]

Site#	Quadrant 1	Quadrant 2	Quadrant 3	Quadrant 4
1	bS/121.9cm/30.5cm	bS/254.0cm/35.6cm	bS/337.7cm/33.0cm	bS/147.3cm/21.6cm
2	bS/345.4cm/19.1cm	bS/104.2cm/22.2	bS/134.6cm/22.9	bS/152.4cm/16.5
3	JP/312.4cm/29.2cm	JP/190.5cm/27.9	bS/198.1cm/13.3	JP/226.1cm/38.1
4	JP/177.8cm/22.9	bS/274.3cm/18.4	JP/88.9cm/24.1	bS/121.9cm/21.6
5	bS/256.6cm/24.1	bS/175.3cm/15.2	JP/127.0cm/30.5	JP/342.9cm/38.1
6	bS/198.1cm/12.7	bS/147.3cm/16.5	JP/243.8cm/26.7	JP/91.4cm/[illegible]
7	bS/45.7cm/20.3	bS/160.0cm/13.3	bS/297.2cm/12.1	bS/132.1cm/15.9
8	bS/53.3cm/15.9	bS/378.5cm/22.2	bS/200.7cm/14.0	bS/50.8cm/17.3
9	JP/256.6cm/26.7	JP/218.5cm/15.9	JP/134.9cm/13.3	JP/71.1cm/10.5
10	JP/81.3cm/54.6	bS/71.1cm/12.1	bS/175.3cm/21.0	bS/160.0cm/21.6
11				
12				
13				
14				
15				

Estimated Tree Coverage: 60% black spruce (10-25')
40% jack pine (20-25')
crown closure 30%
approaching maturity on east side of Cross Lake, less [illegible]

Estimated Understory Coverage:
Cladonia 35%
Juniper 20%
Rock 30%
bearberry, etc 15%

Soil Series Description.
Rock R^{9} Li(s)^{1}

C.1 PLOTLESS SAMPLING TECHNIQUE VEGETATION ANALYSIS PROGRAM

This program was provided by Prof. J. Stewart of the Botany Dept., Univ. of Manitoba.

```
//XXXXTERM JOB '0989,XXX,T=5,I=20',W.FRASER,CLASS=X
/*TSO  XXXX
$JOB  WATFIV   FRASER,LINES=65,NOLIST,NOEXT,NOWARN
C************************************************************
C
C  ECOLOGICAL STUDY BY COMPUTER ANALYSIS
C
C  LAB #3
C  VEGETATION ANALYSIS  PLOTLESS SAMPLING TECHNIQUE
C
C  THIS LAB GIVES A TABLE FOR A COMMUNITY (SET) OF SPECIES
C        TABLE-- DENSITIES DOMINANCES FREQUENCIES AND THEIR
C               RELATIVE VALUES IMPORTANCE VALUES AVG.DOMINANCE
C*************************************************************************
C************************************************************
C*******      DECLARATIONS      *******
C THE FIRST BLOCK OF DECLARATIONS IS THE SAME FOR ALL LABS.
C  THIS BLOCK CONSISTS OF    EXPT--EXPERIMENT NAME
C                           NAME--EXPERIMENTERS NAME
C                         COURSE--NAME OR NUMBER OF LAB COURSE
C                         DATE--DATE OF RUN OF COMPUTER PROGRAM
C                         DURATN--DURATION OF EXPERIMENT(DATE OF
C                                         BEGIN AND END)
C                         REFRNC--REFERENCES USED FOR EXPERIMENT
C                         TEXT--3 CARDS OF ANY ADDITIONAL INFORMATION
C                         COPY--SWITCH FOR COPY OF INPUT DATA OR NOT
C  ALL ARE PUT IN COMMON FOR USE IN VARIOUS INPUR AND OUTPUT ROUTINES
C***********************************************************
      CHARACTER*30 EXPT,NAME,COURSE*10
      CHARACTER*20 DATE,DURATN,REFRNC*30
      CHARACTER*80 TEXT(3)
      INTEGER*2 COPY
      COMMON EXPT,NAME,COURSE,DATE,DURATN,REFRNC,COPY,TEXT
C************************************************************
C  LABS  5--7  HAVE MOST OF THE FOLLOWING DECLARATIONS
C                         SPECIE--NAME OF THE SPECIE
C                         DEN.DOM.FREQ.RELDEN.RELDON.RELFRQ
C                                ARE THE DENSITY DOMINANCE FREQUENCY
C                              AND RELATIVE VALUES OF EACH
C                        IMPVAL--IMPORTANCE VALUES
C                       INDVDL--NUMBER OF INDIVIDUALS PER SPECIES
C                         SPC--S COUNTER USED IN DO-LOOPS
C                         PERMUT--INDEX,S OF DESCENDING ORDERED
C                                IMPORTANCE VALUES
C     LAB #6              AVGDOM--AVERAGE DOMINANCE VALUES
C                         IND--NUMBER OF INDIVIDUALS PER SPECIES
C*************************************************************
```

```
      CHARACTER*30 SPECIE(100)
      REAL*4  DEN(100),DOM(100),FREQ(100),RELDEN(100),RELDOM(100),
     *RELFRQ(100),IMPVAL(100),IND(100),AVGDOM(100)
      REAL*4 PERMUT(100), INDVDL
      INTEGER*2 SPC,TECHNQ
C
C  CALL THE LAB USERS INFORMATION  INPUT SUBROUTINE
C  THIS ROUTINE INPUTS ALL THE USER INFORMATION SUCH AS NAME COURSE ETC.
C
      CALL INTRO
C
C  INPUT FOR LAB #6
C         CARD #1              SPCNUM--NUMBER OF SPECIES
C                          UNIT--UNIT AREA USED IN EXPERIMENT
C                        TOTIND--TOTAL #(NO.) OF INDIVIDUALS ALL SPECIE
C                          TOTPNT--TOTAL POINTS SAMPLED IN EXPERIMENT
C          CARD#2              TECHNQ--TECHNIQUE SWITCH
C                             '1'-POINT-QUATER-TECHNIQUE
C                             '2'-RANDOM POINT TECHNIQUE
C
      READ(5,50,END=99) SPCNUM,UNIT,TOTIND,TOTPNT
   50 FORMAT(4F10.2)
      READ(5,51,END=99) TECHNQ
   51 FORMAT(3X,I2)
      NUMSPC=IFIX(SPCNUM)
C
C  SWITCH COPY--IF GREATER THEN 0 THEN PRINT OUT ALL INPUT DATA
C
      IF(COPY.GT.0) WRITE(6,20) 'COPY OF INPUT DATA'
   20 FORMAT('1',25X,A18)
      IF(COPY.GT.0)   WRITE(6,22) SPCNUM,UNIT,TOTIND,TOTPNT,TECHNQ
   22 FORMAT('0','DATA CONSTANTS',4F10.2,I2)
C
C  SETTING SUM COUNTERS FOR DENSITIES DOMINACES AND FREQUENCIES
C  THEN READ IN AND DO CALCULATIONS FOR ALL SPECIES
C
      TOTDOM=TOTFRQ=TOTVAL=0
      SUMPTP=SUMDOM=SUMFRQ=0
      DO 3 SPC=1,NUMSPC
C
C  READ IN SPECIE NAME--NUMBER OF INDIVIDUALS(ALL POINTS)--BASAL AREA
C  NUMBER OF POINTS WHERE SPECIE OCCURED--TOTAL POINT TO PLANT DISTANCES
C  FOR ALL POINTS WHERE THAT SPECIE ACCURED
C  IF COPY SWITCH SET ON PRINT OUT DATA AS READ IN
C
      READ(5,52,END=999,ERR=888) SPECIE(SPC),INDVDL,BASAL,PNTS,PPDIS
   52 FORMAT(A30,4F10.2)
      IF(COPY.GT.0) WRITE(6,21) SPECIE(SPC),INDVDL,BASAL,PNTS,PPDIS
   21 FORMAT(' ',A30,4F10.2)
C*********************************************************
C
C  DATA CALCULATIONS ON DATA ELEMENTS (FOR EQUATIONS REFER TO LAB MANUAL
C  CALCULATIONS FOR AVERAGE DOMINANCE--RELATIVE DENSITY--FREQUENCY
C
```

```
C************************************************************
      SUMPTP=SUMPTP+PPDIS
      AVGDOM(SPC)=BASAL/INDVDL
      RELDEN(SPC)=INDVDL/TOTIND*100
      FREQ(SPC)=PNTS/TOTPNT
      IND(SPC)=INDVDL
      SUMFRQ=SUMFRQ+FREQ(SPC)
    3 CONTINUE
C
C  NOW CALCULATE TOTAL DENSITY ACCORDING TO THE TECHNIQUE SWITCH GIVEN AS
C  INPUT.  TEC#NQ IS EQUAL TO #1 OR #2
C
      IF(TECHNQ.EQ.1) TOTDEN=UNIT/((SUMPTP/TOTIND)**2)
      IF(TECHNQ.EQ.2) TOTDEN=UNIT/(((SUMPTP/TOTIND)*0.8)**2)
C
C  NOW USE VALUES CALCULATED ON THE FIRST RUN THROUGH THE DATA TO FIND
C  DENSITY DOMINANCE AND RELATIVE FREQUENCY
C
      DO 5 I=1,NUMSPC
      DEN(I)=(RELDEN(I)/100)*TOTDEN
      DOM(I)=DEN(I)*AVGDOM(I)
      RELFRQ(I)=(FREQ(I)/SUMFRQ)*100
      SUMDOM=SUMDOM+DOM(I)
    5 CONTINUE
      DO 6 I=1,NUMSPC
      RELDOM(I)=(DOM(I)/SUMDOM)*100
      IMPVAL(I)=RELDEN(I)+RELDOM(I)+RELFRQ(I)
      TOTVAL=TOTVAL+IMPVAL(I)
    6 CONTINUE
      TOTDOM=SUMDOM
      TOTFRQ=SUMFRQ
C
C
C
C************************************************************
C  OUTPUT SECTION
C  ROUTINE OUTRO PRINTS ALL LAB USER DATA(NAME COURSE DATE ECT.)
C  THEN THE PROGRAM DATA CALCULATIONS ARE PRINTED OUT WITH APPROPRIATE
C  HEADINGS AND REFERENCES
C**********************************************************
      CALL OUTRO
C
C  PRINT OUT TECHNIQUE USED IN THIS EXPERIMENT
C
      IF(TECHNQ.EQ.1) WRITE(6,46)
   46 FORMAT('-','POINT-QUARTER TECHNIQUE')
      IF(TECHNQ.EQ.2) WRITE(6,48)
   48 FORMAT('-','RANDOM PAIRS TECHNIQUE')
C
C  TABLE HEADINGS
C  ROUTINE BBSORT IS COMMON TO LABS #5,#6,#7.
C  THE SPECIES ARE SORTED IN DESCENDING ORDER ACCORDING TO
C  IMPORTANCE VALUES.
C  PERMUT IS A VECTOR OF INDICES OF THE SPECIES IN THE  CORRECT ORDER
```

```
C
      CALL BBSORT (NUMSPC,IMPVAL,PERMUT)
      WRITE(6,40)
   40 FORMAT('-',///'-',10X,'SPECIES',13X,'NUMBER OF',4X,'AVG. DOM.',
     *2X,'  DENSITY',2X,' RELATIVE',2X,'DOMINANCE',2X,' RELATIVE',2X,
     *'FREQUENCY',2X,' RELATIVE',2X,'IMPORTANCE',/' ',
     *30X,'INDIVIDUALS',4X,'VALUE',16X,'DENSITY',13X,'DOMINANCE',13X,
     *'FREQUENCY',4X,'VALUE',/)
C  WRITE OUT TABLE FOR ALL SPECIES
      DO 8 INDEX=1,NUMSPC
      I=PERMUT(INDEX)
      WRITE(6,42) SPECIE(I),IND(I),AVGDOM(I),DEN(I),RELDEN(I),DOM(I),
     *RELDOM(I),FREQ(I),RELFRQ(I),IMPVAL(I)
   42 FORMAT(' ',A30,9(2X,F9.2))
    8 CONTINUE
      WRITE(6,45)  TOTDOM,TOTFRQ,TOTVAL
   45 FORMAT('0',69X,'TOTAL',2X,F9.2,6X,'TOTAL',2X,F9.2,6X,'TOTAL',
     *F9.2)
      WRITE(6,44) NUMSPC, UNIT, TOTIND,TOTPNT,TOTDEN
   44 FORMAT('-',///'-','NUMBER OF SPECIES ',I3,'UNIT AREA',F10.2,3X,
     *'TOTAL NUMBER OF INDIVIDUALS',F8.2,3X,'TOTAL POINTS',F8.2,3X,
     *'TOTAL DENSITY', F8.2)
      WRITE(6,49)EXPT
   49 FORMAT('1','END OF',A30)
      STOP
C
C  ERROR SECTION.... ALL ERRORS STOP THE EXECUTION OF THE PROGRAM
C  ERROR MESSAGE HOPEFULLY GIVES IDEAS OF CORREDTION PROCESS
   99 PRINT,'ERROR....END OF FILE ON INPUT DATA CONSTANTS(AREA.PLOTS)'
      STOP
  999 PRINT,'ERROR,END OF FILE ON INPUT CHECK ACTUAL.VS.GIVEN # SPECIE'
      STOP
  888 PRINT,'ERROR..A DATA CARD IN ERROR CHECK FORMAT AND KEYPUNCHING'
      STOP
      END
      SUBROUTINE INTRO
C*************************************************************
C  THIS ROUTINE IS THE SAME AND IS A PART OF ALL LABS FOR THIS
C  ECOLOGICAL STUDY PACKAGE OF COMPUTER PROGRAMS
C  ALL USERS MUST SUPPLY SOME BASIC INFORMATION(AS GIVEN IN MAIN PROGRAM
C  NAME--EXPERIMENT NAME--COURSE--DATE--DURATION--REFERENCE MATERIALS
C  ANY TEXT DESIRED(3CARDS) AND A CONTROL CARD FOR DESIRED COPY OF
C  INPUT DATA  AS READ IN
C*************************************************************
      CHARACTER*30 EXPT,NAME,COURSE*10
      CHARACTER*20 DATE,DURATN,REFRNC*30
      CHARACTER*80 TEXT(3)
      INTEGER*2 COPY
      COMMON EXPT,NAME,COURSE,DATE,DURATN,REFRNC,COPY,TEXT
      READ(5,30,END=99) EXPT,NAME,COURSE
   30 FORMAT(A30,A30,A10)
      READ(5,31,END=99) DATE,DURATN,REFRNC
   31 FORMAT(A20,A20,A30)
      READ(5,32,END=99) (TEXT(I),I=1,3)
```

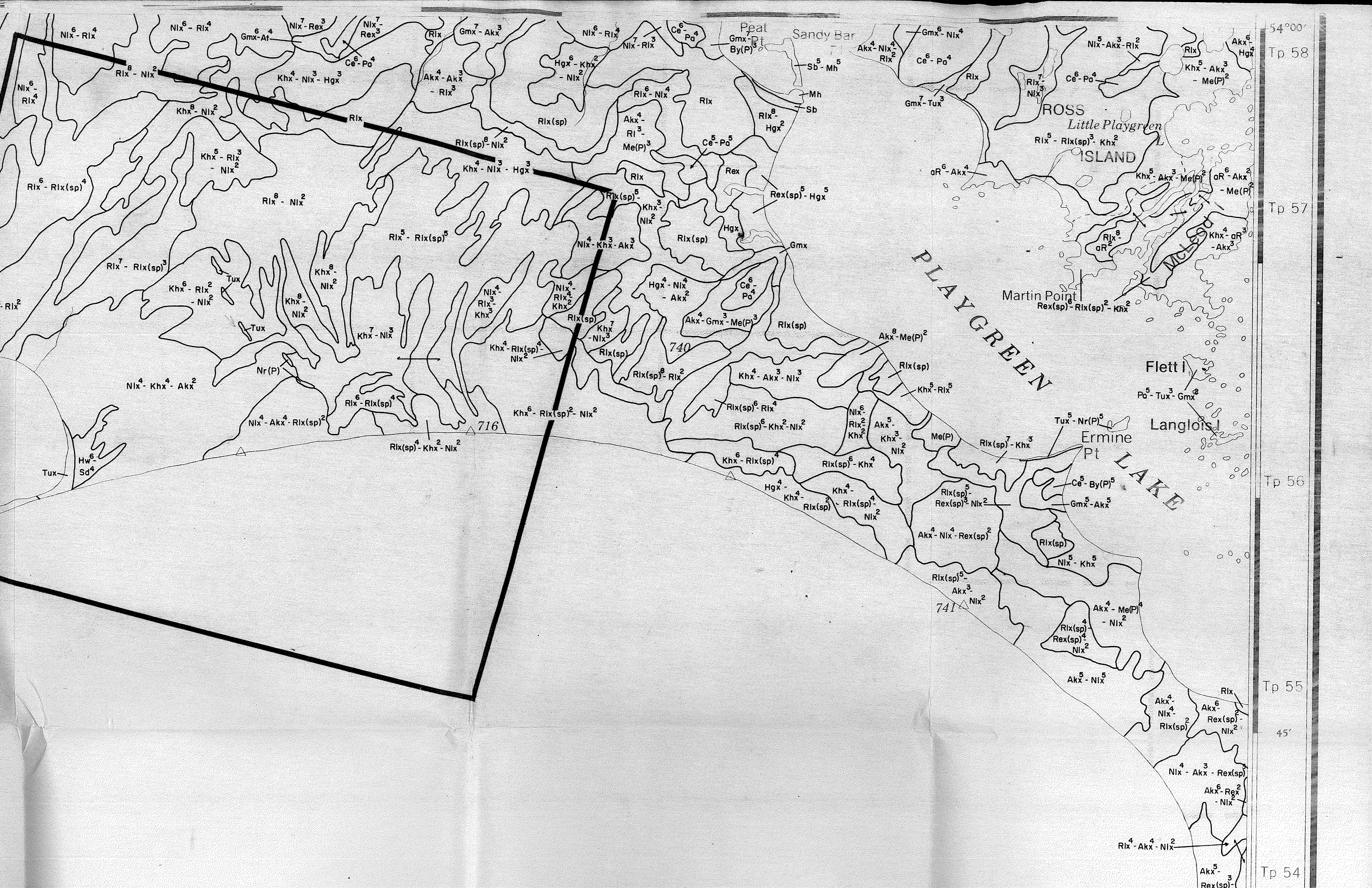
```
   32 FORMAT(A80)
      READ(5,33,END=99) COPY
   33 FORMAT(3X,I2)
      RETURN
   99 PRINT,'ERROR....END OF FILE ON INPUT. CHECK DATA CARDS'
      RETURN
      END
      SUBROUTINE OUTRO
C************************************************************
C  THIS ROUTINE IS THE SAME AND A PART OF ALL LABS FOR THIS
C  ECOLOGICAL STUDY PACKAGE OF COMPUTER PROGRAMS
C  THE ROUTINE PRINTS OUT THE BASIC USER INFORMATION
C  NAME--EXPERIMENTNAME--COURSE--DATE--DURATION--REFERENCE MATERIALS
C  ANY TEXT DESIRED IS ALSO PRINTED OUT
C************************************************************
      CHARACTER*20 DATE,DURATN,REFRNC*30
      CHARACTER*30 EXPT,NAME,COURSE*10
      CHARACTER*80 TEXT(3)
      INTEGER*2 COPY
      COMMON EXPT, NAME,COURSE,DATE,DURATN,REFRNC,COPY,TEXT
      WRITE(6,22) EXPT,NAME,COURSE
   22 FORMAT('1',10X,A30,10X,A30,10X,A10)
      WRITE(6,23) DURATN,REFRNC,DATE
   23 FORMAT('-',5X,'DURATION OF EXPERIMENT ',A20,2X,'REFERENCE ',A30,
     *'DATE OF RUN ',A20)
      WRITE(6,24) (TEXT(I),I=1,3)
   24 FORMAT('0',15X,A80)
      RETURN
      END
      SUBROUTINE BBSORT(NUMSPC,IMPVAL,PERMUT)
C************************************************************
C  THIS ROUTINE IS USED FOR SORTING PROCEDURES IN LABS #5,#6, #7,
C  THE IMPORTANCE VALUES OF ALL SPECIES IS TAKEN AS INPUT AND
C  INITIALIZED TO A WORK VECTOR. ALSO INITIALIZED IS A VECTOR OF INDICES
C  (1 TO THE NUMBER OF SPECIES). THE WORK VECTOR IS SORTED IN DESCENDING
C  ORDER. ANY CHANGES TO THE ORDER OF THE WORK VECTOR IS REFLECTED
C  IN CHANGING THE ORDER OF THE INDICES IN THE VECTOR *PERMUT*
C  A BUBBLE SORT TECHNIQUE IS USED.OUTPUT IS THE VECTOR PERMUT
C  WITH THE INDICES OF THE SPECIES IN DESCENDING ORDER.....
C************************************************************
      REAL*4 IMPVAL(100),PERMUT(100),VALUE(100)
      IF (NUMSPC.EQ.0) RETURN
      DO 3 I=1,NUMSPC
      VALUE(I)=IMPVAL(I)
      PERMUT(I)=I
    3 CONTINUE
      LASTN=NUMSPC
    5 LASTO=LASTN
      DO 7 J=2,LASTO
      IF(VALUE(J-1).GE.VALUE(J)) GO TO 7
      SAVE=VALUE(J)
      PSAVE=PERMUT(J)
      VALUE(J)=VALUE(J-1)
      PERMUT(J)=PERMUT(J-1)
```

```
      VALUE(J-1)=SAVE
      PERMUT(J-1)=PSAVE
      LASTN=J-1
    7 CONTINUE
      IF(LASTN.EQ.LASTO.OR.LASTN.EQ.1) RETURN
      GO TO 5
      END
$ENTRY
C  WALTER FRASER  THESIS
C  APRIL 1978
C GRAND RAPIDS TRAINING AREAS
C  SITE LI (TILL/ROCK)  ON WILLIAM LAKE ROAD
C PHOTO #142  NEW LINE 9
    1
      2.00  10000.00     40.00     10.00
    1
PINUS BANKSIANA(JP)                40.00    4498.74     10.00     165.79
                                    0.00       0.00      0.00       0.00
$END
/*
```

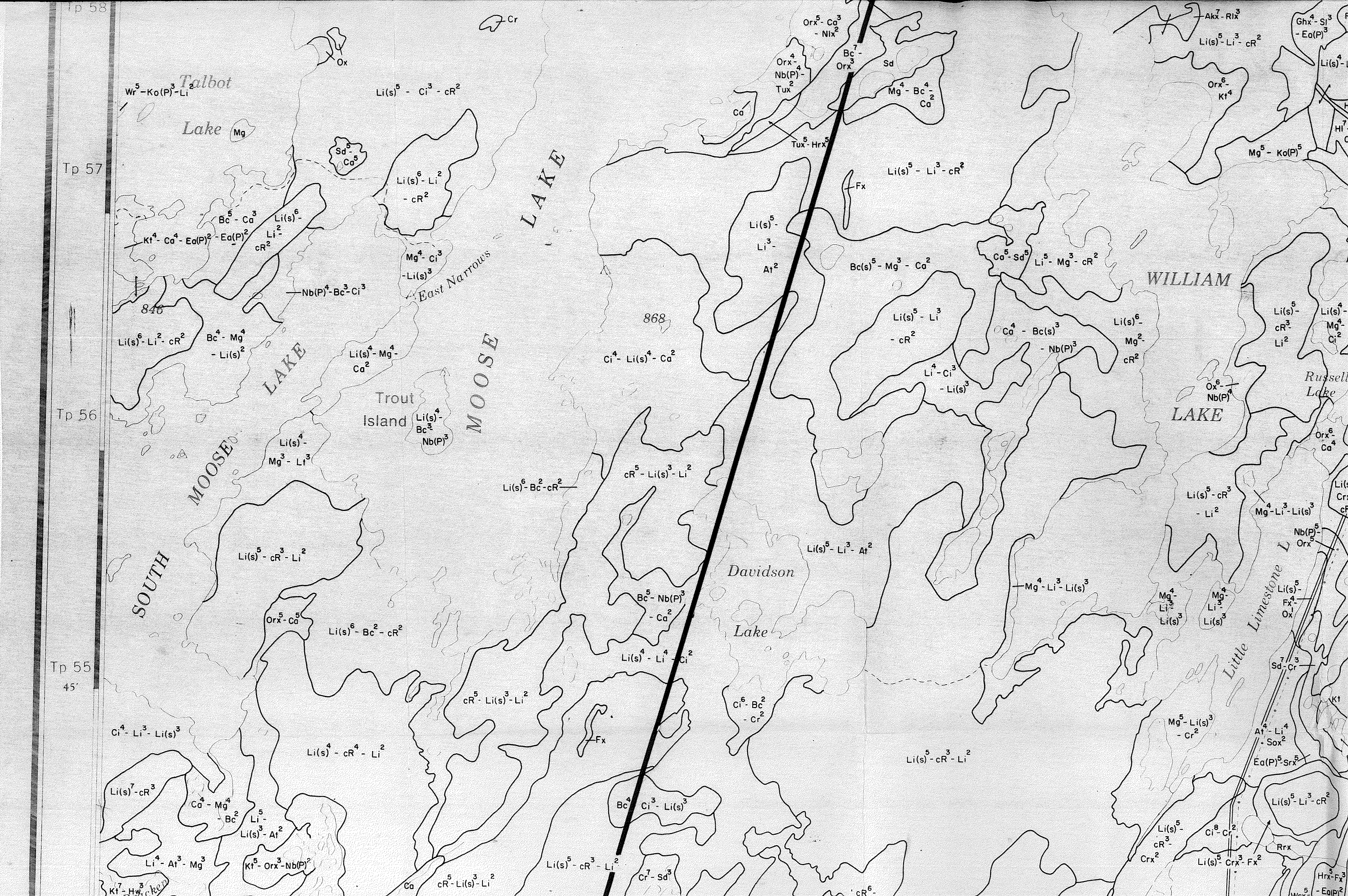
Appendix D

SOIL MAPS OF THE GRAND RAPIDS AREA PRODUCED BY AUTOMATED SUPERVISED, AUTOMATED UNSUPERVISED, AND CONVENTIONAL TECHNIQUES.

(in pocket)


54°00'
Tp 58
Peat Pt
Sandy Bar
ROSS ISLAND
Little Playgreen L
Tp 57
PLAYGREEN LAKE
Martin Point
Flett I
Langlois I
Ermine Pt
Tp 56
Tp 55
45'
Tp 54
716
740
741

WILLIAM
LAKE
Russell Lake
Baker Lake
Little Limestone L
William River
William River
823
LIMESTONE BAY
Limestone Point
716
Creek



Tp 58
Tp 57
Tp 56
Tp 55
45'
Talbot
Lake
SOUTH MOOSE LAKE
MOOSE LAKE
East Narrows
Trout
Island
WILLIAM
LAKE
Russell
Lake
Davidson
Lake
Little Limestone L
846
868
Cr
Ox
Mg
Sd
Ca
Fx
Kt
Rrx
Wr⁵-Ko(P)³-Li²
Li(s)⁵ - Ci³ - cR²
Sd⁵-Ca⁵
Li(s)⁶ - Li² - cR²
Bc⁵ - Ca³
Li(s)⁶ - Li² - cR²
Kt⁴ - Ca⁴ - Ea(P)² - Ea(P)²
Mg⁴ - Ci³ - Li(s)³
Nb(P)⁴-Bc³-Ci³
Li(s)⁶-Li²-cR²
Bc⁴ - Mg⁴ - Li(s)²
Li(s)⁴ - Mg⁴ - Ca²
Li(s)⁴ - Bc³ - Nb(P)³
Li(s)⁴ - Mg³ - Li³
Li(s)⁶-Bc²-cR²
Li(s)⁵ - cR³ - Li²
Orx⁵-Ca⁵
Li(s)⁶ - Bc² - cR²
cR⁵ - Li(s)³ - Li²
Ci⁴- Li³- Li(s)³
Li(s)⁴ - cR⁴ - Li²
Li(s)⁷-cR³
Ca⁴ - Mg⁴ - Bc²
Li⁵ - Li(s)³ - At²
Li⁴ - At³ - Mg³
Kt⁵ - Orx³-Nb(P)²
Kt⁷-Hw³
cR⁵-Li(s)³-Li²
Orx⁵- Ca³ - Nlx²
Orx⁴ - Nb(P)⁴ - Tux²
Bc⁷ - Orx³
Mg⁴ - Bc⁴ - Ca²
Tux⁵- Hrx⁵
Li(s)⁵ - Li³ - cR²
Li(s)⁵ - Li³ - At²
Bc(s)⁵ - Mg³ - Ca²
Ci⁴- Li(s)⁴ - Ca²
cR⁵ - Li(s)³ - Li²
Bc⁵ - Nb(P)³ - Ca²
Li(s)⁴ - Li⁴ - Ci²
Ci⁶ - Bc² - Cr²
Bc⁴ - Ci³ - Li(s)³
Li(s)⁵ - cR³ - Li²
Cr⁷ - Sd³
Li(s)⁵ - Li³ - cR²
Li(s)⁵ - Li³ - At²
Ca⁵ - Sd⁵
Li⁵ - Mg³ - cR²
Li(s)⁵ - Li³ - cR²
Ca⁴ - Bc(s)³ - Nb(P)³
Li⁴ - Ci³ - Li(s)³
Li(s)⁶ - Mg² - cR²
Mg⁴ - Li³- Li(s)³
Li(s)⁵ - cR³ - Li²
Akx⁷- Rlx³
Ghx⁴- Sj³ - Ea(P)³
Li(s)⁵ - Li³ - cR²
Orx⁶ - Kt⁴
Mg⁵ - Ko(P)⁵
Ox⁶ - Nb(P)⁴
Orx⁶ - Ca⁴
Li(s)⁵ - cR³ - Li²
Mg⁴-Li³-Li(s)³
Nb(P)⁵- Orx⁵
Mg⁴ - Li³ - Li(s)³
Li(s)⁵ - Fx⁴ - Ox
Sd⁷-Cr³
Mg⁵ - Li(s)³ - Cr²
At⁴ - Li⁴ - Sox²
Ea(P)⁵-Srx⁵
Li(s)⁵ - Li³ - cR²
Li(s)⁵ - cR³ - Crx²
Ci⁸-Cr²
Li(s)⁵ - Crx³ - Fx²
Hrx⁵-Fx³ - Ea(P)²

MAP 3

RECONNAISSANCE SOILS MAP

OF THE

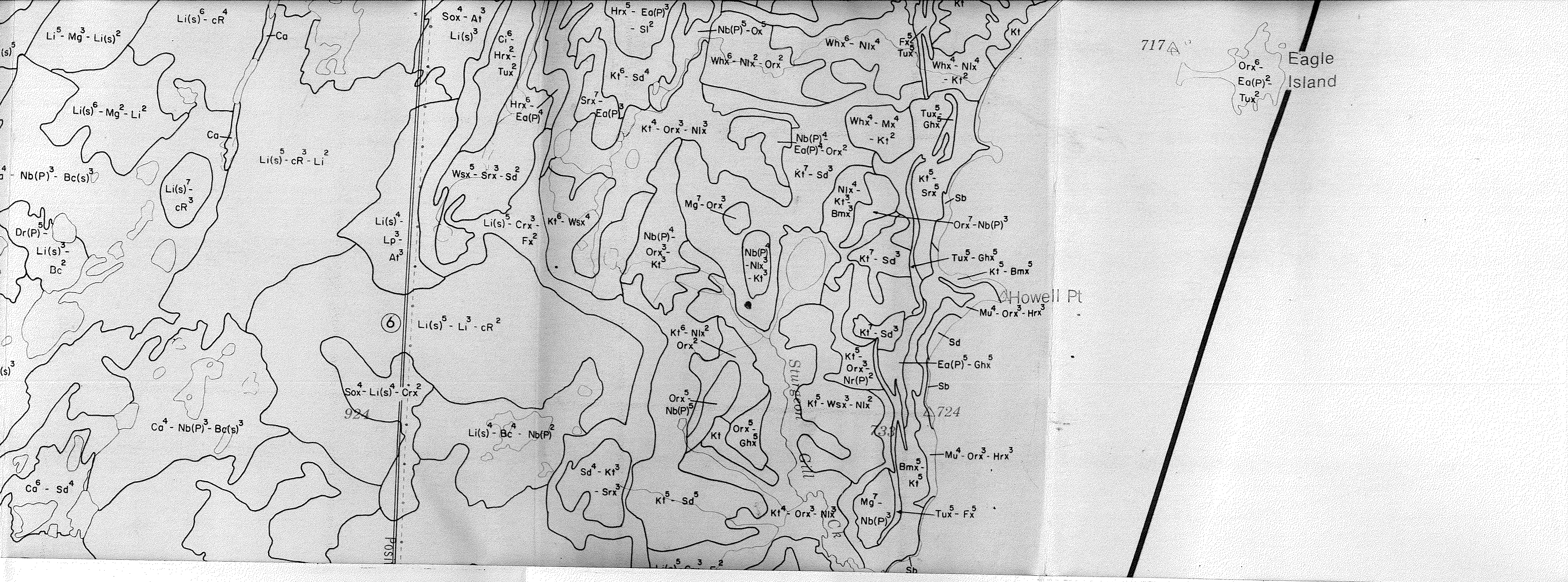
GRAND RAPIDS AREA, MANITOBA (NTS 63G)

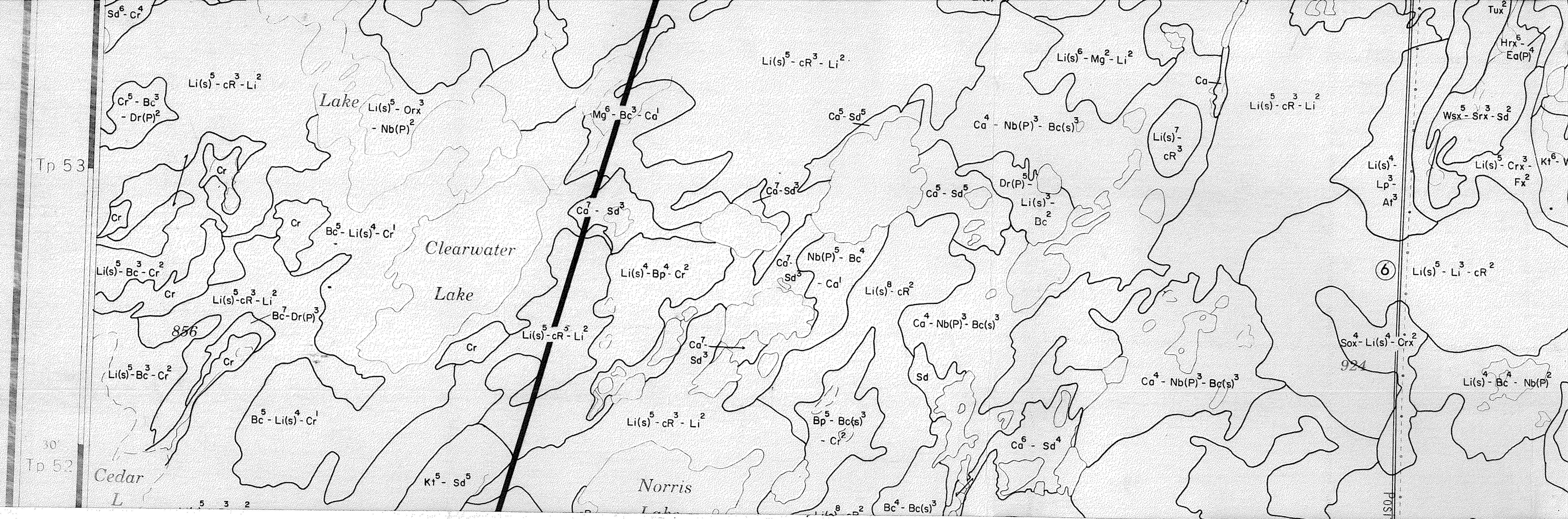
This soils map is provided for comparison of conventional soil survey reconnaissance maps with those of the supervised and unsupervised computer classification techniques (maps 1 and 2). These maps are all reproduced at the same scale (1:127,000). The area classified in maps 1 and 2 is indicated (dark lines).

For each soil series or complex, the closest correct equivalent classification group in each of the automated classification methods is given. These groups are usually much broader in definition than those of the conventional reconnaissance soils map.

LEGEND

Soil Series or Complex		Automated Classification Map Unit Equivalents			
		Supervised Method (Map 1)		Unsupervised Method (Map 2)	
Map Symbol	Soil Name	Map Symbol	Group Name	Map Symbol	Group Name
Akx	Atik Complex	<	OROK	>	OROK-KX
At	Atikameg Series	A	Till	A	Till
Bc, Bc(S)	Birch Bay Series	L	Till/R	L	Till/R
Bmx	Baynham Complex		(none)		(none)
Bp, Bp(S)	Biscuit Point Series		(none)		(none)
Ca	Cayer Series	:	Crane	:	Crane
Chx	Chocolate Complex	>	KXLLX	>	OROK-KX


Eagle Island
Howell Pt
Sturgeon Cr
717
724
733
924
6



Tp 53
30'
Tp 52
Lake
Clearwater
Lake
Cedar
L
Norris
856
924
6
POST
Sd6 - Cr4
Li(s)5 - cR3 - Li2
Cr5 - Bc3 - Dr(P)2
Li(s)5 - Orx3 - Nb(P)2
Mg6 - Bc3 - Ca1
Li(s)5 - cR3 - Li2
Li(s)6 - Mg2 - Li2
Ca5 - Sd5
Ca4 - Nb(P)3 - Bc(s)3
Li(s)7 - cR3
Li(s)5 - cR3 - Li2
Wsx5 - Srx3 - Sd2
Hrx6 - Ea(P)4
Tux2
Cr
Bc5 - Li(s)4 - Cr1
Ca7 - Sd3
Ca7 - Sd3
Ca5 - Sd5
Dr(P)5 - Li(s)3 - Bc2
Li(s)4 - Lp3 - Af3
Li(s)5 - Crx3 - Kt6 - Fx2
Li(s)5 - Bc3 - Cr2
Li(s)5 - cR3 - Li2
Bc7 - Dr(P)3
Li(s)4 - Bp4 - Cr2
Ca7 - Sd3
Nb(P)5 - Bc4 - Ca1
Li(s)8 - cR2
Li(s)5 - Li3 - cR2
Ca4 - Nb(P)3 - Bc(s)3
Li(s)5 - cR5 - Li2
Ca7 - Sd3
Sox4 - Li(s)4 - Crx2
Li(s)5 - Bc3 - Cr2
Bc5 - Li(s)4 - Cr1
Li(s)5 - cR3 - Li2
Bp5 - Bc(s)3 - Cr2
Sd
Ca4 - Nb(P)3 - Bc(s)3
Li(s)4 - Bc4 - Nb(P)2
Ca6 - Sd4
Kt5 - Sd5
Bc4 - Bc(s)3

W I N N I P E G

712±

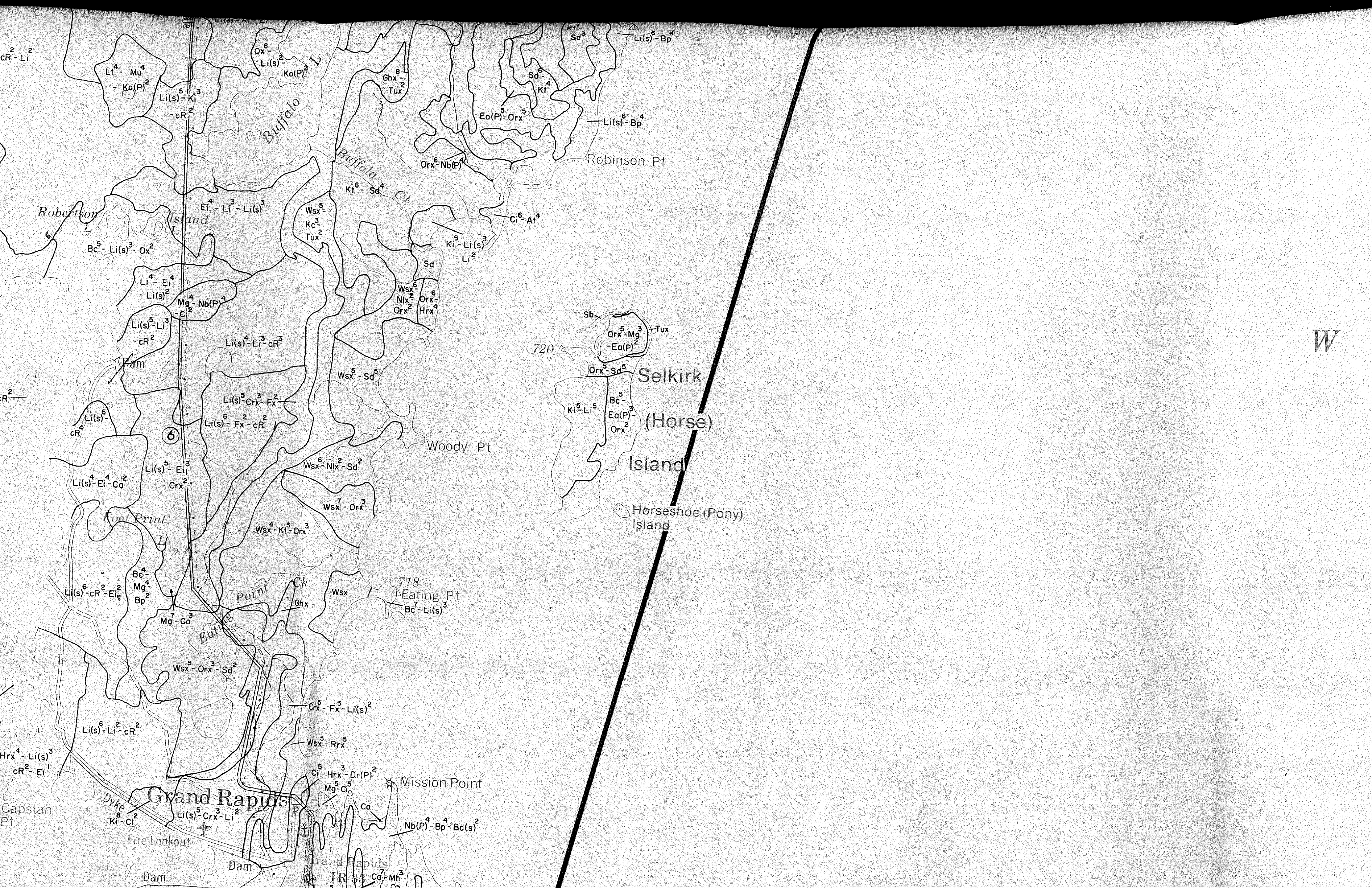
Ea(P)	Easterville Series	D	Dering	D	Dering
Ei	Egg Island Series	A	Till	A	Till
Fx	Freshford Complex		(none)		(none)
Gdx	Grindstone Complex	<	OROK	>	OROK-KX
Ghx	Guy Hill Complex	< >	OROK KXLLX	>	OROK-KX
Gmx	Gormley Lake Complex	< >	OROK KXLLX	>	OROK-KX
Hd	Holditch Series	:	Crane	:	Crane
Hgx	Hargrave Complex	=	WHX	=	WHX
Hl	Halcrow Series		(none)	;	Halcrow
Hrx	Horseshoe Island Complex		(none)		(none)
Hw	Howell Series		(none)	;	Halcrow
Kc	Kircro Series	:	Crane	:	Crane
Khx	Kiskitto Series	=	WHX	=	WHX
Ki	Kinwow Series	A	Till	A	Till
Ko(P)	Koostatak Series	D	Dering	D	Dering
Kt	Katimik Series	-	Katimik	-	Katimik
Klx	Kilkenny Complex	>	KXLLX	>	KXLLX
Li, Li(S)	Limestone Point Series	L	Till/R	L	Till/R
Llx	Lamb Lake Complex	< >	OROK KXLLX	>	OROK-KX
Lt	Lettonia Series	A	Till	A	Till
Mg	Mantagao Series	A	Till	A	Till
Mh	Marsh Complex		(none)[1]		(none)[1]
Mu	Mukatawa Series	A	Till	A	Till
Mx	Molson Complex	>	KXLLX	>	OROK-KX
Nb(P)	Napanee Bay Series	D	Dering	D	Dering
Nlx	Nekik Lake Complex		(none)		(none)
Nr(P)	Norris Series	D	Dering	D	Dering
Orx	Orok Complex	< >	OROK KXLLX	>	OROK-KX
Ox	Okno Complex	<	OKNO	>	OROK-KX
Rex	Reed Lake Complex	:	Crane	:	Crane
Rex(sp)	Reed Lake Complex, sphagnic phase		(none)	;	Halcrow
Rl	Roe Lake Series	A	Till	A	Till
Rlx	Rock Island Complex	.	Stead	.	Stead
Rlx(sp)	Rock Island Complex, sphagnic phase	-	Katimik	-	Katimik
Rrx	Rat River Complex	<	OROK	>	OROK-KX
Sb			(none)[1]		(none)[1]
Sd	Stead Series	.	Stead	.	Stead
Sl	Sturgeon Gill Series		(none)		(none)
Sox	Soul Lake Complex		(none)		(none)
Srx	Sand River Complex	>	KXLLX	>	OROK-KX
Tux	Tremanden Complex	=	WHX	=	WHX
Wsx	Waskwei Complex	=	WHX	=	WHX

1. Marshes, beaches, and other shoreline features are usually misclassified as cloud shadows. These are left blank in both the supervised and unsupervised method soils maps (maps 1 and 2).

SOIL COMPLEXES

Soil complexes are groups of soil series which occur in complex association, and are not separable at reconnaissance mapping scales. The dominant series gives the name to the complex.

SOIL PHASES



Buffalo L
Buffalo Ck
Robinson Pt
Robertson L
Island L
Dam
Woody Pt
720
Selkirk (Horse) Island
Horseshoe (Pony) Island
Foot Print L
718
Eating Pt
Eating Point Ck
Mission Point
Grand Rapids
Capstan Pt
Dyke
Fire Lookout
Dam
Grand Rapids IR 33
W

Clear Bay
(Cedar Lake)
Herring Ck
Tp 51
Tp 50
Tp 49
15'
Li(s)^5 - cR^3 - Li^2
Li^4 - At^3 - Li(s)^3
Kt^8 - Sd^2
Bc^8 - Ca^2
Bp^4 - Bp(s)^3 - Ca^3
Ca^7 - Bp^3
Li(s)^8 - Lp^2 - cR^2
Li(s)^6 - Bc^2 - Cr^2
Li(s)^6 - cR^4
Li(s)^6 - cR^2 - Li^2
Li(s)^5 - cR^3 - Bc^2
Li^5 - Mg^3 - Li(s)^2
Li(s)^6 - Li^2 - cR^2
Mg^5 - Bc(s)^3 - Ca^2
Ox^5 - Hw^5
Sd^7 - Kt^3
Orx^4 - Dr(P)^3 - Hw^3
Li(s)^4 - Bp^3 - Ca^3
Li(s)^5 - Li^3 - At^2
Li^5 - Li(s)^5
Bc^5 - Li(s)^3 - Ca^2
Li^6 - At^4
Ca^6 - Sd^4
Li(s)^7 - Ca^3
Ca^8 - Bp(s)
Ca^8 - Bp(s)^2
Kt^6 - Ca^4
Bc^4 - Mg^3 - Ca^3
Li(s)^8 - Li^2
Ca^8 - Ox^2
McDougall I
Dividing I
Li(s)^7 - cR^3
CROSS
Lamb B
Li^5 - Ci^3 - Li(s)^2
CEDAR
LAKE
Centre I
Lookout Pt
Anchor Pt
Rabbit Pt
Napanee
Bay
Smith I
Collins I
BAY
Portage B
Capstan Pt
Robertson L
Island L
Foot Print L
Buffalo L
Point Ck
Eating
Grand Rapids
Fire Lookout
Dam
Dyke
Hrx^4 - Li(s)^3 - cR^2 - Ei^1
Li(s)^5 - Crx^3 - Li^2
Ki^8 - Ci^2
Wsx^5 - Orx^3 - Sd^2
Mg^7 - Ca^3
Li(s)^6 - cR^2 - Ei^2
Li(s)^4 - Ei^4 - Ca^2
Li(s)^5 - Ei^3 - Crx^2
Wsx^6 - Nlx^2 - Sd^2
Wsx^7 - Orx^3
Wsx^4 - Kt^3 - Orx^3
Li(s)^5 - Crx^3 - Fx^2
Li(s)^6 - Fx^2 - cR^2
Li(s)^4 - Li^3 - cR^3
Ei^4 - Li^3 - Li(s)^3
Bc^5 - Li(s)^3 - Ox^2
Lt^4 - Mu^4 - Ko(P)^2
Li(s)^4 - Ki^3 - Li^3
Crx^5 - Fx^3 - Li(s)^2
Wsx^5 - Rrx^5
Li(s)^5 - Li^3 - cR^2

Nlx	Nekik Lake Complex		(none)		(none)
Nr(P)	Norris Series	D	Dering	D	Dering
Orx	Orok Complex	<	OROK	>	OROK-KX
		>	KXLLX		
Ox	Okno Complex	<	OKNO	>	OROK-KX
Rex	Reed Lake Complex	:	Crane	:	Crane
Rex(sp)	Reed Lake Complex, sphagnic phase		(none)	;	Halcrow
Rl	Roe Lake Series	A	Till	A	Till
Rlx	Rock Island Complex	.	Stead	.	Stead
Rlx(sp)	Rock Island Complex, sphagnic phase	-	Katimik	-	Katimik
Rrx	Rat River Complex	<	OROK	>	OROK-KX
Sb			(none)[1]		(none)[1]
Sd	Stead Series	.	Stead	.	Stead
Sl	Sturgeon Gill Series		(none)		(none)
Sox	Soul Lake Complex		(none)		(none)
Srx	Sand River Complex	>	KXLLX	>	OROK-KX
Tux	Tremanden Complex	=	WHX	=	WHX
Wsx	Waskwei Complex	=	WHX	=	WHX

1. Marshes, beaches, and other shoreline features are usually misclassified as cloud shadows. These are left blank in both the supervised and unsupervised method soils maps (maps 1 and 2).

SOIL COMPLEXES

Soil complexes are groups of soil series which occur in complex association, and are not separable at reconnaissance mapping scales. The dominant series gives the name to the complex.

SOIL PHASES

Soil phases serve to recognize significant differences in soil characteristics and/or management requirements apart from the properties used in the taxonomic classification system. Soil phases recognized here are as follows:

(P) Mineral soils having an organic surface layer of 15 to 40 cm of mesic peat, or up to 60 cm of fibric moss peat.

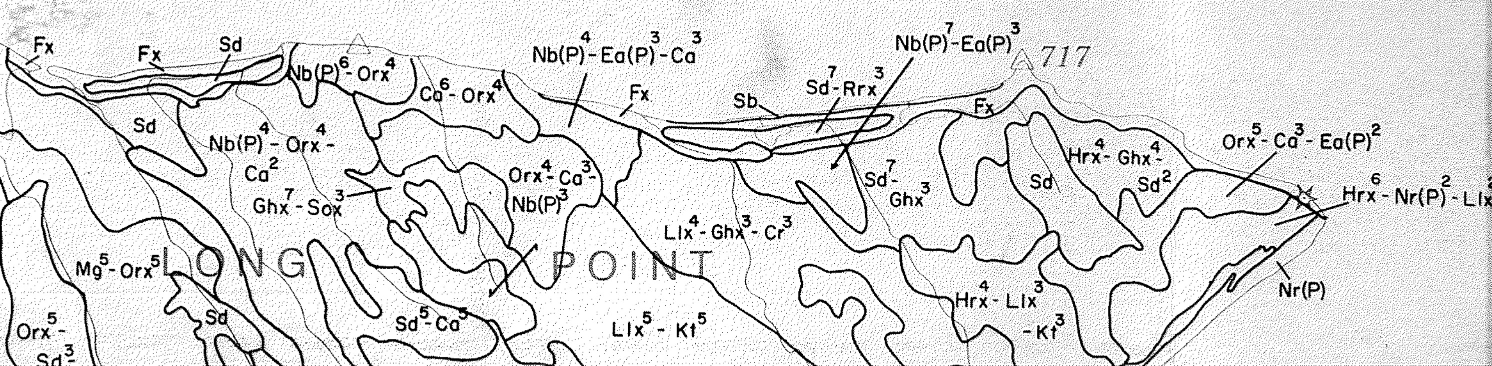
(S) Shallow mineral soils composed of 10-20 cm of mineral soil overlying bedrock.

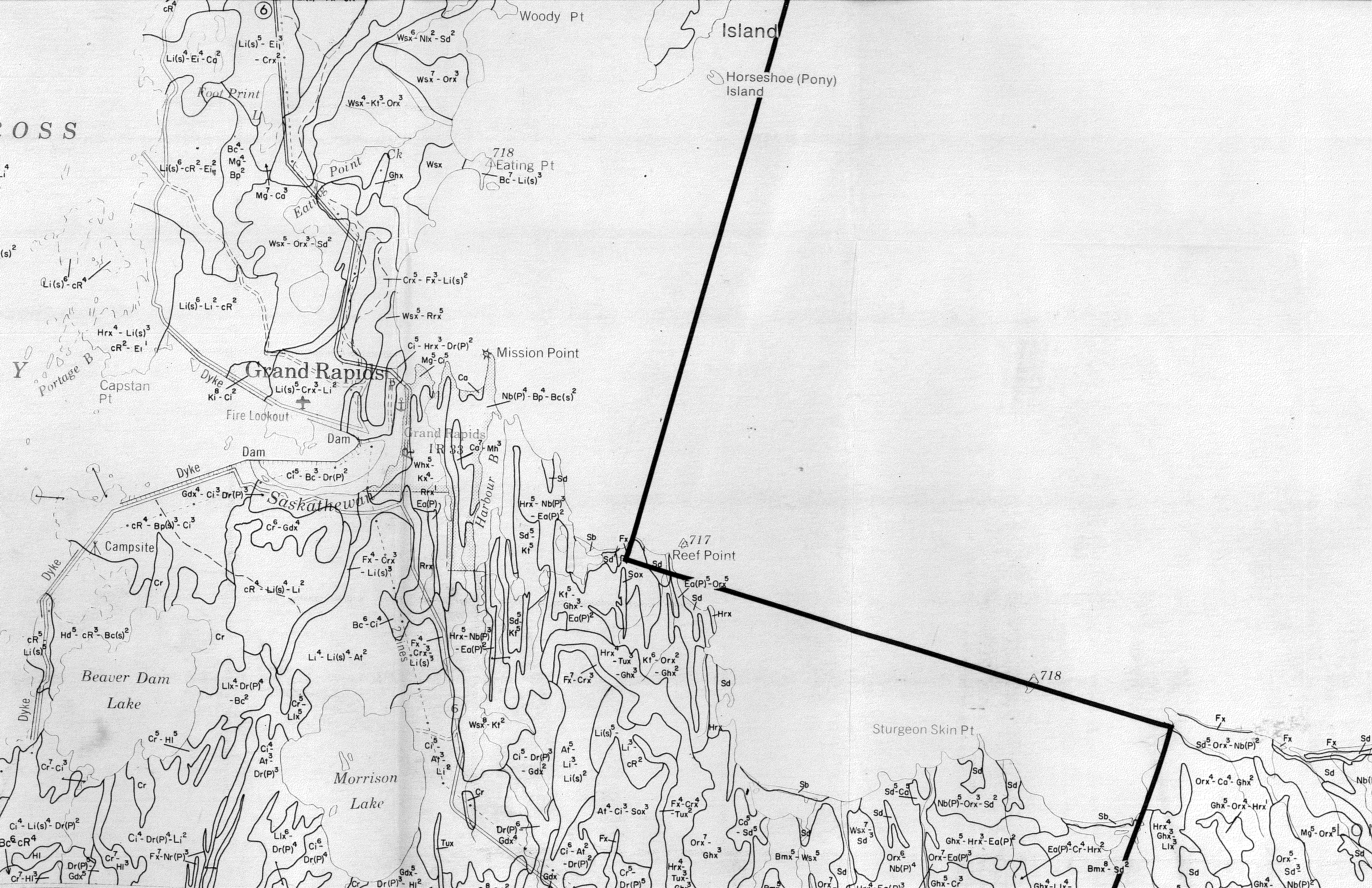
(Sp) Organic soils (Terric Mesisols and Typic Mesisols) having a significant surface layer of fibric Sphagnum peat.

SOIL MAP UNITS

Soil map units are named according to the soil complexes, series, and phases they contain. Arabic numerals placed after each symbol indicate the approximate proportion of each soil type within the map unit.

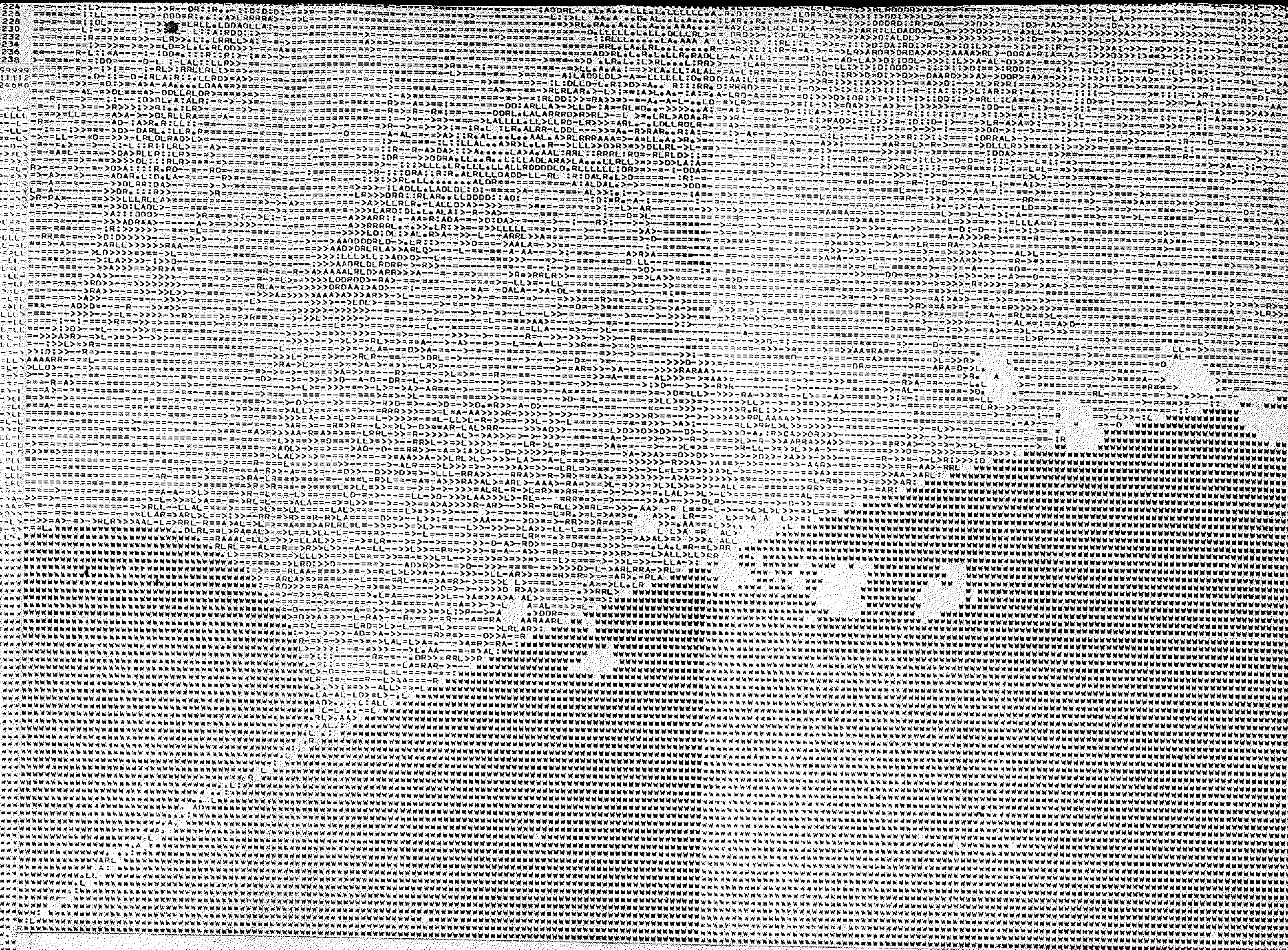
This soils map is reproduced through the courtesy of the Canada-Manitoba Soil Survey (Soils Report No. 25, unpublished data).





Woody Pt
Island
Horseshoe (Pony) Island
Foot Print L
Point Ck
Eating
718
Eating Pt
Grand Rapids
Mission Point
Capstan Pt
Portage B
Fire Lookout
Dam
Dyke
Grand Rapids IR 33
Harbour B
Saskatchewan
Campsite
717
Reef Point
718
Beaver Dam Lake
Morrison Lake
Sturgeon Skin Pt

CEDAR LAKE
CROSS BAY
Napanee Bay
Muskeg L
Shallow Bay
Beaver Dam Lake
Morrison Lake
McDougall I
Dividing I
Centre I
Lookout Pt
Anchor Pt
Capstan Pt
Lamb B
Portage B
Rabbit Pt
Smith I
Collins I
Easterville
Grand Rapids
Fire Lookout
Campsite
Dam
Dyke
Saskatchewan
Foot Print L
Eating Point Ck
Position Approximate
327
841
Tp 49
Tp 47
Tp 46
15′
53°00′



MAP 2

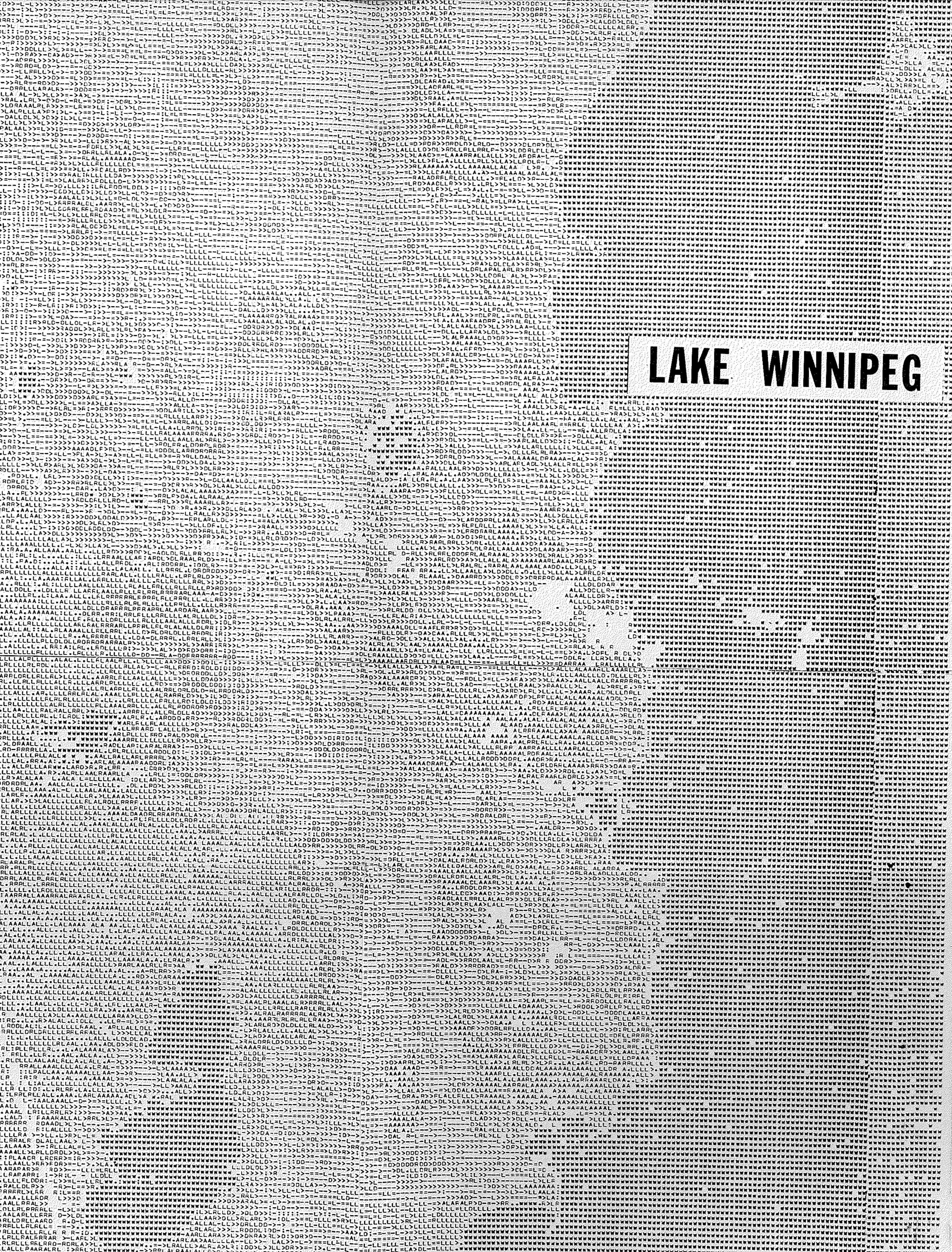
UNSUPERVISED CLASSIFICATION SOILS MAP

OF THE

GRAND RAPIDS AREA (NTS 63G)

Channels Used Wavelengths


WILLIAM LAKE
LIM

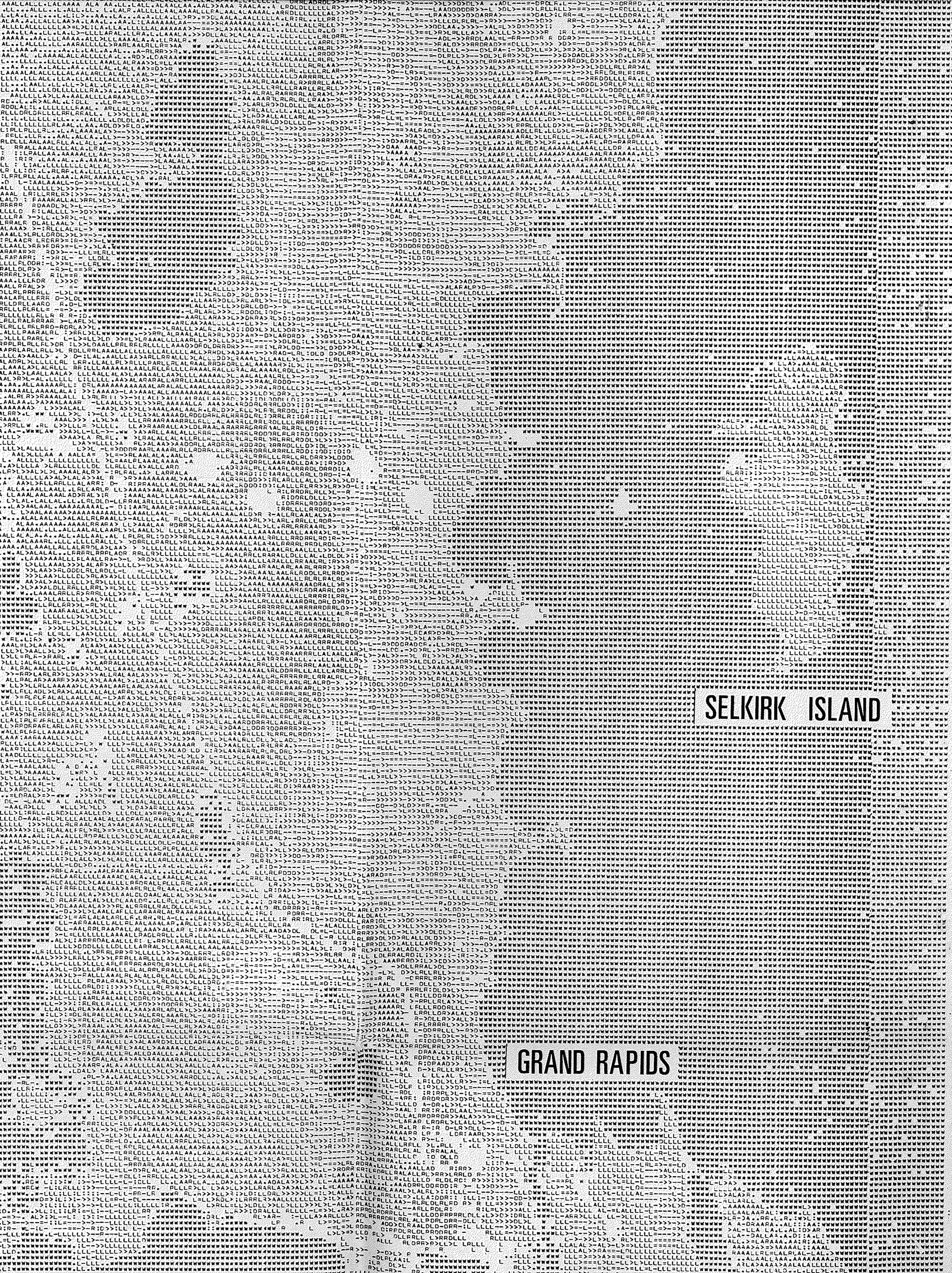


2 (red)	0.6 to 0.7 micrometers
3 (infrared)	0.7 to 0.8 micrometers
4 (infrared)	0.8 to 1.1 micrometers

LEGEND

Map Symbol	Soil Group[1]	Parent Material	Soil Profile Type[2]	Drainage	Vegetation
A	Till	Extremely calcareous loamy glacial till* Clay veneer over extremely calcareous, loamy glacial till.	Eluviated Eutric Brunisol* Gleyed Eluviated Eutric Brunisol Orthic Gray Luvisol Gleyed Gray Luvisol	Well to imperfect	Black spruce, jack pine, white spruce, with an understory of feathermoss and ericaceous shrubs.
D	Dering	15 to 40 cm of mesic peat overlying extremely calcareous loamy glacial till.	Rego Humic Gleysol, carbonated, peaty phase.	Poor	Black spruce with a ground cover of Sphagnum and feathermoss.
L	Till/R	Approx. 50% dolomite bedrock outcrop and 50% 10-25 cm of extremely calcareous loamy till over dolomite bedrock.	Eluviated Eutric Brunisol	Well	Jack pine with a ground cover of juniper, lichens and pine needles.
R	Rock	Dolomite bedrock outcrops with minor areas of extremely calcareous loamy till over bedrock.		Well	Jack pine and black spruce with a ground cover of lichens, juniper and exposed bedrock.
•	Stead	Deep (> 160 cm) mesic fen peat with little or no (< 15 cm) fibric Sphagnum moss peat on the surface.	Typic Mesisol	Very poor	Sedges, mosses and reeds with scattered tamarack and swamp birch.
-	Katimik	Deep (> 160 cm) mesic fen peat with a thin (15 to 65 cm) fibric Sphagnum peat surface layer.	Typic Mesisol, sphagnic phase.	Poor to very poor	Scattered thin stands of stunted black spruce and some tamarack with an understory of **Sphagnum** moss and ericaceous shrubs.
=	WHX	Deep (> 160 cm) organic soils composed of 65 to 160 cm of fibric Sphagnum peat overlying mesic forest or fen peat.	Mesic Fibrisol* Typic Fibrisol Fibric Mesisol	Poor to very poor	Stunted black spruce with an understory of Sphagnum moss and ericaceous shrubs.
: ,	Crane	Shallow (40-160 cm) mesic fen peat with little or no (< 15 cm) fibric Sphagnum moss peat on the surface.	Terric Mesisol	Very poor to poor	Sedges, mosses, reeds and grasses, with a few scattered tamarack and swamp birch.
: ;	Halcrow	Shallow (40-160 cm)	Terric M[illegible]		


LAKE



		surface layer.			moss and ericaceous shrubs.
=	WHX	Deep (> 160 cm) organic soils composed of 65 to 160 cm of fibric Sphagnum peat overlying mesic forest or fen peat.	Mesic Fibrisol* Typic Fibrisol Fibric Mesisol	Poor to very poor	Stunted black spruce with an understory of Sphagnum moss and ericaceous shrubs.
: ,	Crane	Shallow (40-160 cm) mesic fen peat with little or no (< 15 cm) fibric Sphagnum moss peat on the surface.	Terric Mesisol	Very poor to poor	Sedges, mosses, reeds and grasses, with a few scattered tamarack and swamp birch.
' ;	Halcrow	Shallow (40-160 cm) mesic fen peat with a thin (15-65 cm) surface layer of fibric Sphagnum moss peat.	Terric Mesisol, sphagnic phase	Very poor to poor	Stunted black spruce and tamarack with an understory of Sphagnum, sedges, reeds, and ericaceous shrubs.
>	OROK-KX	Shallow (40-160 cm) organic soils with a 0 to 160 cm surface layer of fibric Sphagnum moss peat overlying mesic forest peat.	Terric Mesisol, sphagnic phase* Terric Mesisol Terric Fibric Mesisol Terric Mesic Fibrisol Terric Fibrisol	Poor to very poor	Stunted black spruce and tamarack with an understory of Sphagnum moss and ericaceous shrubs.
W	Water	Water			
	Cloud	Clouds			
	Shadow	Cloud Shadows			

* Indicates dominant parent material or soil series.

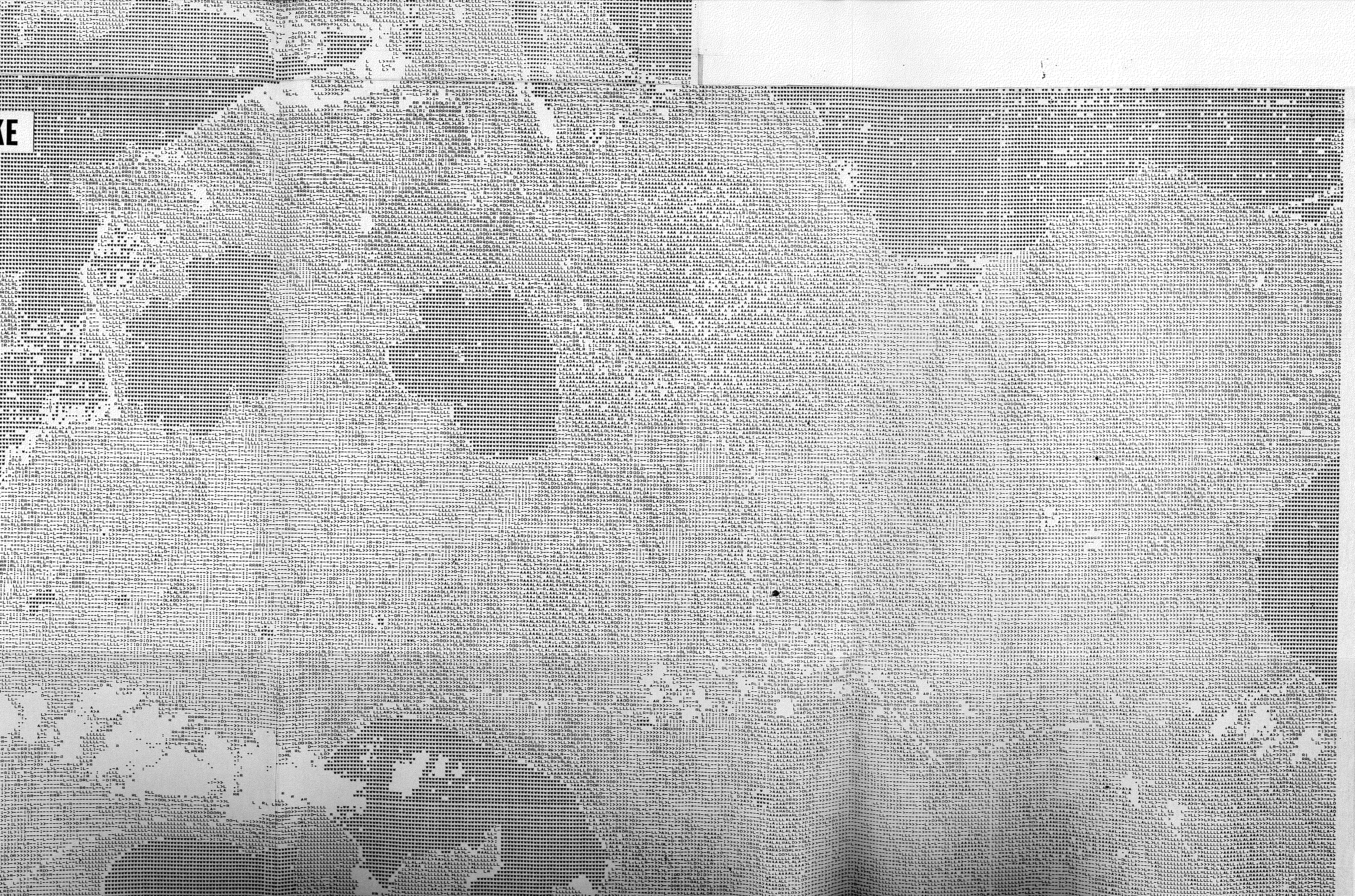
1. Groups may contain several training fields and classes with different spectral characteristics.

2. Soil classification according to the Canadian System of Soil Classification (revised, 1976). Canada Soil Survey Committee. Agriculture Canada, Ottawa.

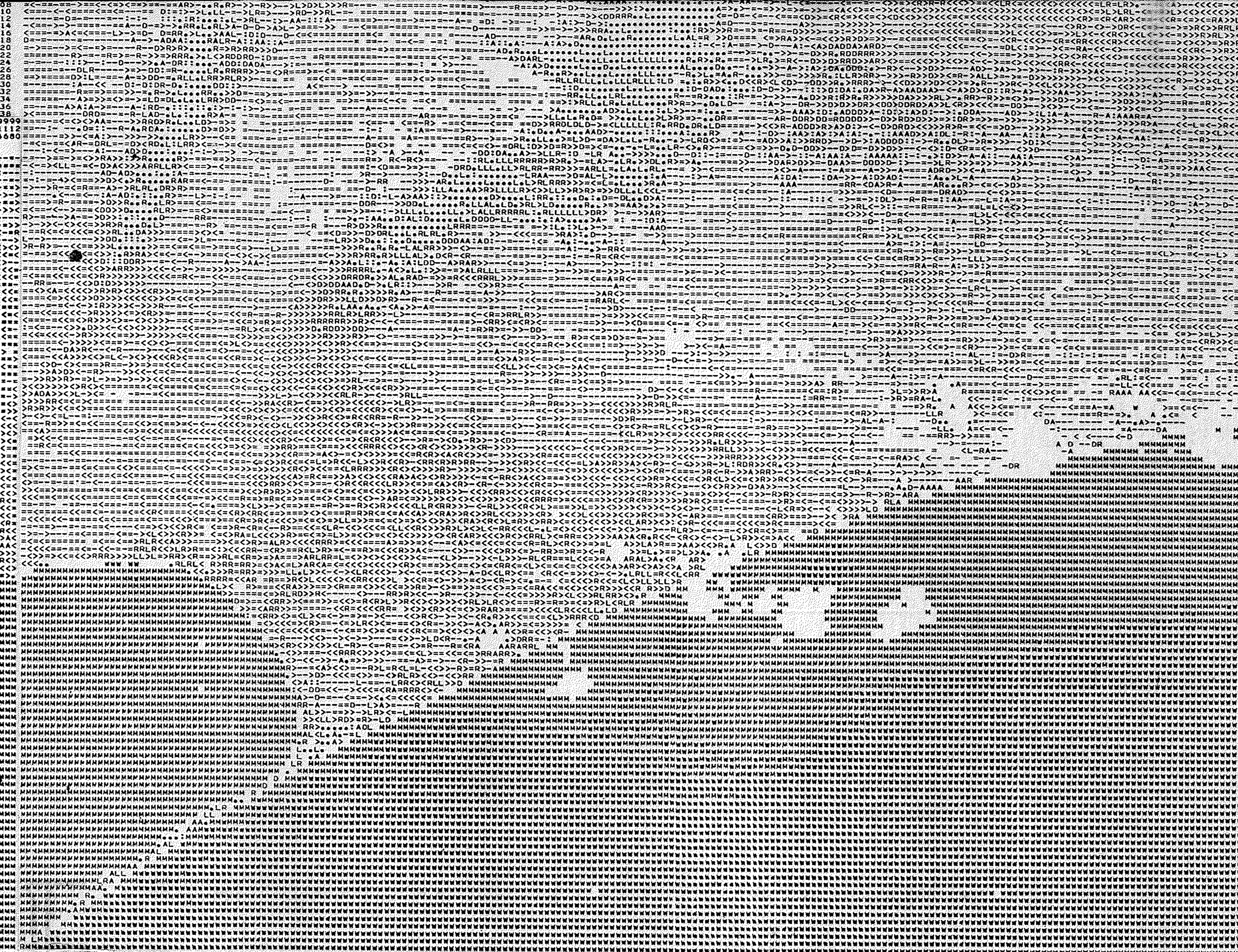
Scale approx. 1 inch to 2 miles (1:127,000).


SELKI
GRAND RAPIDS


SEL
GRAND RAPIDS


KE


CEDAR LAKE
EASTERVILLE

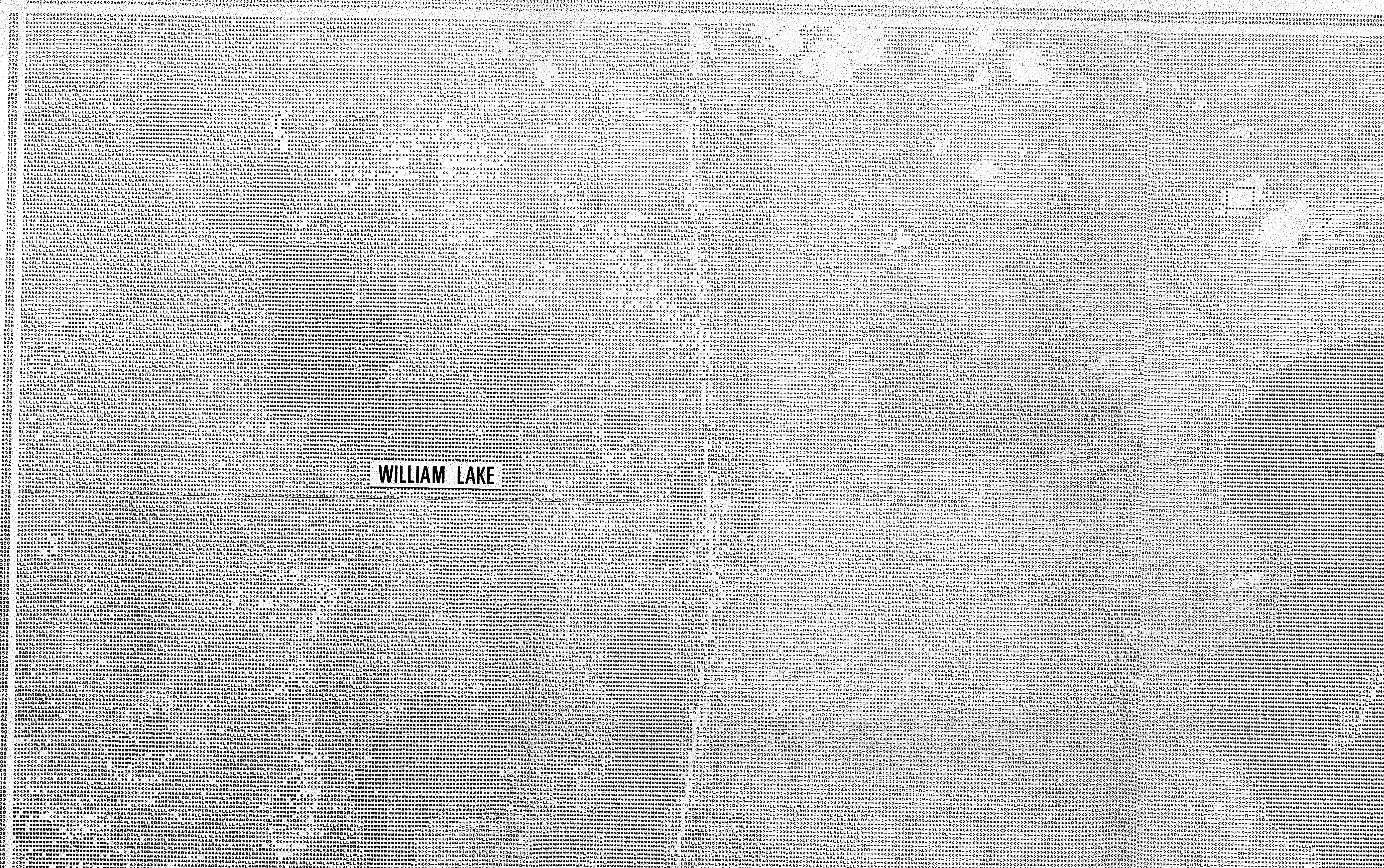


MAP 1

SUPERVISED CLASSIFICATION SOILS MAP

OF THE

GRAND RAPIDS AREA (NTS 63G)


WILLIAM LAKE

2 (red) 0.6 to 0.7 micrometers

3 (infrared) 0.7 to 0.8 micrometers

4 (infrared) 0.8 to 1.1 micrometers

LEGEND

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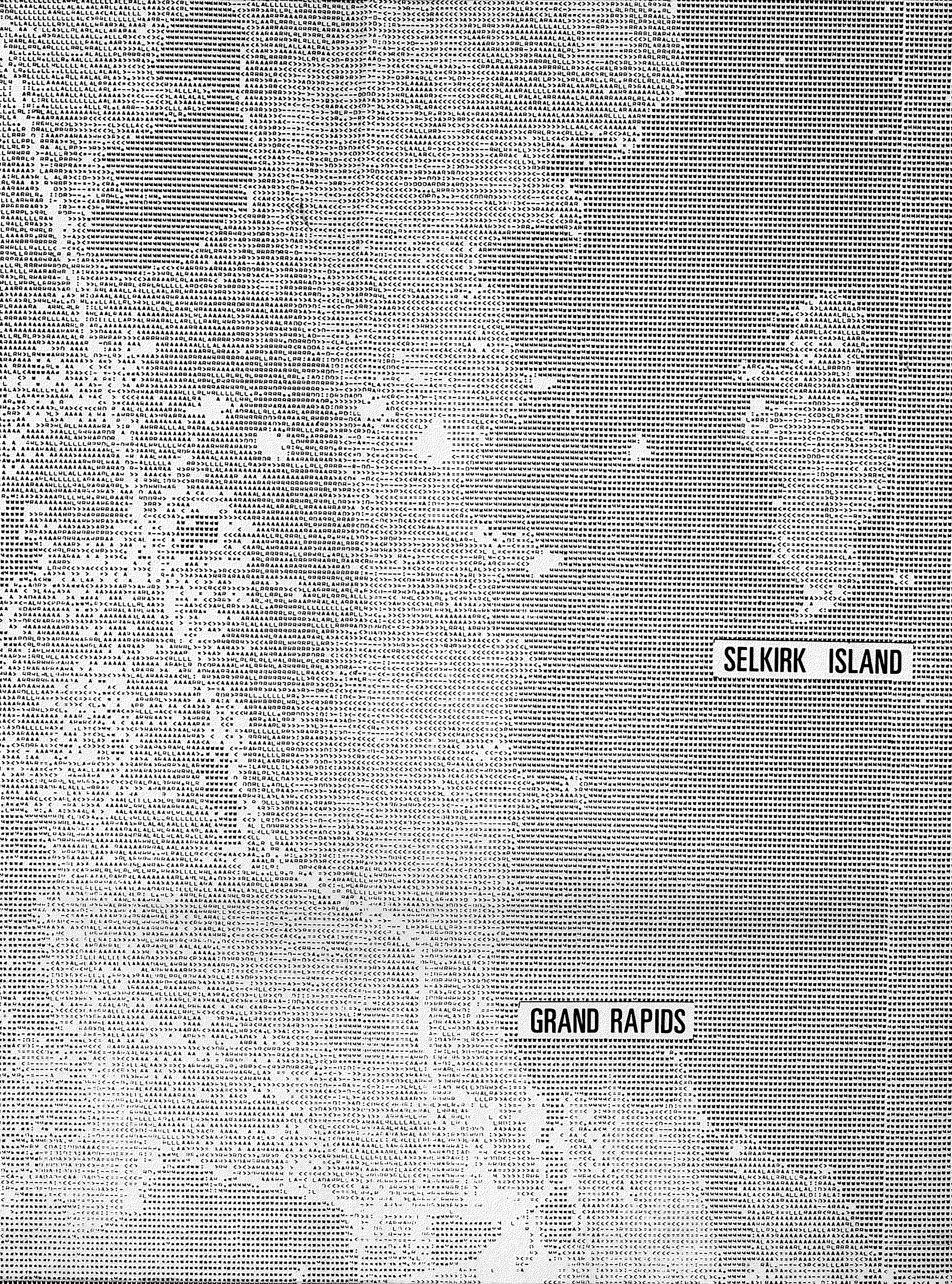
D	Dering	15 to 40 cm of mesic peat overlying extremely calcareous, loamy glacial till.	Rego Humic Gleysol, carbonated, peaty phase.	Poor	Black spruce with a ground cover of Sphagnum and feathermoss.
L	Till/R	Approx. 50% dolomite bedrock outcrop and 50% 10-25 cm of extremely calcareous loamy till over dolomite bedrock.	Eluviated Eutric Brunisol.	Well	Jack pine with a ground cover of juniper, lichens and pine needles.
R	Rock	Dolomite bedrock outcrops with minor areas of extremely calcareous loamy till over bedrock.		Well	Jack pine and black spruce with a ground cover of lichens, juniper and exposed bedrock.
•	Stead	Deep (> 160 cm) mesic fen peat with little or no (< 15 cm) fibric sphagnum moss peat on the surface.	Typic Mesisol	Very Poor	Sedges, mosses and reeds with scattered tamarack and swamp birch.
-	Katimik	Deep (> 160 cm) mesic fen peat with a thin (15 to 65 cm) fibric Sphagnum peat surface layer.	Typic Mesisol, sphagnic phase.	Poor to very poor	Scattered thin stands of stunted black spruce and some tamarack with an understory of Sphagnum moss and ericaceous shrubs.
● =	WHX	Deep (> 160 cm) organic soils composed of 65 to 160 cm of fibric Sphagnum peat overlying mesic forest or fen peat.	Mesic sphagnic Typic Fibrisol Fibric Mesisol	Poor to very poor	Stunted black spruce with an understory of Sphagnum moss and ericaceous shrubs.
:	Crane	Shallow (40-160 cm) mesic fen peat with little or no (< 15 cm fibric Sphagnum moss peat on surface.	Terric Mesisol	Very poor to poor	Sedges, mosses, reeds and grasses, with a few scattered tamarack and swamp birch.

LAK



		composed of 65 to 160 cm of fibric Sphagnum peat overlying mesic forest or fen peat.	Fibric Mesisol	poor	of Sphagnum moss and ericaceous shrubs.
:	Crane	Shallow (40-160 cm) mesic fen peat with little or no (<15 cm fibric Sphagnum moss peat on surface.	Terric Mesisol	Very poor to poor	Sedges, mosses, reeds and grasses, with a few scattered tamarack and swamp birch.
<	Orok	Shallow (40-160 cm) mesic forest peat with a discontinuous surface layer of fibric Sphagnum peat.	Terric Mesisol* Terric Mesisol, sphagnic phase Terric Fibric Mesisol.	Poor to very poor	Stunted black spruce and tamarack with an understory of Sphagnum moss, reeds, and ericaceous shrubs.
>	KXLLX	Shallow (40-160 cm) mesic forest or fen peat with a continuous surface layer of fibric Sphagnum peat.	Terric Mesisol, sphagnic phase* Terric Fibric Mesisol Terric Mesic Mesisol Terric Fibric Mesisol Terric Fibrisol.	Poor to very poor	Stunted black spruce and tamarack with an understory of Sphagnum moss and ericaceous shrubs.
M	M Water	Shallow water containing a large amount of suspended sediment			
W	Water	Water			
S	Shadow	Cloud Shadows			
?	Cloud	Clouds			

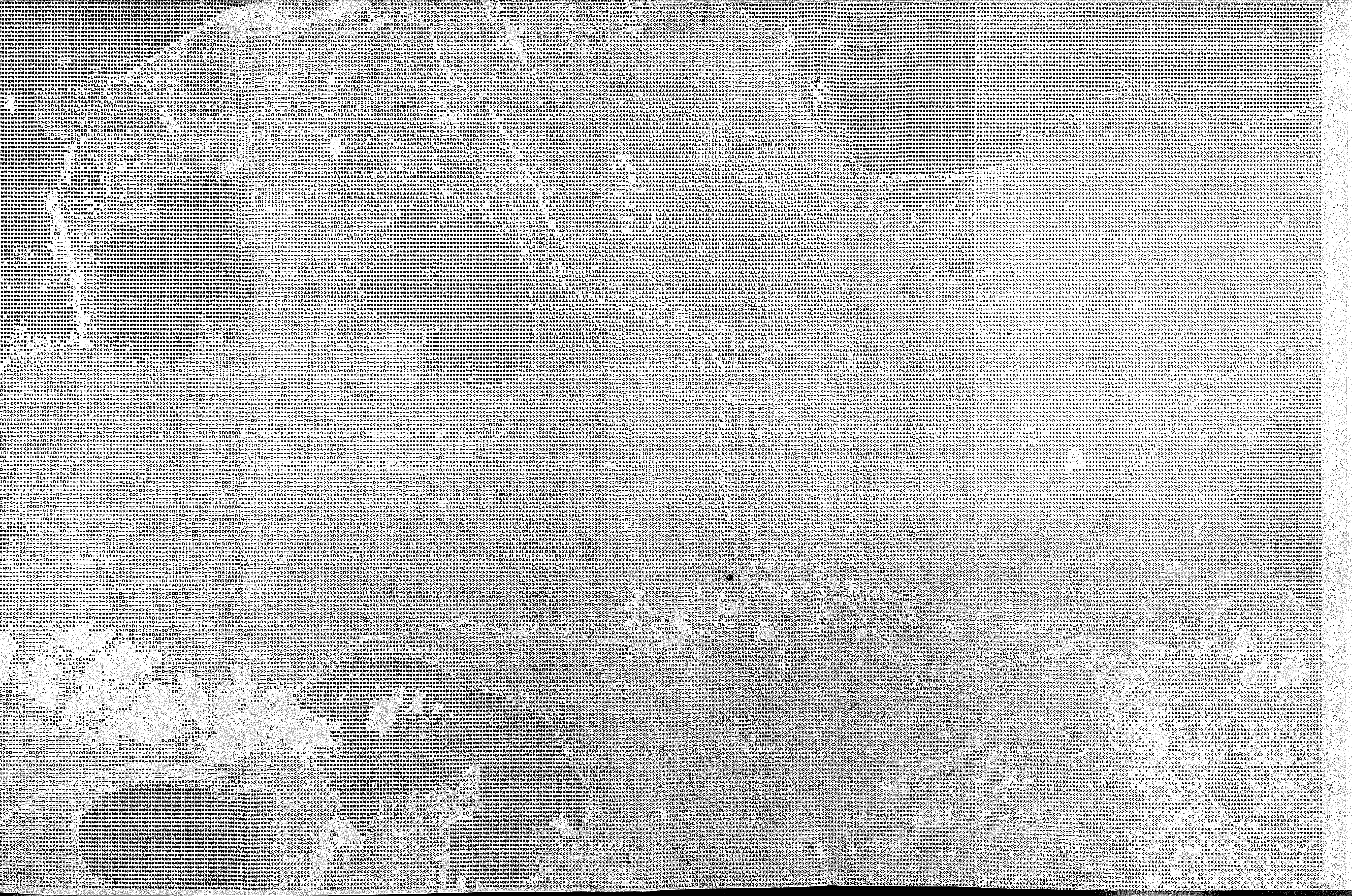
* Indicates dominant parent material or soil series.

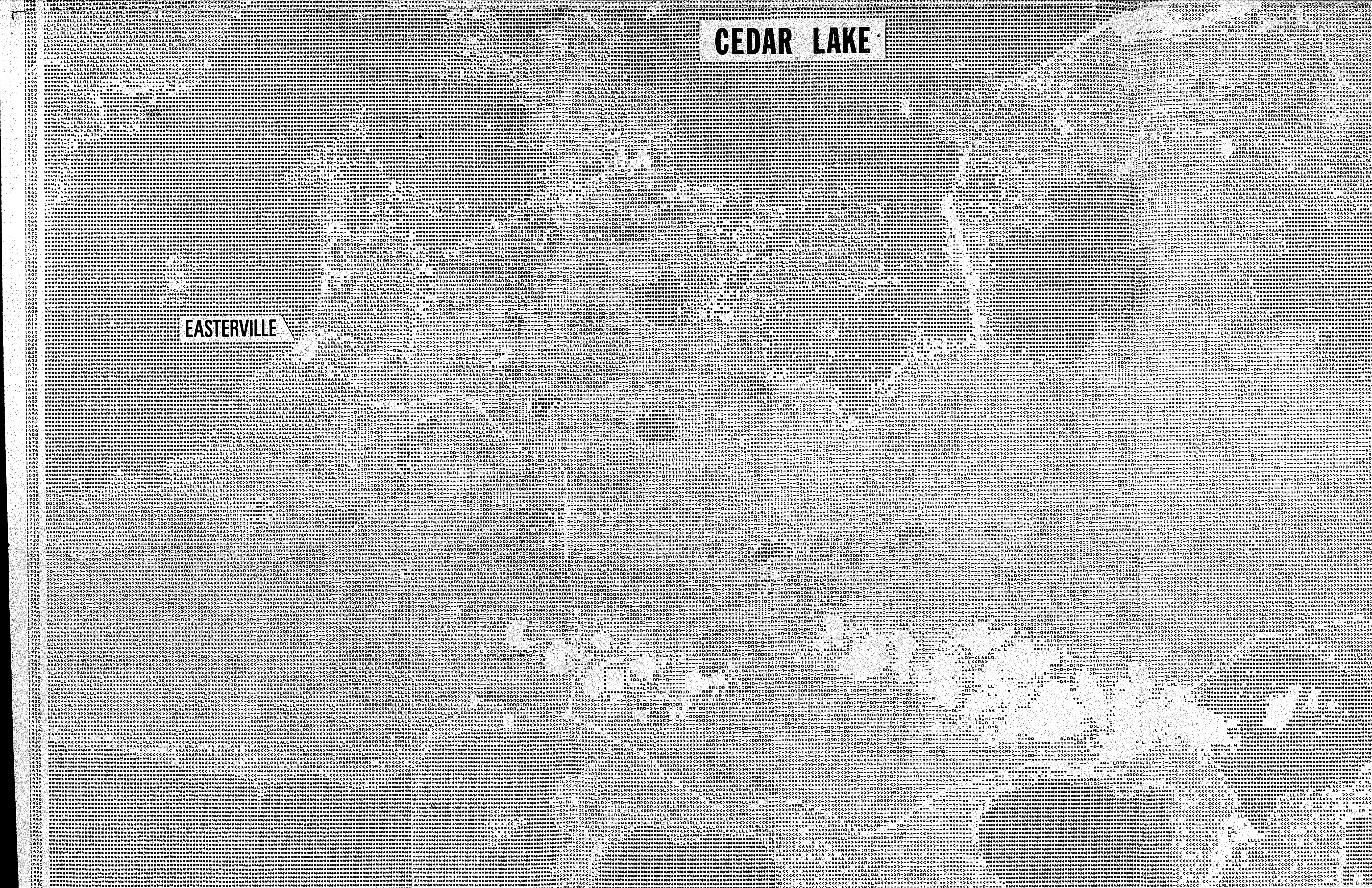
1. Groups may contain several training fields and classes with different spectral characteristics.

2. Soil classification according to the Canadian System of Soil Classification (revised, 1976). Canada Soil Survey Committee. Agriculture Canada, Ottawa.

Scale approx. 1 inch to 2 miles (1:127,000).

GRAND RAPIDS




CEDAR LAKE
EASTERVILLE