

**DETECTING SOIL INFORMATION ON THE KONZA PRAIRIE
USING HIGH RESOLUTION SATELLITE DATA**

by

Haiping Su

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Approved by:



Major Professor

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I. Introduction

Landsat Multispectral Scanner (MSS) data have been available since July 1972, when the Earth Resources Technology Satellite (ERTS, now called Landsat) was launched. Landsat MSS has four spectral bands (0.5 - 0.6 μm , 0.6 - 0.7 μm , 0.7 - 0.8 μm , and 0.8 - 1.1 μm) with a coarse spatial resolution of 79 m. Landsat MSS data are multispectral, temporal, synoptic, and near-orthographic. These properties were not previously available in photographs taken from airplanes; however, there are some limitations on Landsat MSS data, such as low spatial resolution (79 m), atmospheric attenuation, and fixed intervals of data acquisition (Westin et al., 1976). Consequently, the application of Landsat MSS data has focused on soil reconnaissance surveys, soil association delineation, and other soil resources inventories (Lewis et al., 1975; Westin et al., 1976; Wang et al., 1986).

The launch of Landsat Thematic Mapper (TM) and French SPOT (Système Probatoire d'Observation de la Terre) satellites has opened a new era for remote sensing from space. Landsat TM has seven bands (0.45 - 0.52 μm , 0.52 - 0.60 μm , 0.63 - 0.69 μm , 0.76 - 0.90 μm , 1.55 - 1.75 μm , 10.40 - 12.50 μm , and 2.08 - 2.35 μm) with an improved spatial resolution of 30 m, except band 6 (thermal band), which has a resolution of 120 m. Landsat TM also has improved multispectral separation (more bands), geometric fidelity, and radiometric accuracy. French SPOT includes two image modes. One is a panchromatic mode with single band (0.51 - 0.73 μm) and 10 m spatial resolution; another is a multispectral mode with three bands (0.50 - 0.59 μm , 0.61 - 0.68 μm , and 0.79 - 0.89 μm) and 20 m resolution. Such high resolution Landsat TM and SPOT data enable a detailed examination for soil information that had

previously been available only from aircraft-acquired data over small areas. Consequently, compared to Landsat MSS data, Landsat TM and SPOT data have much higher potential for use in making detailed soil surveys.

The extensive native grasslands in the Bluestem Hills resource area of Kansas (Soil Conservation Service, 1981) should be especially suited for using high resolution satellite data to detect the variations of soil information since such high resolution satellite data can discriminate the important spectral response of ground covers in much detail. The use of high resolution satellite data could improve the conventional soil surveys and decrease their cost of preparation by reducing the extensive field work required by soil surveyors.

The purpose of this investigation is to use computer pattern recognition techniques to examine (1) the variations of soil information from high resolution Landsat TM and SPOT satellite data and (2) the different transformation techniques in supervised classification from SPOT satellite data. A statistical divergence analysis will be used to extract the optimum feature (band) of Landsat TM data which provides detailed soil information. The digital elevation model (DEM) data will be merged to Landsat TM and SPOT satellite data to delineate soil mapping units within the study area. Landsat TM and SPOT data acquired in the dormant and growing seasons will be analyzed to compare the soil mapping possibilities. An overall accuracy assessment will be conducted to compare the resultant soil maps produced from high resolution Landsat TM and SPOT satellite data to the soil maps of the soil survey of Riley County (Jantz et al., 1975). The possibility of using Landsat TM and SPOT satellite data for second order soil surveys will be discussed.

II. Literature Review

A. Remote Sensing for Soil Surveys

Remote sensing techniques have been used for soil surveys since the 1930's. Most soil surveys published since 1957 contain soil maps printed on a photomosaic base at a scale of 1:24 000, 1:20 000, or 1:15 840. Although Landsat MSS imagery has been available since 1972 (Myers, 1983), it has not been used in making detailed soil surveys. Because of the factor of coarse spatial resolution, Landsat MSS data have been used only to (1) delineate major soil associations (Lewis et al., 1975), (2) aid low intensity soil surveys, and (3) serve as a base map for publishing soil information (Westin et al. 1976).

The launch of Landsat TM satellite in 1982 resulted in improved spatial resolution data from space and provided more detailed soil information (Thompson et al., 1984 a and b). The French SPOT satellite launched in 1986 further improved spatial resolution (10 - 20 m). Even though high resolution satellite data are now readily available, their use for soil surveys is still not popular. Probable reasons include (1) the hybrid technology required for both soil science and image processing techniques, (2) the lack of facilities, and (3) the limitations of soil spectral response in environmental conditions.

B. Potential for Detailed Soil Surveys

Many soil survey and mapping studies have been conducted using Landsat MSS data since Landsat-1 was launched in 1972. Cipra (1973) reported that computer pattern recognition techniques could be used to map soil associations using Landsat MSS data in humid cropland areas. He also indicated that significant amounts of vegetation reduced the usefulness of these techniques

for providing soil information. Lewis et al. (1975) delineated soil associations in the Sand Hills region of Nebraska using Landsat imagery. Westin and Frazee (1976) used Landsat scenes to delineate soil association boundaries using photointerpretation techniques. Kirschner et al. (1978) studied map unit composition assessment using drainage classes defined by Landsat data and obtained results similar to Cipra (1973). Westin and Lemme (1978) indicated that soil differences had a more pronounced influence on the spectral properties of grassland than on cropland. Thompson et al. (1981) found that Landsat MSS could be used to separate vegetated (grassland and woodland) soil landscapes on the basis of soil characteristics related to vegetative growth conditions. Kornblau and Cipra (1983) found that computer pattern recognition techniques applied to Landsat MSS data under range vegetation for one observation date agreed with soil survey information developed by conventional means 47% of the time. Due to coarse spatial resolution of Landsat MSS, it is difficult to obtain a sufficiently detailed soil map (photo scale larger than 1:24 000) based on either photointerpretation (Singh et al. 1986; Wang et al. 1986) or digital image analysis (Kornblau and Cipra, 1983).

For a study area in Iowa, Thompson et al. (1984b) recently found that Landsat TM data can provide information on within-field (the same crop type) variability related to soil differences. In a study located in the Mississippi River Delta of Arkansas, Thompson et al. (1984a) concluded that the 0.76 to 0.90 μm (band 4), 1.55 to 1.75 μm (band 5), and 10.4 to 12.5 μm (band 6 or thermal band) wavelength bands were the most useful for identifying soil association boundaries. Thompson and Henderson (1984c) also conducted a study on grassland in the East Texas Timberlands and Claypan area

and found that TM band 7 (2.08 to 2.35 μm) was sensitive to soil mineralogy and that soil properties important to the plant could be detected using TM data. They also concluded that soil properties could be separated using Landsat TM even in a region with similar soils and under a dense vegetation canopy.

In a study conducted in England, Wright and Birnie (1986) suggested that SPOT imagery could be used to map within-field soil variations. Buchan et al. (1986) and Betts et al. (1986) also demonstrated that SPOT data could be used for land use planning and mapping.

C. Techniques of Soil Information Interpretation

There are two common approaches to interpreting digital data in remote sensing. The first is called quantitative analysis and involves the use of a computer to examine each pixel in an image individually with the purpose of making judgements about pixels specially based upon their attributes. The second approach is visual interpretation or photointerpretation, which refers to a human analyst or interpreter extracting information by visual inspection of imagery composed from the image data. Those two approaches have their own roles and often these are complementary (Richards, 1986). For soil interpretation, both techniques have been used. Lewis et al. (1975) delineated soil association information by using visual interpretation techniques. Westin et al. (1976) visually interpreted Landsat MSS imagery for a low intensity soil survey and also used the imagery as a base map for publishing soil information. Wang et al. (1986) studied soil mapping techniques using visual interpretation for an area near the southeastern coast of China. Thompson et al. (1984a) was also used visual interpretation techniques to identify soil association boundaries from Landsat TM data. Results from visual interpretation are difficult to quantify and

have limitations on distinct brightness levels (e.g., the human eye can identify only 16 levels in each feature), In most cases, however, the shape of the image pattern can be easily determined.

Cipra (1973), Kirschner et al. (1978), and Weismiller et al. (1977) found that Landsat MSS data analyzed by computer pattern recognition techniques could be used for soil mapping in humid cropland areas when bare soils were exposed. In these studies, significant amounts of vegetation seriously lessened the usefulness of these techniques for providing soil information. Kornblau et al. (1983) concluded that the "cleaned" supervised classification method produced appreciably greater agreement between Landsat computer classification maps and soil maps than did the traditional supervised method or the unsupervised method. Fugbami (1986) indicated that computer pattern recognition was cost-effective for reconnaissance soil and resource surveys and that a Geographic Information System (GIS) could improve Landsat data interpretation for soils applications. Thompson et al. (1984b) evaluated Thematic Mapper Simulator (TMS) and Landsat TM data for their ability to discriminate soil mapping units at various levels of Soil Taxonomy (Soil Survey Staff, 1975) on cultural vegetated landscapes by discrimination analysis. The same method was used to detect soil properties under grassland vegetation (Thompson et al., 1984c).

A recent study by Haack et al. (1987) used statistical divergence analysis to examine the separability of Landsat MSS and TM data. Their results suggested that the use of a low pass filter may increase class separability from Landsat TM data. Mulders (1987) indicated that soil features in Landsat imagery may be extracted by an intensity transformation. Band ratioing can also be used for smoothing the radiometric variation as part of noise reduction

(Swain et al., 1978; Jensen et al., 1986).

In summary, the computer pattern recognition techniques used for soil interpretation vary with the purpose of application, but the different transformations, such as ratioing, intensity, and low frequency filtering, may improve the feature extraction and accuracy of soil information mapping. Merging of GIS data may also be useful for soil information interpretation.

III. Materials and Methods

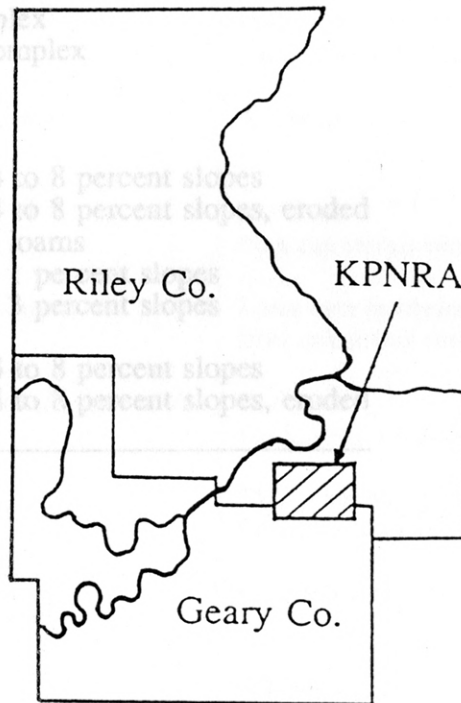
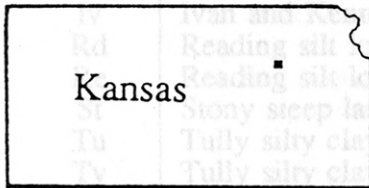
A. Study Area

The study area is located about 7 km south of Manhattan, Kansas (Fig. 1) within the Bluestem Hills resource area (Soil Conservation Service, 1981). The southwest and northeast coordinates of study area are N39°3'30"-W96°36'54" and N39°5'00"-W96°32'23". The total area, which encompasses part of the Konza Prairie Natural Research Area (KPNRA), covers about 2687 hectares. Climate of the region is humid subtropical with a temperature range of -15 to 47°C. Average normal precipitation is 800 mm/year with a variable seasonal distribution resulting in many soil wet-dry cycles in the normal growing season of 176 days (Weiser et al., 1986).

Soils information for the study area was obtained from the soil survey of the Riley County (Jantz et al., 1975), which is a second order soil survey. This soil survey was made at a scale of 1:24 000. Table 1 indicates that 14 soil mapping units were identified within the study area. The family classification and parent materials of the soils of the study area are given in Table 2. The most extensive soil parent materials of the study area are weathered Permian limestones and shales, which have a surficial covering of loess of variable thickness on broad, stable interflures. Colluvium and alluvium also occur along drainage ways (Table 2). The main geologic factors, such as the permeability of the limestone and shale, the dip of the beds, the orientation of deposited rocks, and the geomorphology of the ground surface, control the soil hydrologic characteristics of this area. The distribution of soils may be related to the elevation, slopes, and aspects of the hilly area. The major types of vegetation on the area are classified as the Bluestem-Indian Grass Eastern Subhumid Prairie

Table 1. Soil mapping units found in the study area*.

Symbol	Soil Mapping Units
Ad	Alluvial land
Bf	Benfield-Florence complex
Bk	Breaks-Alluvial land complex
Ch	Chase silty clay loam
Cs	Clime-Soga complex
Dr	Dwight-Irwin complex
Ic	Irwin silty clay loam, 4 to 8 percent slopes
Id	Irwin silty clay loam, 4 to 8 percent slopes, eroded
It	Irwin and Quebec silt loams
Rd	Reading silt loam, 0 to 3 percent slopes
Re	Reading silt loam, 1 to 3 percent slopes
St	Stony steep land
Tu	Tully silty clay loam, 4 to 8 percent slopes
Tv	Tully silty clay loam, 4 to 8 percent slopes, eroded



* From Jantz et al. (1975).

Fig. 1. Location of study area within KPNRA.

Table 1. Soil mapping units found in the study area*.

Symbol	Soil Mapping Units
Ad	Alluvial land
Bf	Benfield-Florence complex
Bk	Breaks-Alluvial land complex
Ch	Chase silty clay loam
Cs	Clime-Sogn complex
Dr	Dwight-Irwin complex
Ic	Irwin silty clay loam, 4 to 8 percent slopes
Id	Irwin silty clay loam, 4 to 8 percent slopes, eroded
Iv	Ivan and Kennebec silt loams
Rd	Reading silt loam, 0 to 1 percent slopes
Re	Reading silt loam, 1 to 3 percent slopes
St	Stony steep land
Tu	Tully silty clay loam, 4 to 8 percent slopes
Tv	Tully silty clay loam, 4 to 8 percent slopes, eroded

* From Jantz et al. (1975).

Table 2. Family classification and parent material of the soils of the study area*.

Soil Series or undifferentiated unit	Family classification	Parent material
Alluvial land	----	Recent alluvium
Benfield	Fine, mixed, mesic Udic Agriustolls	Colluvium-residuum from shale and limestone
Chase	Fine, montmorillonitic, mesic Aquic Agriudolls	Alluvium
Clime	Fine, mixed, mesic Udic Haplustolls	Residuum from calcareous clayey shale
Dwight	Fine, montmorillonitic, mesic Typic Natrustolls	Loess over residuum from calcareous shale
Florence	Clayey-skeletal, montmorillonitic, mesic Udic Agriustolls	Residuum from cherty limestone
Irwin	Fine, mixed, mesic Pachic Agriustolls	Clayey sediments from clay shales
Ivan	Fine-silty, mixed, mesic Cumulic Hapludolls	Calcareous alluvium
Reading	Fine, mixed, mesic Typic Agriudolls	Alluvium
Sogn	Loamy, mixed, mesic Lithic Haplustolls	Residuum from shale and limestone
Stony land	----	Residuum from limestone-shale material
Tully	Fine, mixed, mesic Pachic Agriustolls	Colluvium from limestone-shale material

*According to the soil series descriptions contained in Jantz et al. (1975).

(Bulletin 622, Oct., 1978, Agricultural Experiment Station, Kansas State University, Manhattan, Kansas). The dominant species of grass include big bluestem (*Andropogon gerardii* Vitman), little bluestem (*Andropogon scoparius* Michx.), and Indian grass [*Sorghastrum nutans* (L.) Nash]. Other species of grass, forbs and small shrubs are also found in the study area. The variations of vegetation canopy characteristics, such as growing density and human disturbance (burned and unburned), may influence soil development.

B. Data Source and Software

Landsat-4 TM data for the study area were acquired on Aug. 12, 1983 and on Nov. 16, 1983 with cloud free imagery and 6 bands, except band 6 was not used because of 120 m spatial resolution. French SPOT-1 HRV data of this study area were acquired on March 20, 1987 and on June 26, 1987 with cloud free imagery and 3 multibands. The digital elevation model (DEM) data and digital soil maps on the Konza prairie with 30 m resolution (per pixel) were available from the First ISLSCP Field Experiment (FIFE) data base system (Sellers et al., 1988). The DEM data include the digital elevation, slopes, and aspects. The digital elevation data were calculated using the following equations:

$$m_H = \frac{(z(x_{i+1}) - z(x_{i-1})))}{(x_{i+1} - x_{i-1})} \quad (1)$$

$$m_V = \frac{(z(y_{i+1}) - z(y_{i-1})))}{(y_{i+1} - y_{i-1})} \quad (2)$$

$$M = \sqrt{(m_H^2 + m_V^2)} \quad (3)$$

$$\phi = \arctan\left(\frac{m_H}{m_V}\right) \quad (4)$$

$$DEM_{slope} = INT(100M) \quad (5)$$

$$DEM_{aspect} = INT(\frac{\phi}{2}) \quad (6)$$

where $z(x_i, y_i)$ is the absolute elevation data point of x and y coordinates in i th pixel. The values of m_H and m_V are the horizontal and vertical ratios of digital elevation in i th pixel. Seriously geometric errors of DEM data were corrected before use with image data merging and registering. The digital soil map was digitized from the 1:24 000 Riley County soil maps (Jantz et al., 1975). The digital soil map of the study area was assumed as a true soil map in this study.

Image processing software, such as geometric correction, training, statistical divergence, maximum likelihood classification, and other utilities was developed in Pascal language. The program for maximum likelihood classification is given in Appendix A. All the software for image processing was tested according to Jensen (1986). Sun work stations (Unix operating system) with I²S image processing system were used throughout the study.

C. Image Processing Techniques

The procedures used for image processing were divided into four steps: preprocessing, training, statistical analysis, and classification. The basic stages from training to classified output are illustrated in Fig. 2. A, B, C, D, and E in Fig. 2 were assumed five training classes. It should be noted that the different transformations, such as ratioing, intensity, and low frequency filtering, were also used to modify original satellite data after the preprocessing stage was conducted.

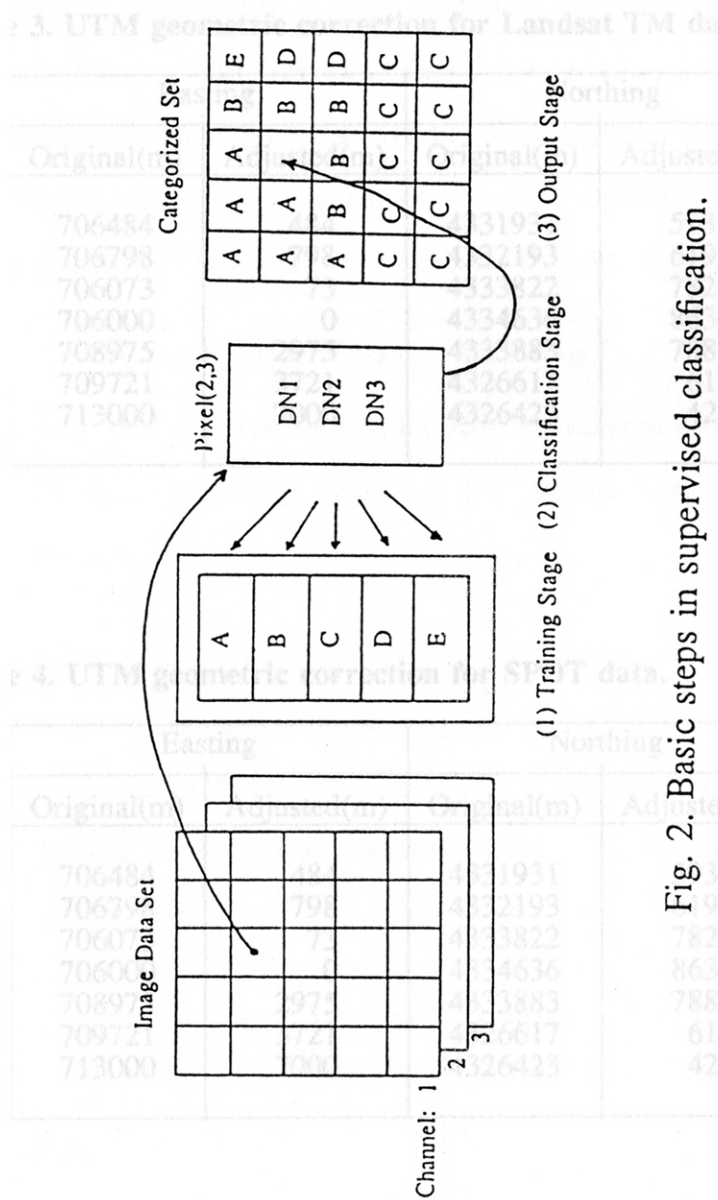


Fig. 2. Basic steps in supervised classification.

Table 3. UTM geometric correction for Landsat TM data.

No.	Easting		Northing		X0 (pixel)	Y0 (pixel)
	Original(m)	Adjusted(m)	Original(m)	Adjusted(m)		
1	706484	484	4331931	5931	87	195
2	706798	798	4332193	6193	95	185
3	706073	73	4333822	7822	63	135
4	706000	0	4334636	8636	55	106
5	708975	2975	4333883	7883	162	116
6	709721	3721	4326617	617	229	362
7	713000	7000	4326423	423	344	351

Table 4. UTM geometric correction for SPOT data.

No.	Easting		Northing		X0 (pixel)	Y0 (pixel)
	Original(m)	Adjusted(m)	Original(m)	Adjusted(m)		
1	706484	484	4331931	5931	75	186
2	706798	798	4332193	6193	87	170
3	706073	73	4333822	7822	33	96
4	706000	0	4334636	8636	21	57
5	708975	2975	4333883	7883	173	72
6	709721	3721	4326617	617	293	419
7	713000	7000	4326423	423	456	400

Image Preprocessing: The geometric distortion was found on both Landsat TM and SPOT images after they were obtained from a quarter scene of original image data. Seven ground control points were located on Landsat TM and SPOT imagery and U. S. G. S. 7½' quadrangle topographical maps. Two examples of ground control point data from Landsat TM and SPOT are given in Table 3 and 4. The Universal Transverse Mercator (UTM) grid on the topographical maps was used for geometric correction. Root mean square error (RMSError) analysis was employed to select minimum error of those points. The equation for computing root mean square error is given by Jenson (1986):

$$RMS_{error} = \sqrt{(x' - x_{orig})^2 + (y' - y_{orig})^2} \quad (7)$$

where x_{orig} and y_{orig} are the original row and column coordinates of the ground control point in the image, and x' and y' are the computed coordinates in the original image.

Finally, four ground control points were selected from the satellite imagery and topographical maps with an error of 0.7 pixels for Landsat TM (Table 5) and 0.3 pixels for SPOT imagery (Table 6). The Affine transformation equations (Jenson, 1986) for both Landsat TM and SPOT were obtained:

(1) Landsat TM:

$$X_o = 159.2972 + 0.0347X_1 - 0.0057Y_1 \quad (8a)$$

$$Y_o = 394.5498 - 0.0053X_1 - 0.0343Y_1 \quad (8b)$$

(2) SPOT:

$$X_o = 117.4356 + 0.0490X_1 - 0.0112Y_1 \quad (9a)$$

$$Y_o = 481.8891 - 0.0087X_1 - 0.0492Y_1 \quad (9b)$$

Table 5. Ground control points used to rectify Landsat TM imagery*.

No.	Easting Adjusted(X1)	Northing Adjusted(Y1)	X0	Y0	RMSerror
2	798	6193	152	178	0.2112
5	2975	7883	218	109	0.1580
6	3721	617	285	354	0.2055
7	7000	423	400	343	0.1523
Total RMSerror					0.7270

* Affine transformation equations:

$$(1) X0 = 159.2972 + 0.0347X1 - 0.0057Y1$$

$$(2) Y0 = 394.5498 - 0.0053X1 - 0.0343Y1$$

Table 6. Ground control points used to rectify SPOT imagery*.

No.	Easting Adjusted(X1)	Northing Adjusted(Y1)	X0	Y0	RMSerror
1	484	5931	75	186	0.1044
4	0	8636	21	57	0.0686
6	3721	617	293	419	0.0611
7	7000	423	456	400	0.0252
Total RMSerror					0.2593

* Affine transformation equations:

$$(1) X0 = 117.4356 + 0.0490X1 - 0.0112Y1$$

$$(2) Y0 = 481.8891 - 0.0087X1 - 0.0492Y1$$

where X_o , Y_o are the rectified coordinates of locations on a Landsat TM or SPOT image; X_1 , Y_1 are the coordinates of the adjusted easting and northing UTM from U. S. G. S. topographical maps, respectively.

Nearest-neighbor interpolation was used to resample the pixel of original input image to closest to the pixel of the rectified output image. After resampling the geometric corrected output image had the same digital value as the original input image, but the geometric position of the pixel was changed. This interpolation method can keep subtle variations of soil information from disturbance (Jenson, 1986).

Training and Statistical Extraction: Each training class has $>10n$ pixels (n is the number of band) and was analyzed statistically to yield a mean measurement vector, M_c , for each class.

$$M_c = \begin{bmatrix} \mu_{c1} \\ \mu_{c2} \\ \mu_{c3} \\ \vdots \\ \mu_{ck} \end{bmatrix} \quad (10)$$

where μ_{ck} represents the mean value of the data obtained from class c in band k . The covariance matrix, V_c , was also obtained

$$V_c = \begin{bmatrix} Cov_{11} & Cov_{12} & Cov_{13} & \cdot & Cov_{1l} \\ Cov_{21} & Cov_{22} & Cov_{23} & \cdot & Cov_{2l} \\ Cov_{31} & Cov_{32} & Cov_{33} & \cdot & Cov_{3l} \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ Cov_{k1} & Cov_{k2} & Cov_{k3} & \cdot & Cov_{kl} \end{bmatrix} \quad (11)$$

where Cov_{kl} is the covariance of class c between bands k through l .

The mean, standard deviation, variance, minimum value, maximum value, variance-covariance matrix, and correlation matrix for the training statistics of 5 major soil mapping units of the study area from Landsat TM data are given in Appendix B. These data provided the optimum band selection information for supervised classification.

Feature Selection: From Landsat TM data, six of the seven available bands were used. In addition, the digital elevation model (DEM) data, which include elevation, slopes, and aspects, were merged to Landsat TM data as three additional "bands". As the dimensionality of the feature (band) increased, the cost of the digital image classification would increase rapidly. In order to select useful features (bands), feature selection techniques were used.

Graphic methods of feature selection were applied to a two-dimensional display. The mean vectors from each band were plotted against the digital number for each training class. The separation of each training class in different bands was interpreted for feature (band) selection.

Statistical divergence of feature selection was also used to measure the statistical separability of training classes for interpreting the feature selection. The number of pair combination, C , of n bands taken q bands at a time was obtained by using the following equation:

$$C\left(\frac{n}{q}\right) = \frac{n!}{q!(n-q)!} \quad (12)$$

The degree of divergence or "separability" between c and d , $Diverg_{cd}$, was computed according to the formula:

$$\begin{aligned} Diverg_{cd} = & \frac{1}{2} Tr[(V_c - V_d) (V_d^{-1} - V_c^{-1})] \\ & + \frac{1}{2} Tr[(V_c^{-1} + V_d^{-1}) (M_c - M_d) (M_c - M_d)^T] \end{aligned} \quad (13)$$

where $Tr[.]$ is the trace of a matrix, V_c and V_d are the covariance matrices from the two classes, c and d , under investigation, and M_c and M_d are the mean vectors from classes c and d .

In order to scale the divergence value to lie between 0 to 2000, Kumar and Silva (1977) suggested computing a transformed divergence, $Diverg_{cd}^T$. It can be expressed as

$$Diverg_{cd}^T = 2000 \left[1 - \exp \frac{(-Diverg_{cd})}{8} \right] \quad (14)$$

Where a transformed divergence value of 2000 represents excellent between-class separation, above 1900 provides good separation, while below 1500 is poor. Consequently, the number of >1500 transformed divergence was also counted to compare the separability of different features (bands).

Maximum Likelihood Classification: This is one of the important supervised classifications. After statistics and feature selection from training class, maximum likelihood classification was applied to classify the satellite image data. Maximum likelihood classification as a decision rule assigned each pixel having pattern measurements or features X to the class c whose units are most likely to have given rise to feature vector X . It was assumed that training data statistics for each class in each band were normally distributed. The decision rule applied to the unknown measurement vector, X , was used to decide X is in class c if, and only if,

$$p_c \geq p_i \quad (15)$$

where $i = 1, 2, 3, \dots, m$ possible classes and

$$p_c = \left[-\frac{1}{2} \ln(\det(V_c)) \right] - \left[\frac{1}{2} (X - M_c)^T (V_c^{-1}) (X - M_c) \right] \quad (16)$$

where $\det(V_c)$ is the determinant of the covariance matrix V_c . M_c is the mean measurement vector for class c . The program of maximum likelihood classification is available in Appendix A.

Output of Digital Image: The resultant digital maps from classified output were in integer format. The hard copy of these maps either was processed and printed on an Apple Laser Printer using Postscript language or photographed from the I²S image processing color monitor.

Image Transformation: Band ratioing, intensity, and low frequency filtering were used to smooth radiometric variations from the original image which may be caused by noise. The expression of band ratioing can be described

$$DN'_{ijk} = \left[\frac{DN_{ijk}}{DN_{ij(k \pm s)} + 0.1} \right] \quad s = 1, 2, 3, \dots, n \quad (17)$$

where DN is digital number of i th row and j th column in band k . The value 0.1 was added to avoid a dominance equal to zero. The number of band was given by n .

The intensity transformation was computed with the following formula:

$$I_{ijk} = \frac{DN_{jik}}{\sum_{k=1}^n DN_{ijk}} \quad (18)$$

where I is the intensity of i th row and j th column from band k . $\sum_{k=1}^n DN_{ijk}$ is the sum of the DN_{ij} from n bands.

For low frequency filtering, a 3×3 matrix mask was used.

$$mask = \begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix} \quad (19)$$

The formula for low frequency filtering is expressed

$$LFF_{3 \times 3} = Int \left[\frac{\sum_{i=1}^9 c_i DN_i}{n} \right] \quad (20)$$

where LFF is low frequency filtering value from 3×3 mask, and n is the size of mask ($3 \times 3 = 9$). The coefficient from mask cell, i is c , and DN is the original digital number in a image, which refers to mask cell, i .

D. Accuracy Assessment

Published soil survey maps (Jantz et al., 1975) were used for ground truth to assess the accuracy of the resultant soil map obtained from satellite data. The resultant soil map was accurately registered to the soil survey maps at 30 m per pixel level. The registering error was about 0.5 pixels. The overall accuracy was calculated based upon the error matrix method (Aronoff, 1982; Jensen, 1986). Errors of omission for each class were computed by summing the number of pixels assigned to incorrect categories along each row and dividing this number by the total number of "true" pixels in the category. Errors of commission were computed by summing the number of pixels assigned to

incorrect categories along each column and dividing this number by the total number of pixels assigned to the column category.

E. Soil Sampling and Laboratory Analysis

Representative pedons of Clime, Dwight, Florence, Benfield, and Tully were sampled within the study area. Backhoe pits were dug to a depth of approximately 2 m, and samples were collected from each horizon. Laboratory analyses, including particle size distribution, organic carbon, extractable bases, extractable acidity, CEC, and calcium carbonate equivalent, were obtained by the National Soil Survey Laboratory in Lincoln, Nebraska. The procedures are given in Soil Conservation Service (1982). The results of the analyses of these pedons are given in Appendix C.

IV. Results

Part I. Landsat TM

A. The Separation of Soil Mapping Units From the Graphic Method

The total of 14 major soil mapping units occur within the study area (Jantz et al., 1975). The soil mapping units of Ic, Bk, Re, and Tv were grouped with Id, Ad, Rd, and Tu (symbol of soil mapping units is listed on Table 1), respectively. Therefore, a total of 10 soil mapping units were used for training classes. The mean measurement vector of each training class was plotted with 6 bands (band 1 to 5, and 7) of Landsat TM. To facilitate classification, the soil mapping units of the study area were divided into two groups: lowland soil mapping units, which include both recent floodplain and terrace positions, and upland soil mapping units, which include landscape positions where soils are developing in residuum or colluvium. Six major soil mapping units, including Bf, Cs, Dr, Id, Tu, and St, were found on the upland areas, and other four, including Ad, Ch, Iv, and Rd, on the lowland areas (Figs. 3 and 4). The histograms of 6 TM bands of the study area in dormant season are given in Figs. 5, 6, 7, 8, 9, and 10.

B. Statistical Separability of Soil Mapping Units

The statistical divergence for different band combinations was performed from Landsat TM data and DEM merging data. A total of 9 bands, including 6 Landsat TM bands and 3 additional DEM data "bands", were used to calculate divergence and the transformed divergence. The number of >1500 and the average transformed divergences were obtained from two band combinations (Table 7), three band combinations (Table 8), four band combinations (Table 9), and five band combinations (Table 10). The intraclass and interclass variability of

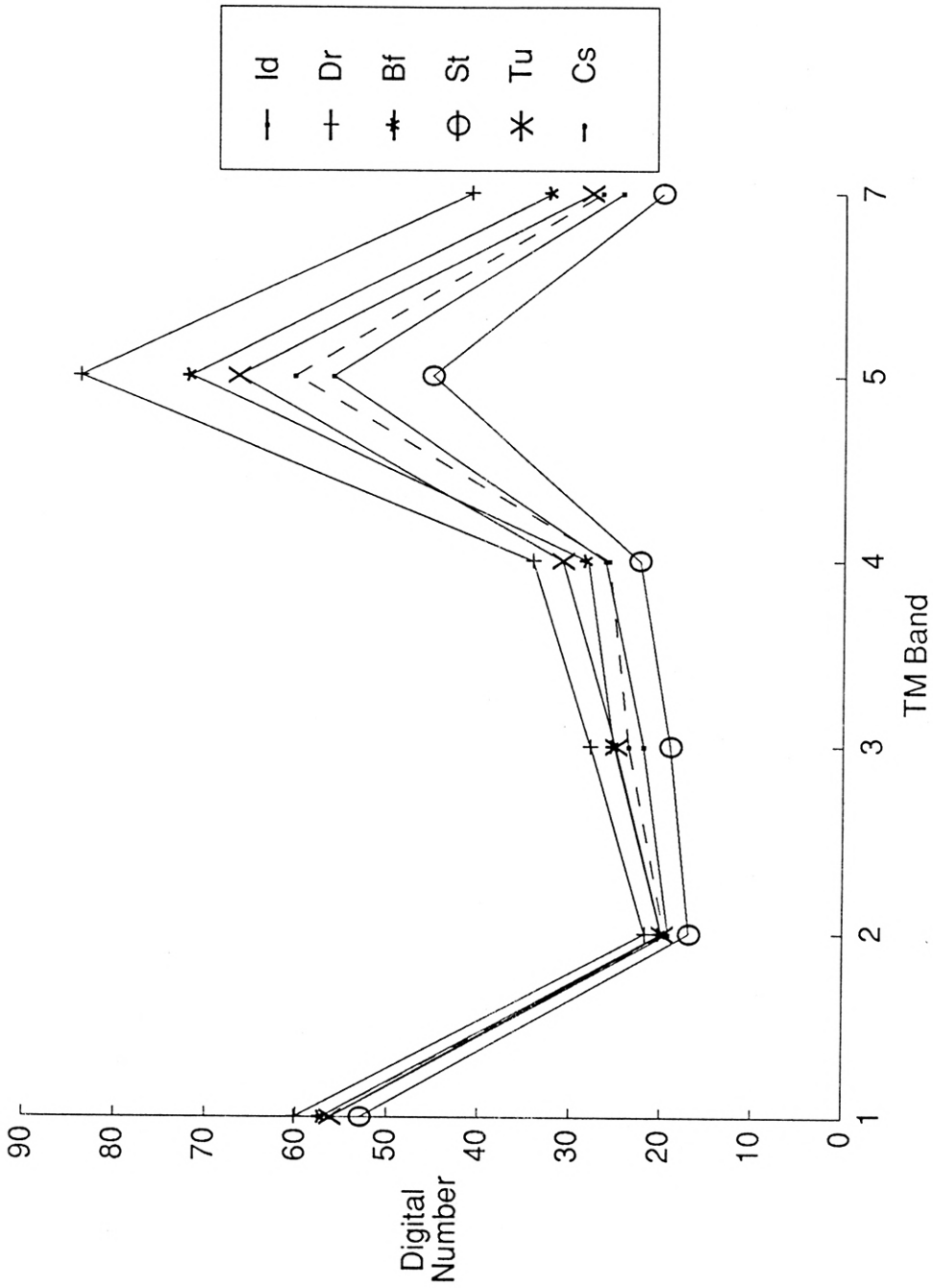


Fig. 3. Separation of upland soil mapping units from training data.

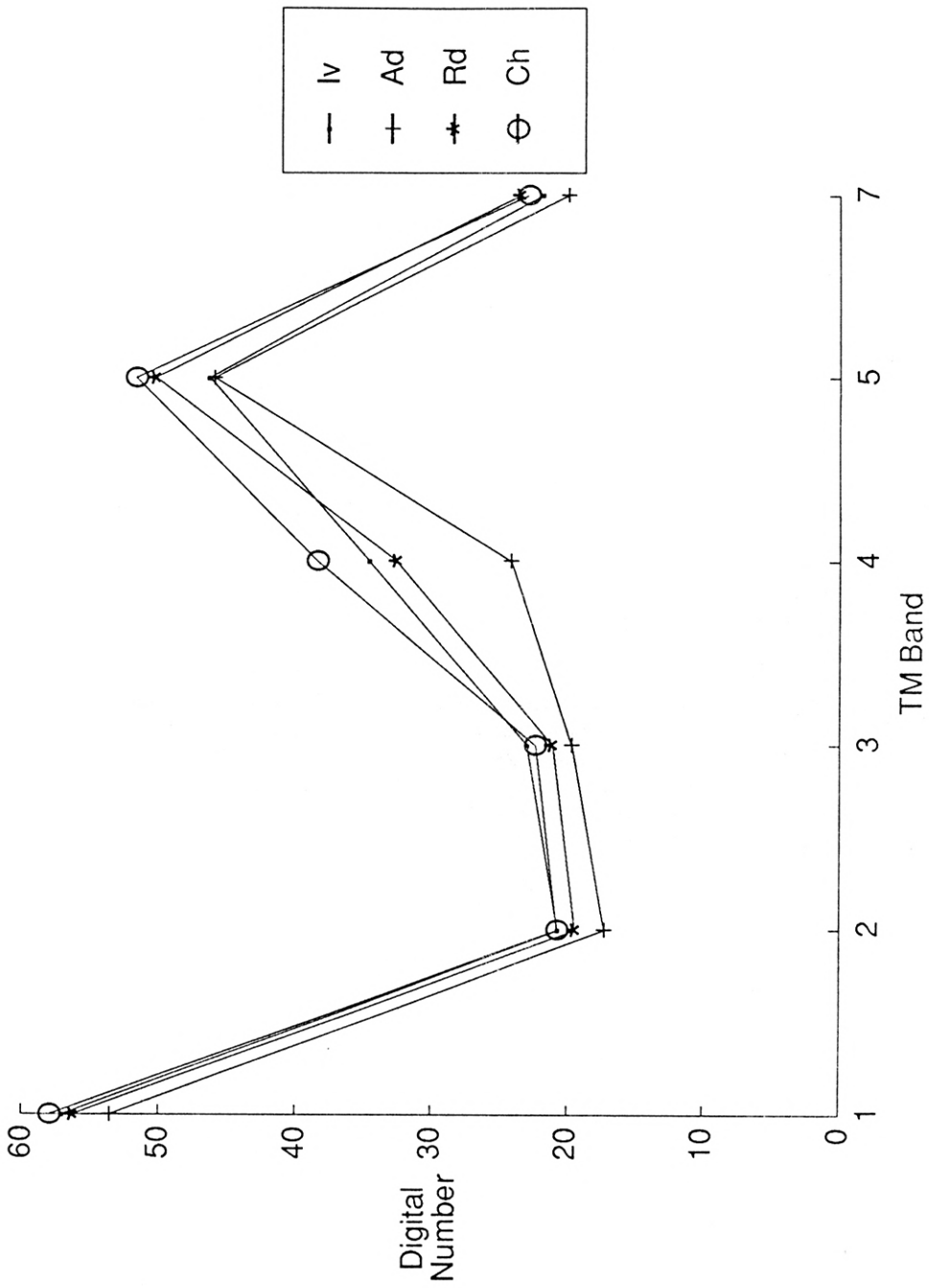


Fig. 4. Separation of lowland soil mapping units from training data.

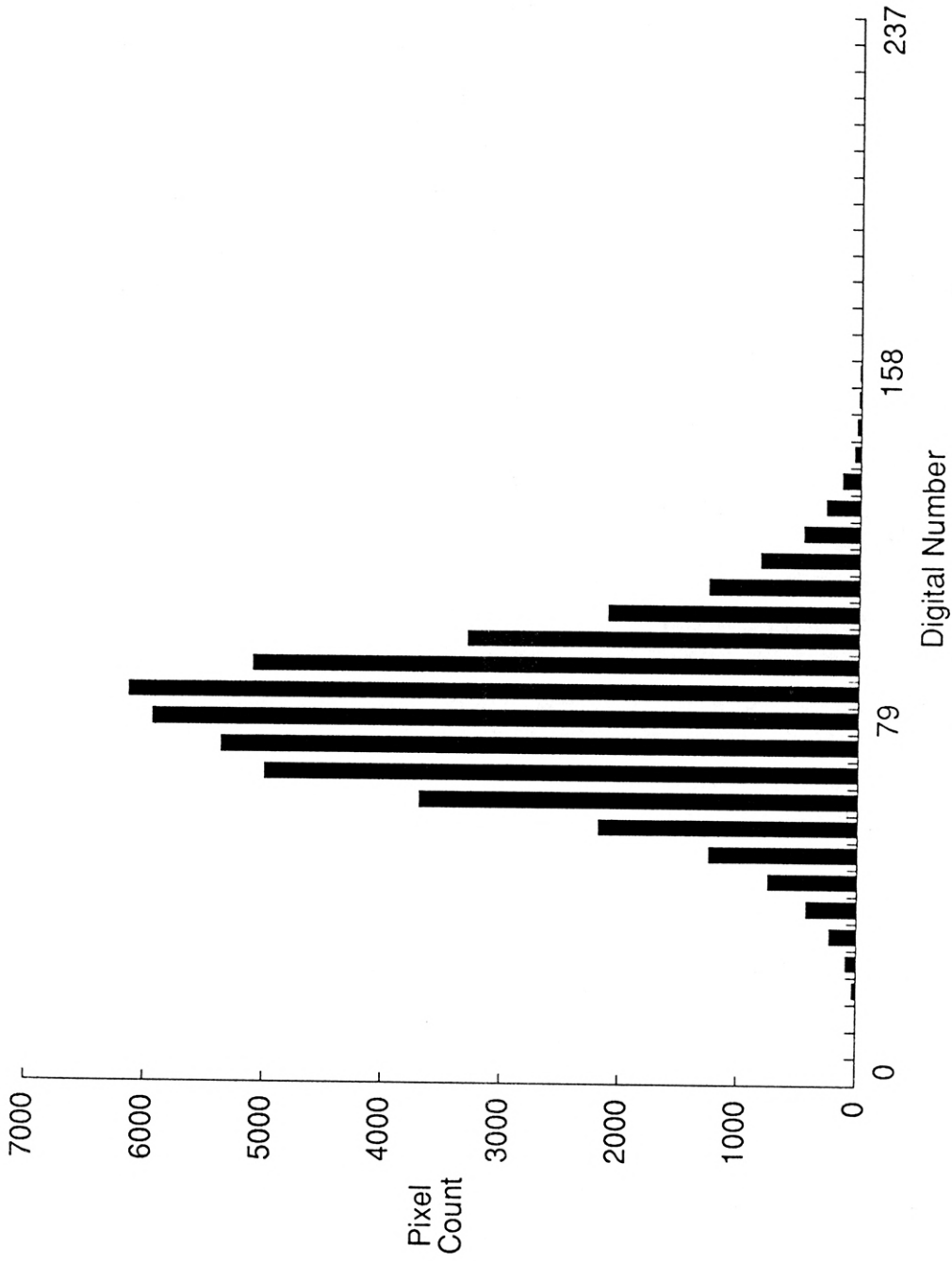


Fig. 5. Histogram of Landsat TM band 1.

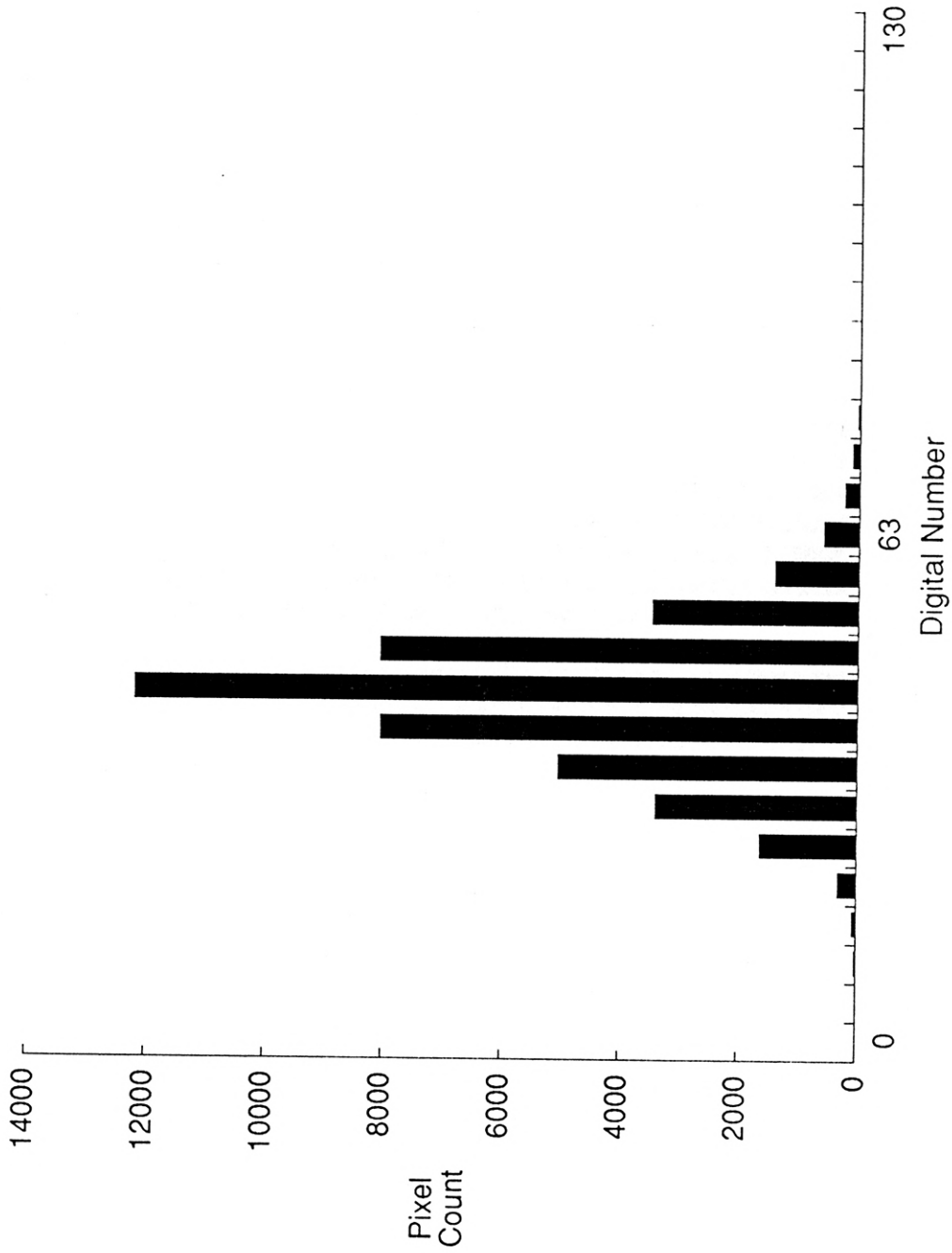


Fig. 6. Histogram of Landsat TM band 2.

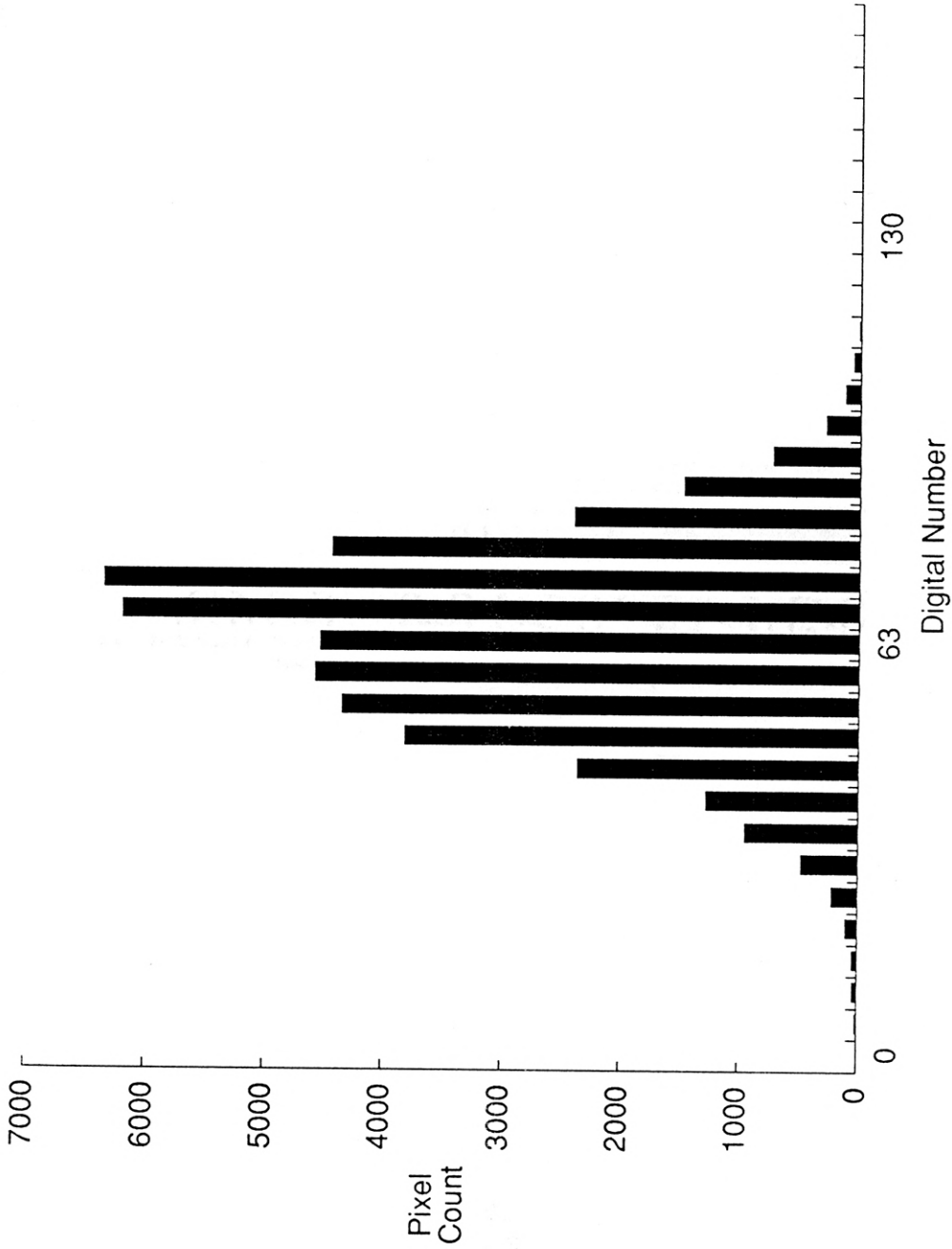


Fig. 7. Histogram of Landsat TM band 3.

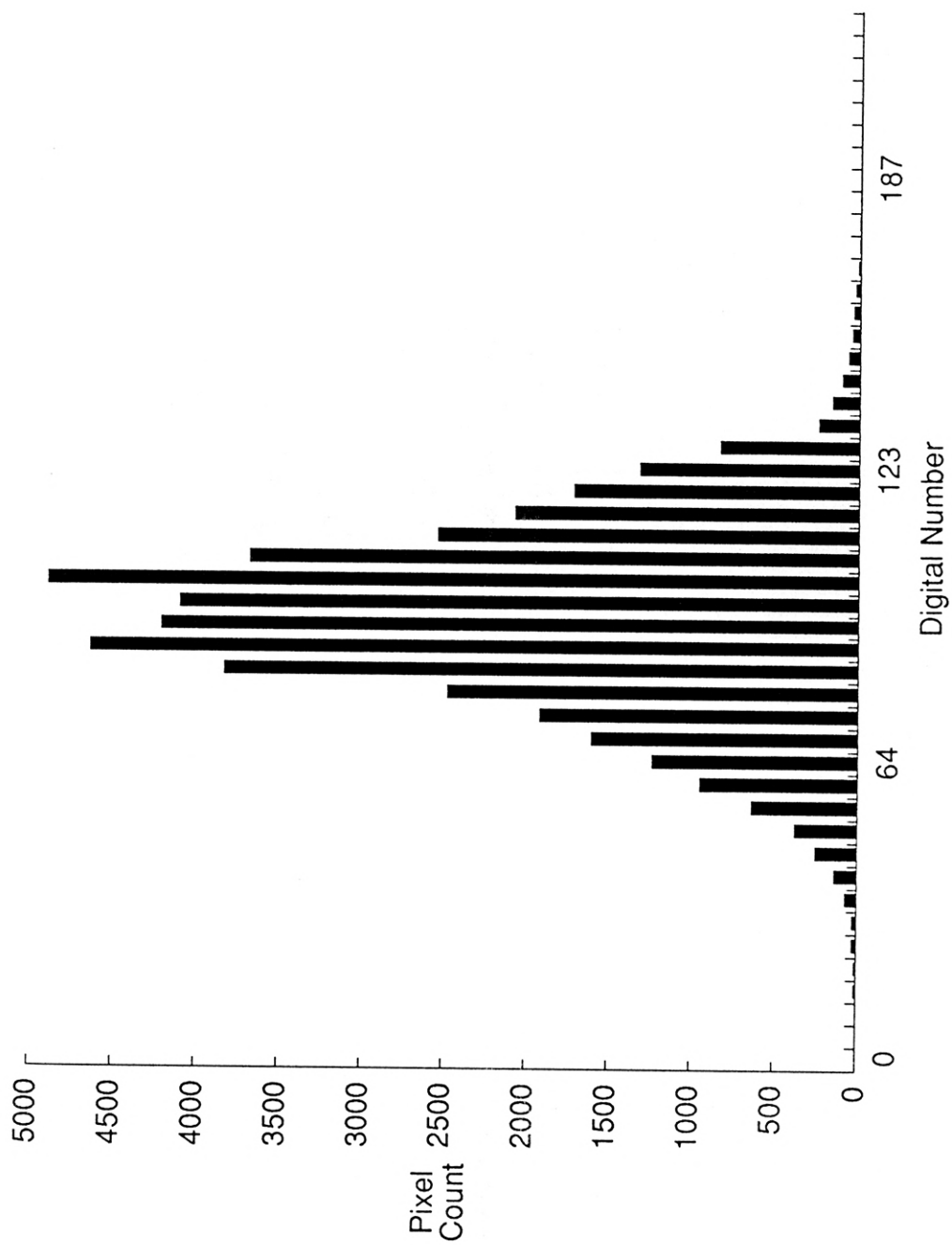


Fig. 8. Histogram of Landsat TM band 4.

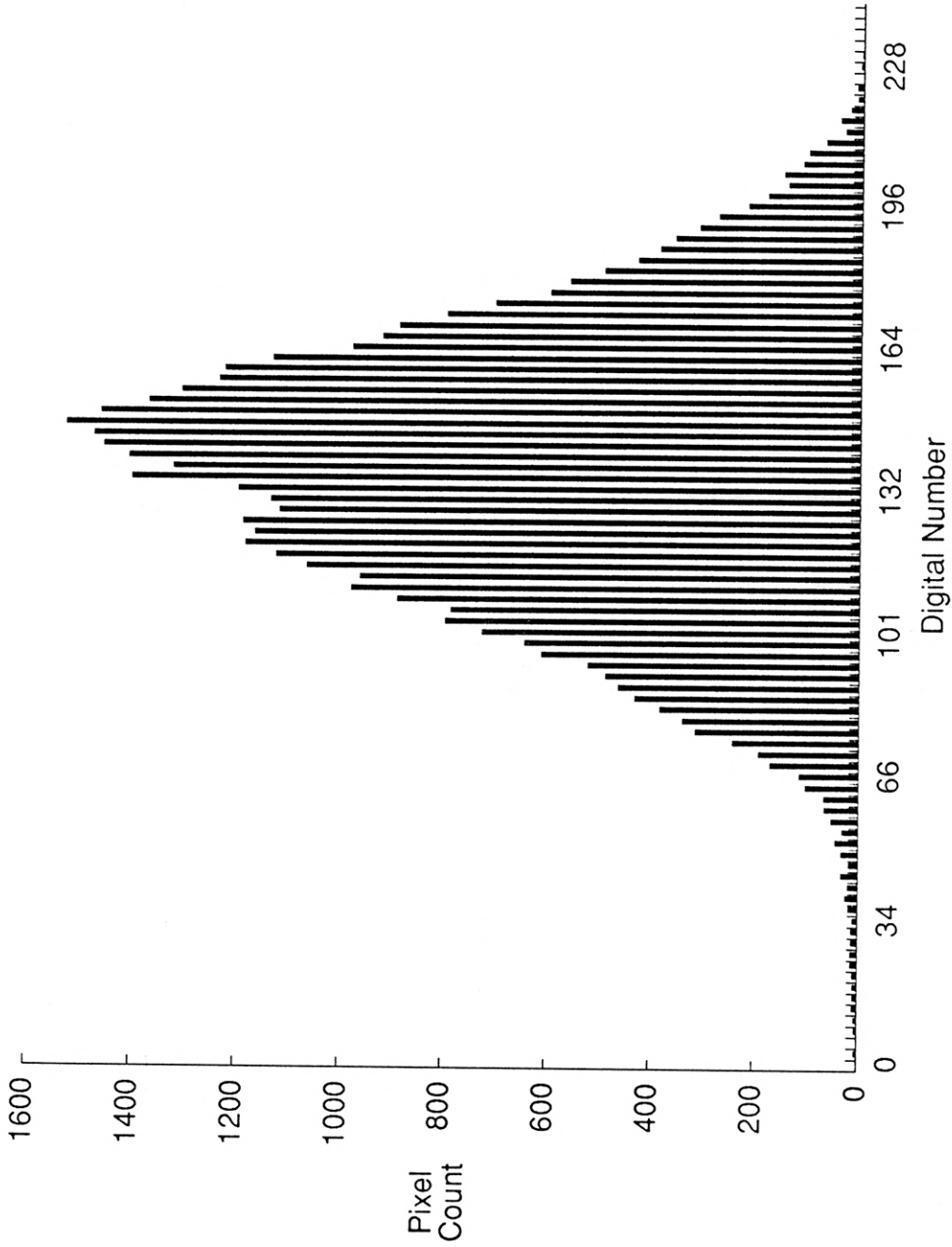


Fig. 9. Histogram of Landsat TM band 5.

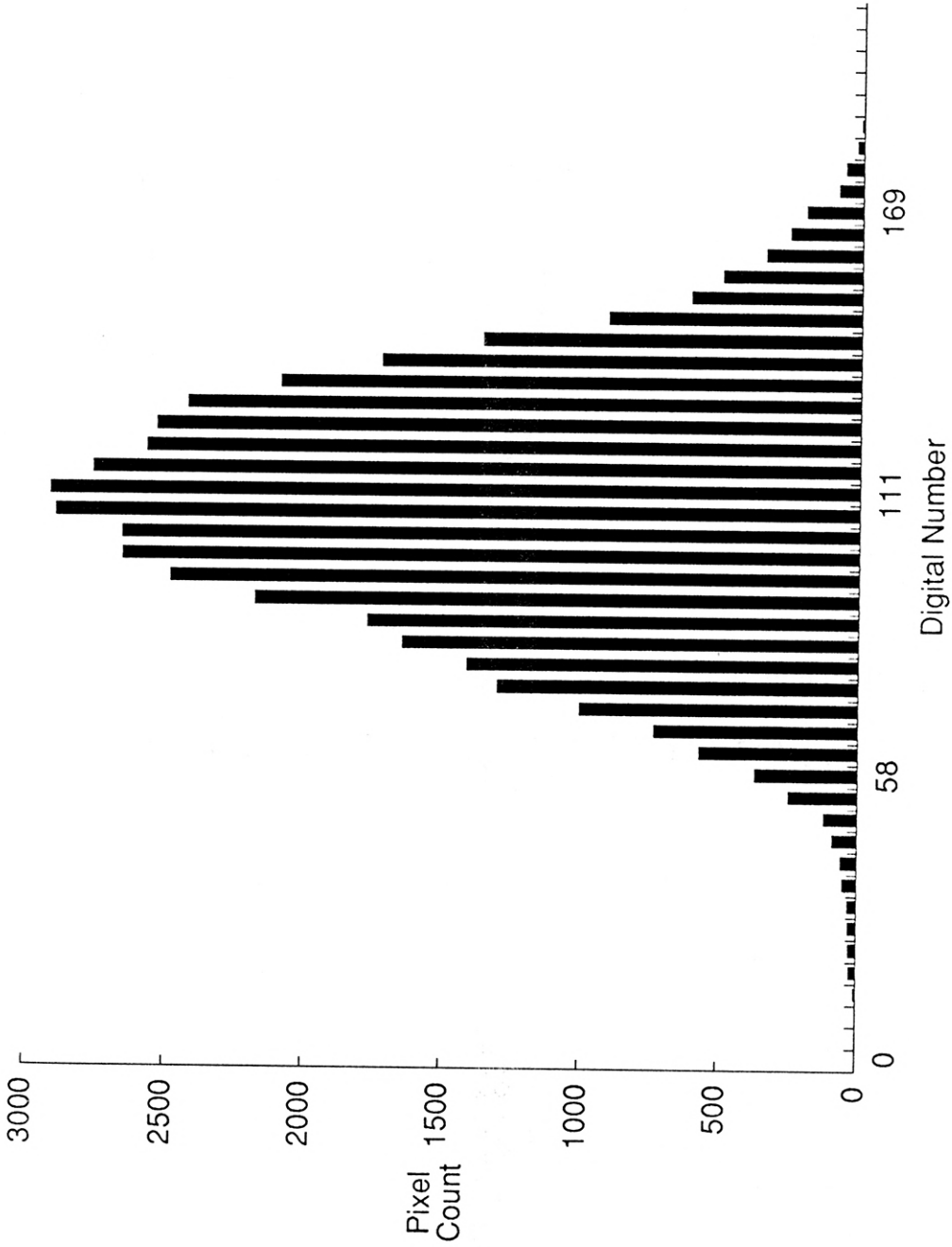


Fig. 10. Histogram of Landsat TM band 7.

Table 7. Statistical divergence for two band combinations.

Combinations*	Transformed Divergence	
	No. (>1500)	Average(>1500)
1,E	60	1683
2,E	60	1700
3,E	61	1714
4,E	60	1664
5,E	65	1759
7,E	62	1713

* E refers to digital elevation data.

Table 8. Statistical divergence for three band combinations.

Combinations*	Transformed Divergence	
	No. (>1500)	Average(>1800)
1,E,A	70	1860
2,E,A	71	1869
3,5,E	65	1813
3,E,A	72	1881
4,E,A	70	1843
5,E,S	68	1823
5,E,A	73	1890
7,E,S	66	1802
7,E,A	72	1860

* E, S, and A refer to digital elevation, slopes, and aspects data, respectively.

Table 9. Statistical divergence for four band combinations.

Combinations*	Transformed Divergence	
	No. (>1500)	Average(>1900)
1,5,E,A	73	1902
1,E,S,A	72	1905
2,5,E,A	73	1909
2,E,S,A	72	1902
3,4,E,A	72	1907
3,5,E,A	73	1916
3,E,S,A	72	1910
4,5,E,A	73	1909
4,E,S,A	72	1903
5,7,E,A	73	1908
5,E,S,A	74	1920
7,E,S,A	73	1908

* E, S, and A refer to digital elevation, slopes, and aspects data, respectively.

Table 10. Statistical divergence for five band combinations.

Combinations*	Transformed Divergence	
	No. (>1500)	Average(>1930)
2,5,E,S,A	74	1934
3,4,5,E,A	74	1931
3,4,E,S,A	73	1933
3,5,7,E,A	74	1935
4,5,E,S,A	75	1936
5,7,E,S,A	74	1933

* E, S, and A refer to digital elevation, slopes, and aspects data, respectively.

soils was found from transformed divergence. A transformed divergence value of 1500 or greater indicates an acceptable separability of classes (Haack et al., 1987).

C. Digital Elevation Model (DEM) Data Merging

Statistical divergence results for digital elevation model (DEM) data merging were obtained with different band combinations on Table 7, 8, 9, and 10. The smaller average transformed divergence was obtained with no DEM data merging. The results of no DEM data merging were not included in Table 7, 8, 9, and 10. DEM data were plotted against Landsat TM band 5 using training class samples. These plots show the relationships between DEM data and Landsat TM band 5 on lowland and upland of the study area (Figs. 11, 12, 13, 14, 15, and 16).

D. Assessment of Resultant Soil Map

The soil map obtained from Landsat TM and DEM data merging was registered to the ground truth soil map pixel by pixel to examine an overall accuracy assessment. Because of serious variation of soil mapping units found in the lowland areas, the mapping units, Ad, Ch, Iv, and Rd, were grouped and redefined as a single lowland complex (Lo). The soil mapping units, Id, Ic, Tu, and Tv in upland area were grouped with Cs and redefined as Cs because of the small areas of Id, Ic, Tu, and Tv. Consequently, a total of 5 mapping units, Lo, Bf, Dr, Cs, and St, were used for an overall accuracy assessment. The error matrices derived from Landsat TM data in different growing seasons are shown in Table 11, 12, 13, 14, and 15. The omission and commission errors and accuracy of each class are also included. The soil mapping units, Lo, St, Dr, Cs, and Bf, from digital soil map of the study area were assumed as five

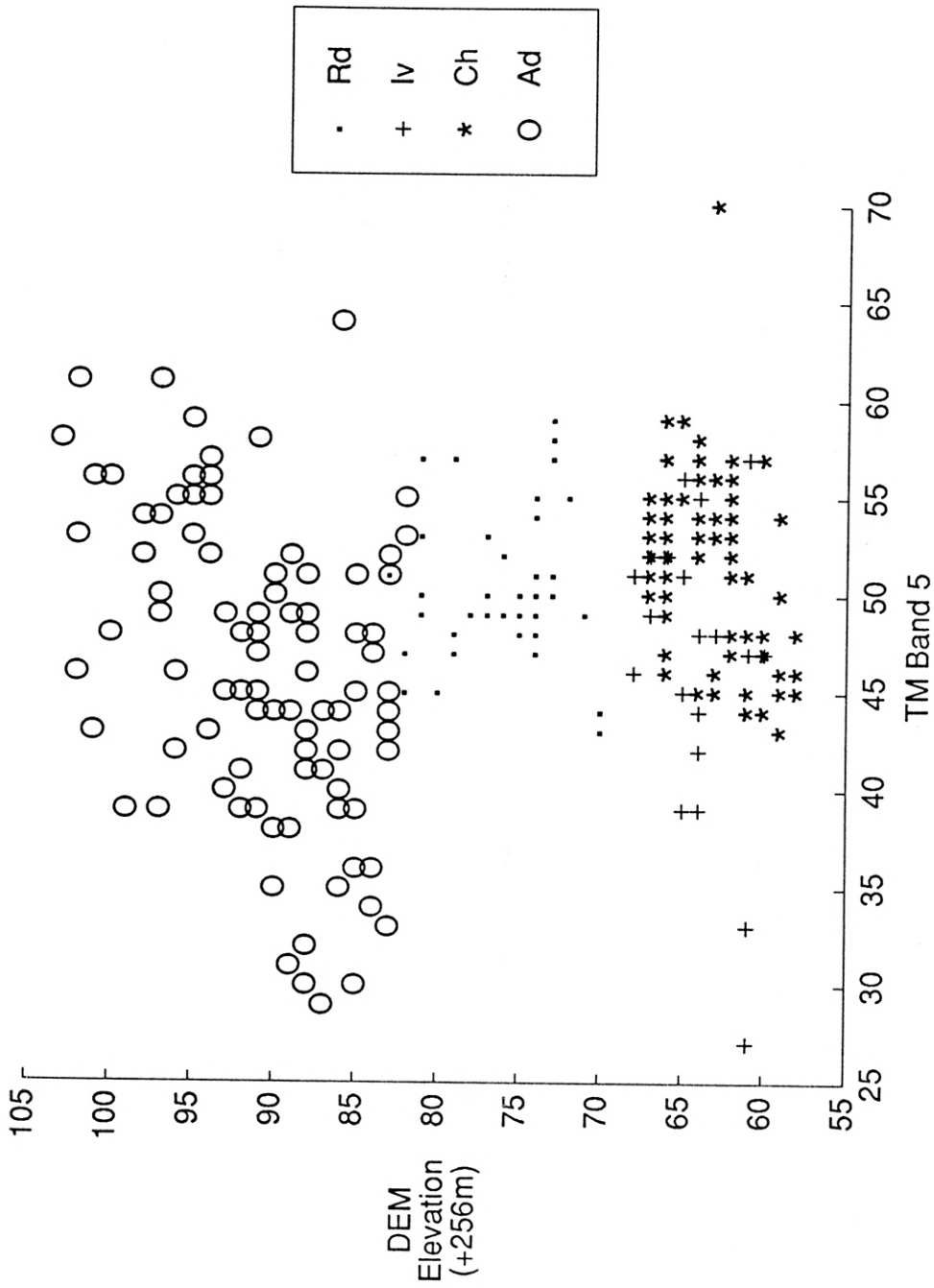


Fig. 11. Relationship between elevation and TM band 5 on lowland mapping units.

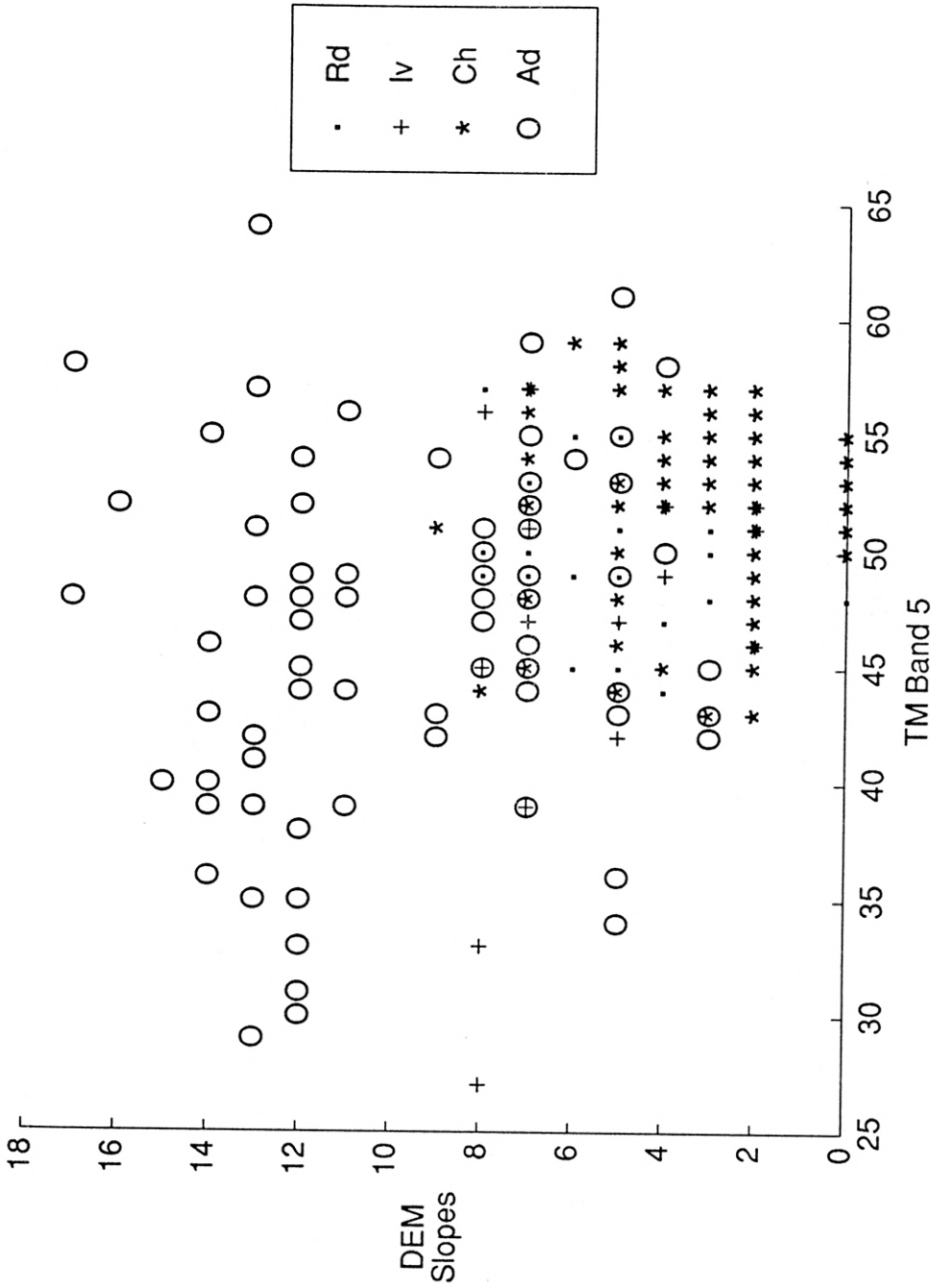


Fig. 12. Relationship between slopes and TM band 5 on lowland mapping units.

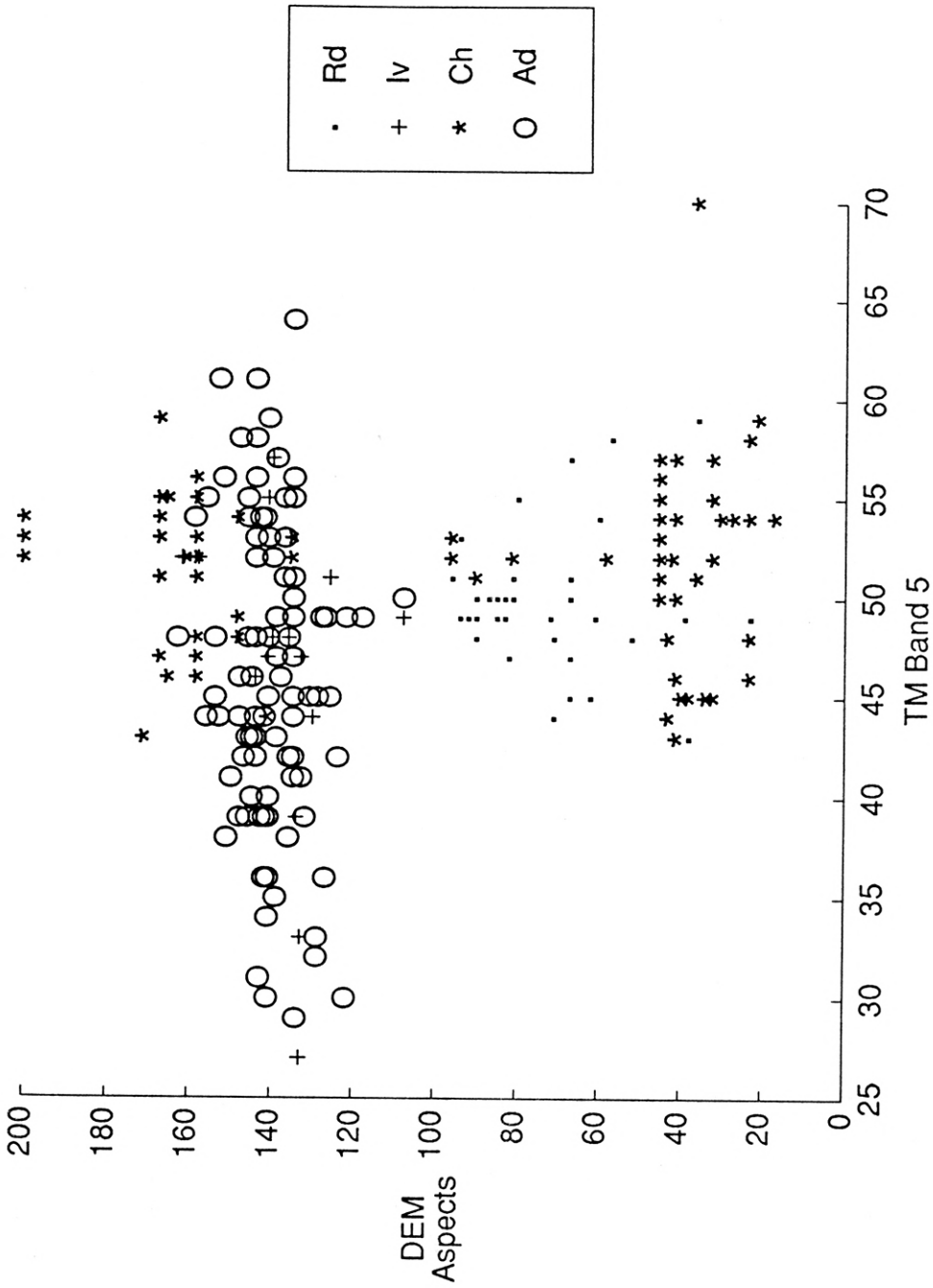


Fig. 13. Relationship between aspects and TM band 5 on lowland mapping units.

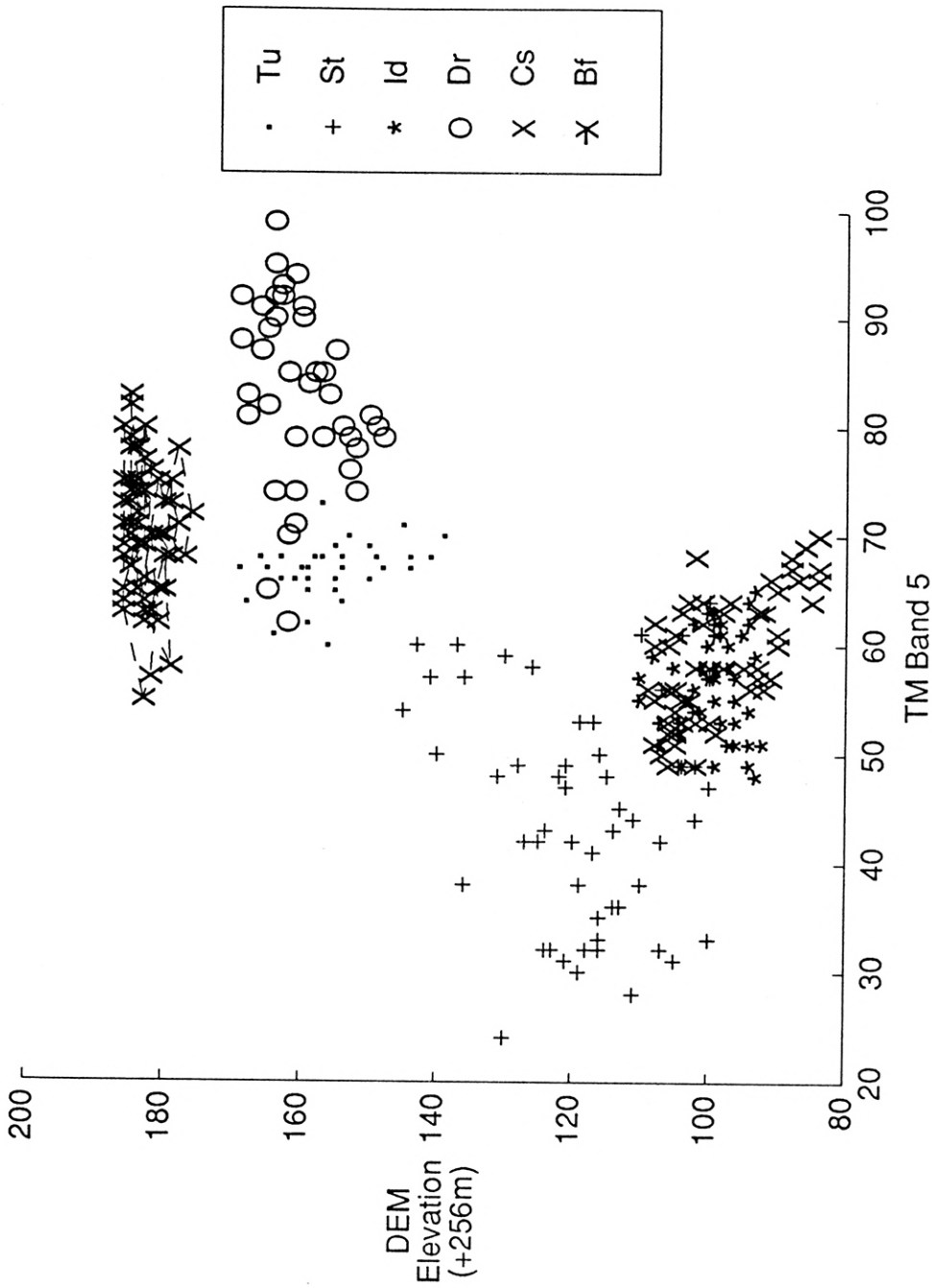


Fig. 14. Relationship between elevation and TM band 5 on upland mapping units.

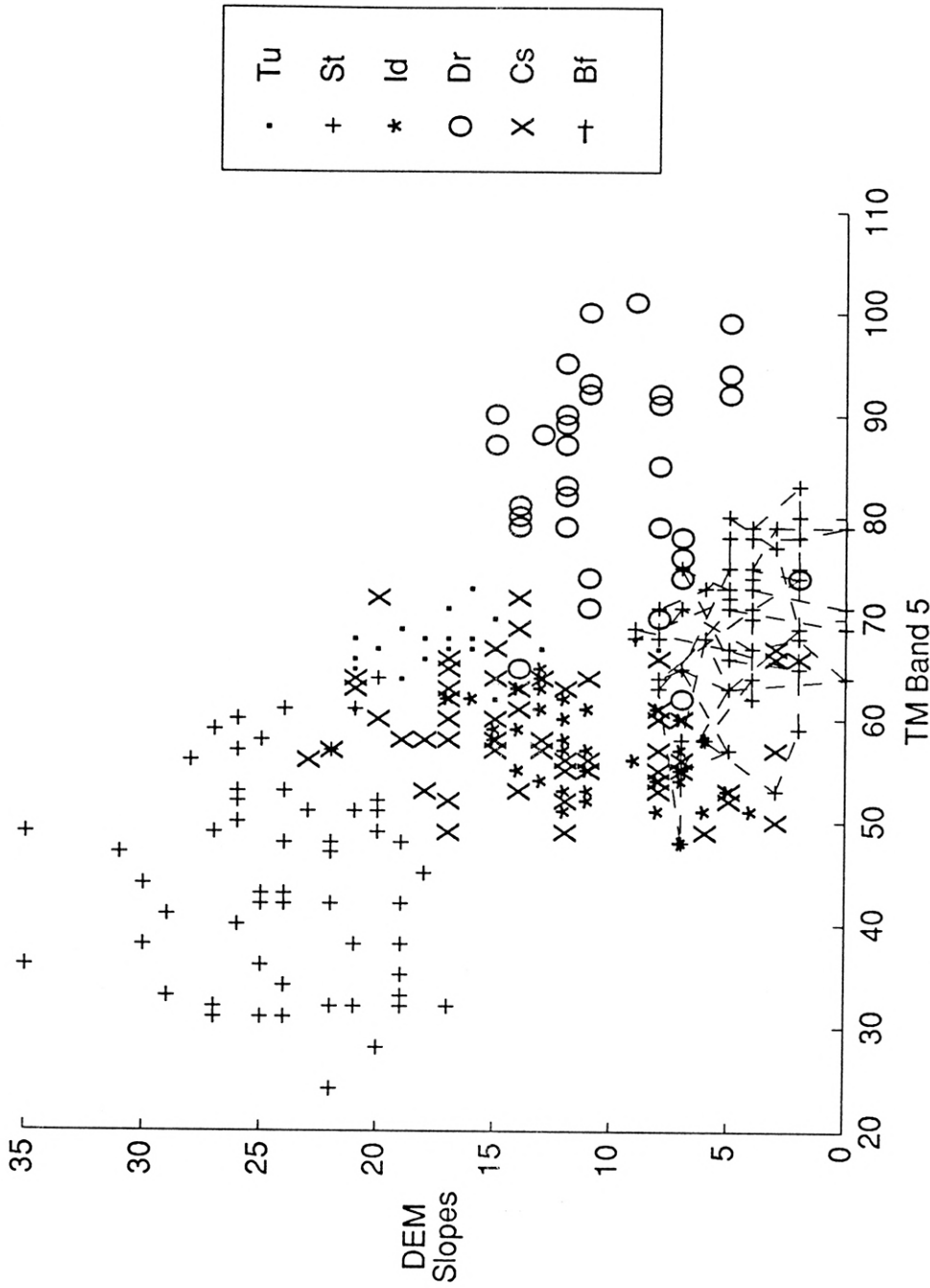


Fig. 15. Relationship between slopes and TM band 5 on upland mapping units.

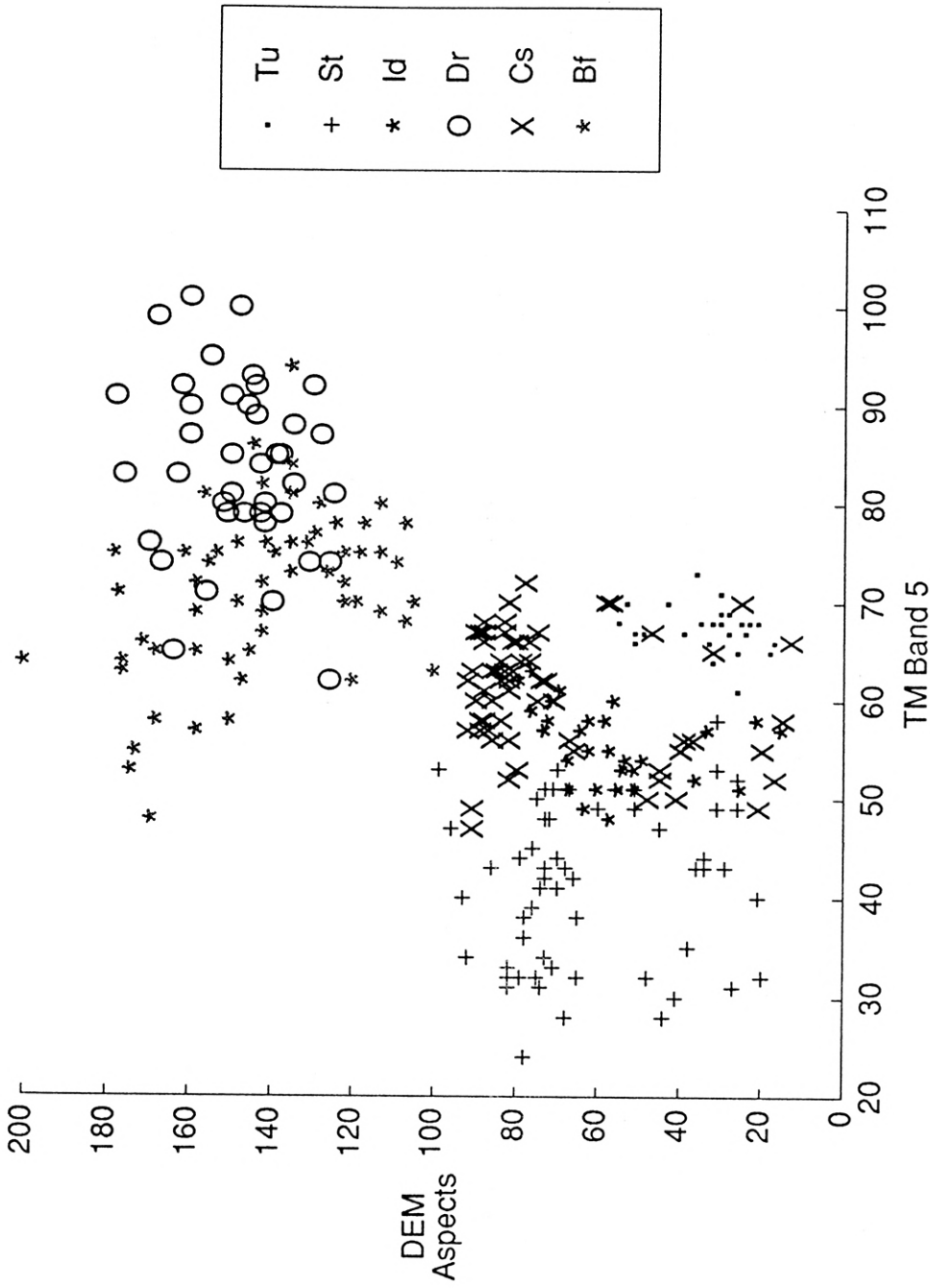


Fig. 16. Relationship between aspects and TM band 5 on upland mapping units.

**Table 11. Overall accuracy assessment
after DEM data were merged to TM bands 4 and 5
in growing season.**

True Classes	Interpreted Classes (pixel)					Total
	1	2	3	4	5	
1. Lo*	3094	637	286	676	447	5140
2. St	915	708	62	170	181	2036
3. Dr	18	51	398	10	650	1127
4. Cs	2618	2292	597	2199	2138	9844
5. Bf	82	637	2623	3275	11537	11683
Total	6727	4325	3966	3275	11537	29830

Classes	Omission Error(%)	Commission Error(%)	Accuracy(%)
1. Lo*	39.81	70.68	60.19
2. St	65.23	177.65	34.77
3. Dr	64.69	316.59	35.31
4. Cs	77.66	10.93	22.34
5. Bf	30.49	29.24	69.51
Average	55.58	121.02	44.42

* Lo includes all the soils in lowlands of the study area.
Overall accuracy = 48.68 %.

**Table 12. Overall accuracy assessment
after DEM data were merged to TM bands 3, 4 and 5
in growing season.**

True Classes	Interpreted Classes (pixel)					Total
	1	2	3	4	5	
1. Lo*	3036	678	226	642	558	5140
2. St	866	793	53	171	153	2036
3. Dr	27	32	399	2	667	1127
4. Cs	2455	2503	513	2096	2277	9844
5. Bf	67	665	2354	193	8404	11683
Total	6451	4671	3545	3104	12059	29830

Classes	Omission Error(%)	Commission Error(%)	Accuracy(%)
1. Lo*	40.93	66.44	59.07
2. St	61.05	190.47	38.95
3. Dr	64.60	279.15	35.40
4. Cs	78.71	10.24	21.29
5. Bf	28.07	31.28	71.93
Average	54.80	115.52	45.33

* Lo includes all the soils in lowlands of the study area.

Overall accuracy = 49.37 %.

**Table 13. Overall accuracy assessment
after DEM data were merged to TM bands 4 and 5
in dormant season.**

True Classes	Interpreted Classes (pixel)					Total
	1	2	3	4	5	
1. Lo*	2823	700	23	575	1019	5140
2. St	404	1090	1	191	350	2036
3. Dr	14	20	125	13	955	1127
4. Cs	1352	2477	14	1926	4075	9844
5. Bf	39	669	580	82	10313	11683
Total	4632	4956	743	2787	16712	29830

Classes	Omission Error(%)	Commission Error(%)	Accuracy(%)
1. Lo*	45.08	35.19	54.92
2. St	46.46	189.88	53.54
3. Dr	88.91	54.84	11.09
4. Cs	80.43	8.75	19.57
5. Bf	11.73	54.77	88.27
Average	54.52	68.69	45.48

* Lo includes all the soils in lowlands of the study area.
Overall accuracy = 54.57 %.

**Table 14. Overall accuracy assessment
after DEM data were merged to TM bands 3, 4 and 5
in dormant season.**

True Classes	Interpreted Classes (pixel)					Total
	1	2	3	4	5	
1. Lo*	2733	944	33	448	982	5140
2. St	341	1241	0	166	288	2036
3. Dr	21	11	191	17	887	1127
4. Cs	1119	2741	30	1813	4141	9844
5. Bf	39	573	905	61	10105	11683
Total	4253	5510	1159	2505	16403	29830

Classes	Ommission Error(%)	Commission Error(%)	Accuracy(%)
1. Lo*	46.83	29.57	53.17
2. St	39.05	209.68	60.95
3. Dr	83.05	85.89	16.95
4. Cs	81.58	7.03	18.42
5. Bf	13.51	53.91	86.49
Average	52.80	77.22	47.20

* Lo includes all the soils in lowlands of the study area.

Overall accuracy = 53.92 %.

**Table 15. Overall accuracy assessment
after DEM data were merged to TM bands 2, 3, and 4
in dormant season.**

True Classes	Interpreted Classes (pixel)					Total
	1	2	3	4	5	
1. Lo*	2710	1043	62	446	879	5140
2. Bf	354	1266	2	140	274	2036
3. Dr	22	18	215	13	859	1127
4. Cs	1162	2810	71	1860	3941	9844
5. St	46	628	1125	84	9800	11683
Total	4294	5765	1475	2543	15753	29830

Classes	Ommission Error(%)	Commission Error(%)	Accuracy(%)
1. Lo*	47.28	30.82	52.72
2. St	37.82	220.97	62.18
3. Dr	80.92	111.80	19.08
4. Cs	81.11	6.94	18.89
5. Bf	16.12	50.95	83.88
Average	52.65	84.30	47.35

* Lo includes all the soils in lowlands of the study area.
Overall accuracy = 53.14 %.

true classes.

E. Differences Between Dormant and Growing Seasons Using Landsat TM Data

The same image classification techniques were used to process the Landsat TM data that were acquired on Nov. 16, 1983 and on Aug. 12, 1983. There was no green vegetation patterns found in the TM image of Nov. 16, 1983. However, green vegetation patterns were clearly observed in the TM image of Aug. 12, 1983. Consequently, Nov. 16 was considered to represent the dormant season and Aug. 12 as the growing season. The overall accuracy assessment from these two seasons was performed in two different optimum band combinations. The results of overall accuracy assessment are given in Table 11, 12, 13, and 14).

Part II. SPOT

A. Statistical Separability of Soil Mapping Units Using Band Ratioing, Intensity Transformation, and Low Frequency Filtering

Bands 1, 2, and 3 of original SPOT multiband data were transformed using ratioing, intensity transformation, and low frequency filtering techniques. The three transformed bands from ratioing were 1/3, 2/3, and 3/2. The results of statistical divergence from SPOT bands 1, 2, and 3 by different transformations are given in Table 16. The highest number of >1500 and average transformed divergences were found with the low frequency filtering method. Ratioing and intensity transformations resulted in no significant difference from the no transformed method and even had lower average transformed divergences.

B. Histograms From No Transformed and Low Frequency Filtering Methods

The results of histograms from no transformed and low frequency filtering methods in the dormant season are illustrated in Figs. 17, 18, 19, 20, 21, and 22. All the histograms exhibited a normal distribution of digital number. The digital ranges were similar between no transformed and low frequency filtering. After low frequency filtering, the normal distribution of brightness was smoother in shape.

C. Digital Elevation Model (DEM) Data Merging

SPOT data with 20 m resolution were resampled to meet the 30 m resolution of the DEM data. The resampling error was about 0.5 pixels. Statistical divergence of 5 band combinations, which were derived from 3 SPOT multibands and 3 additional DEM "bands", are given in Table 17 and 18. The error

**Table 16. Results of statistical divergence
for SPOT band 1, 2, 3 combinations.**

Method	Transformed Divergence	
	No. (>1500)	Average(>1500)
No transformed	27	1655
Intensity	21	1552
Ratioing	23	1590
Filtering	31	1814

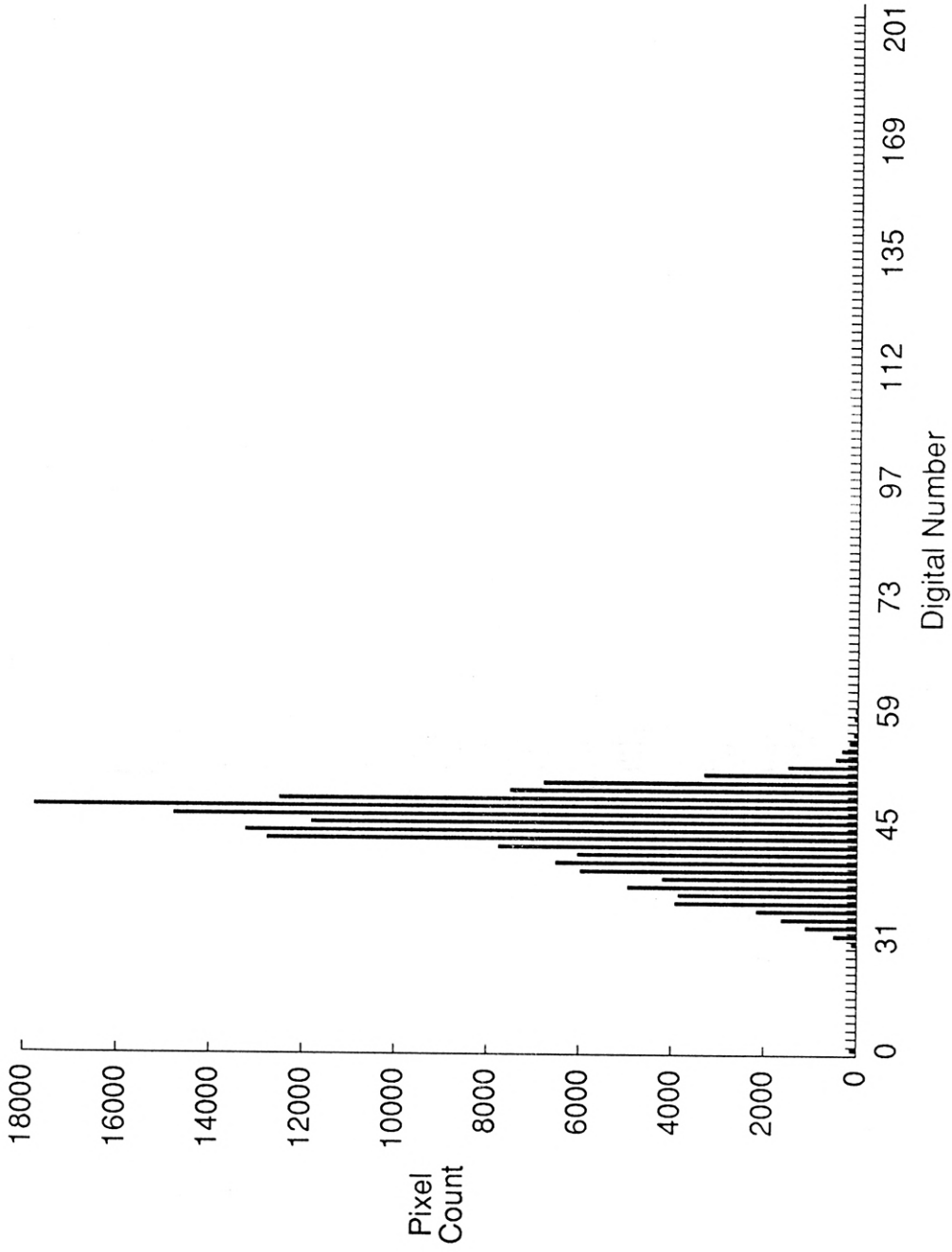


Fig. 17. Histogram of SPOT band 1.

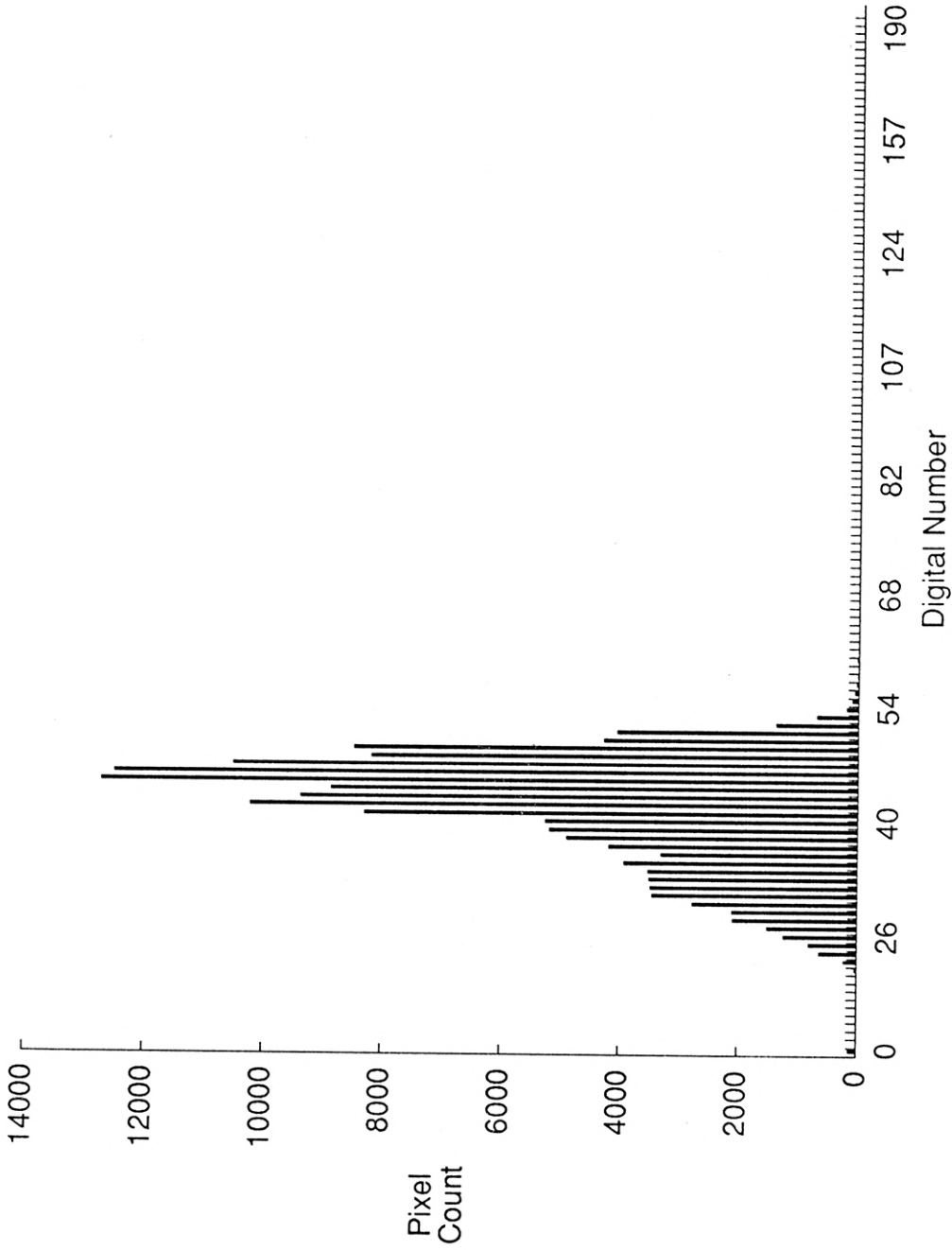


Fig. 18. Histogram of SPOT band 2.

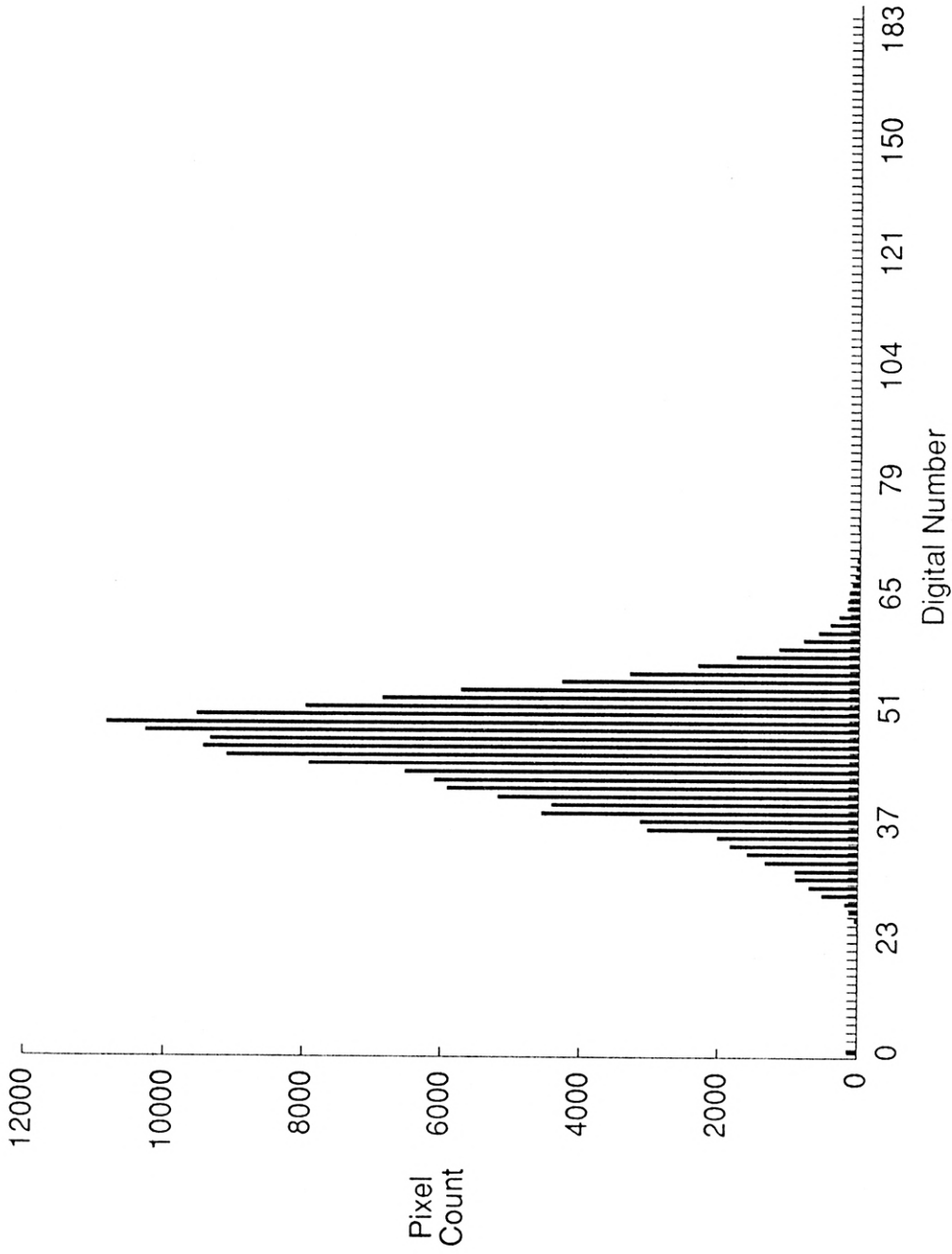


Fig. 19. Histogram of SPOT band 3.

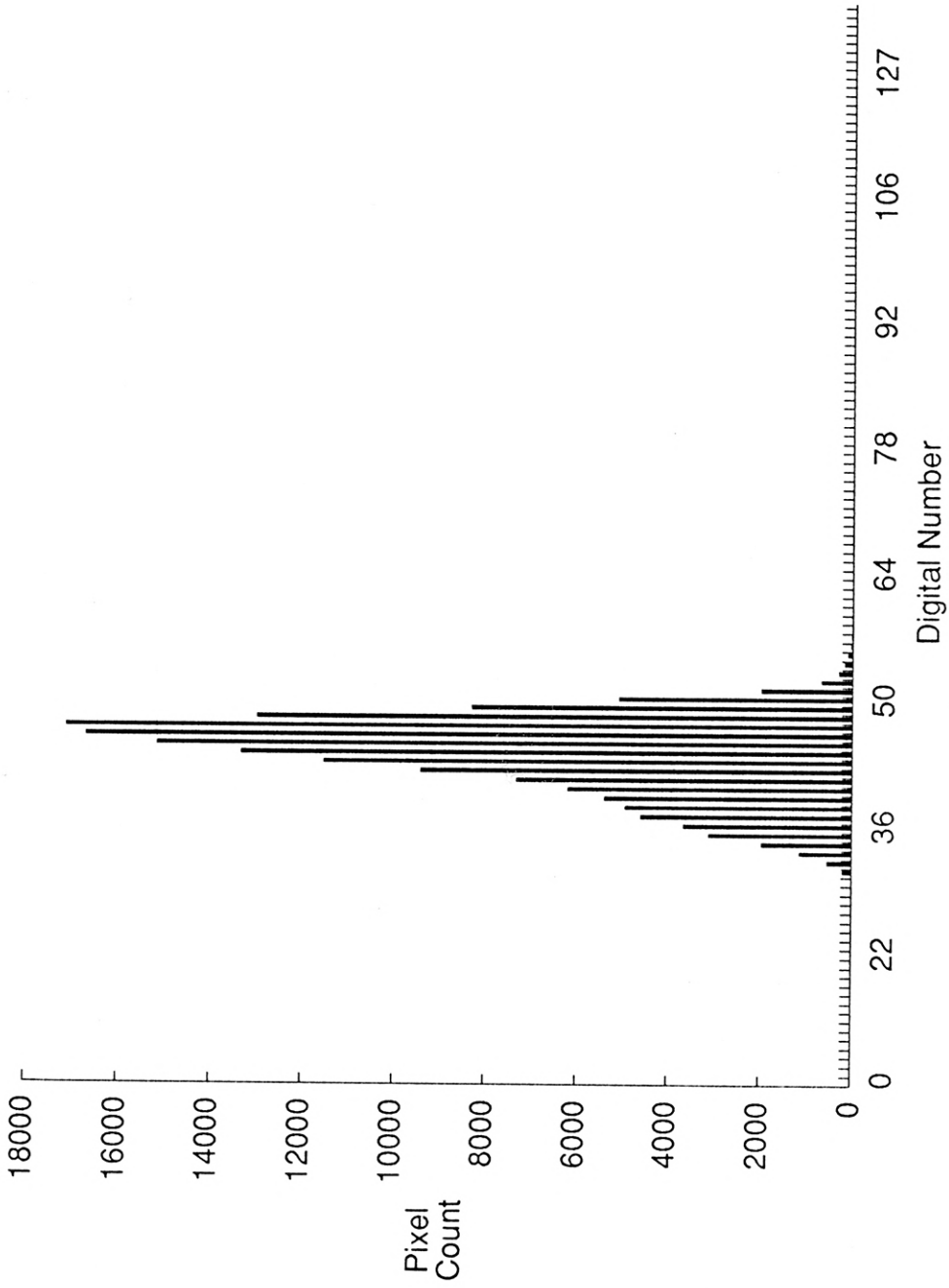


Fig. 20. Histogram of SPOT band 1 after low filtering was used.

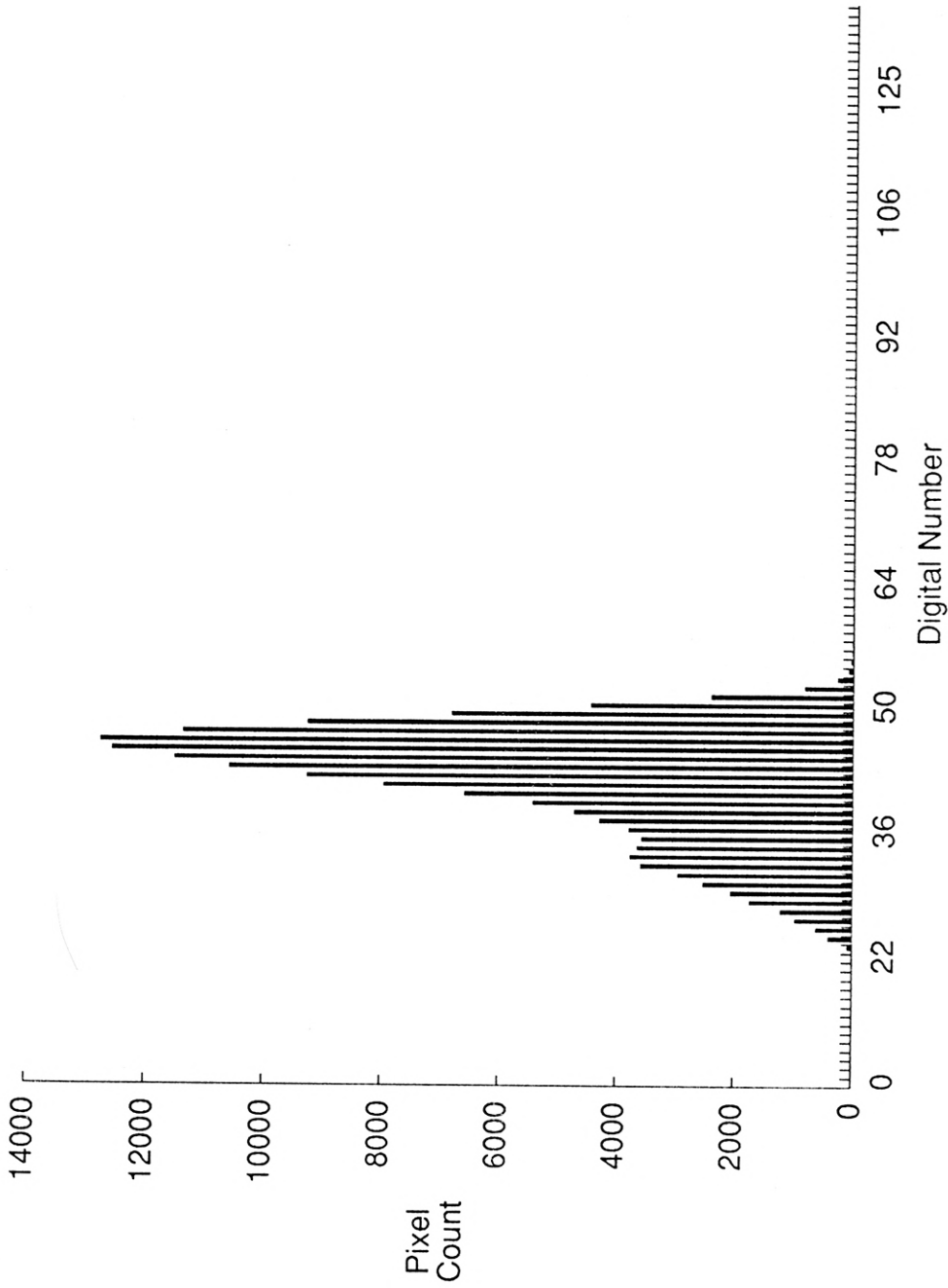


Fig. 21. Histogram of SPOT band 2 after low filtering was used.

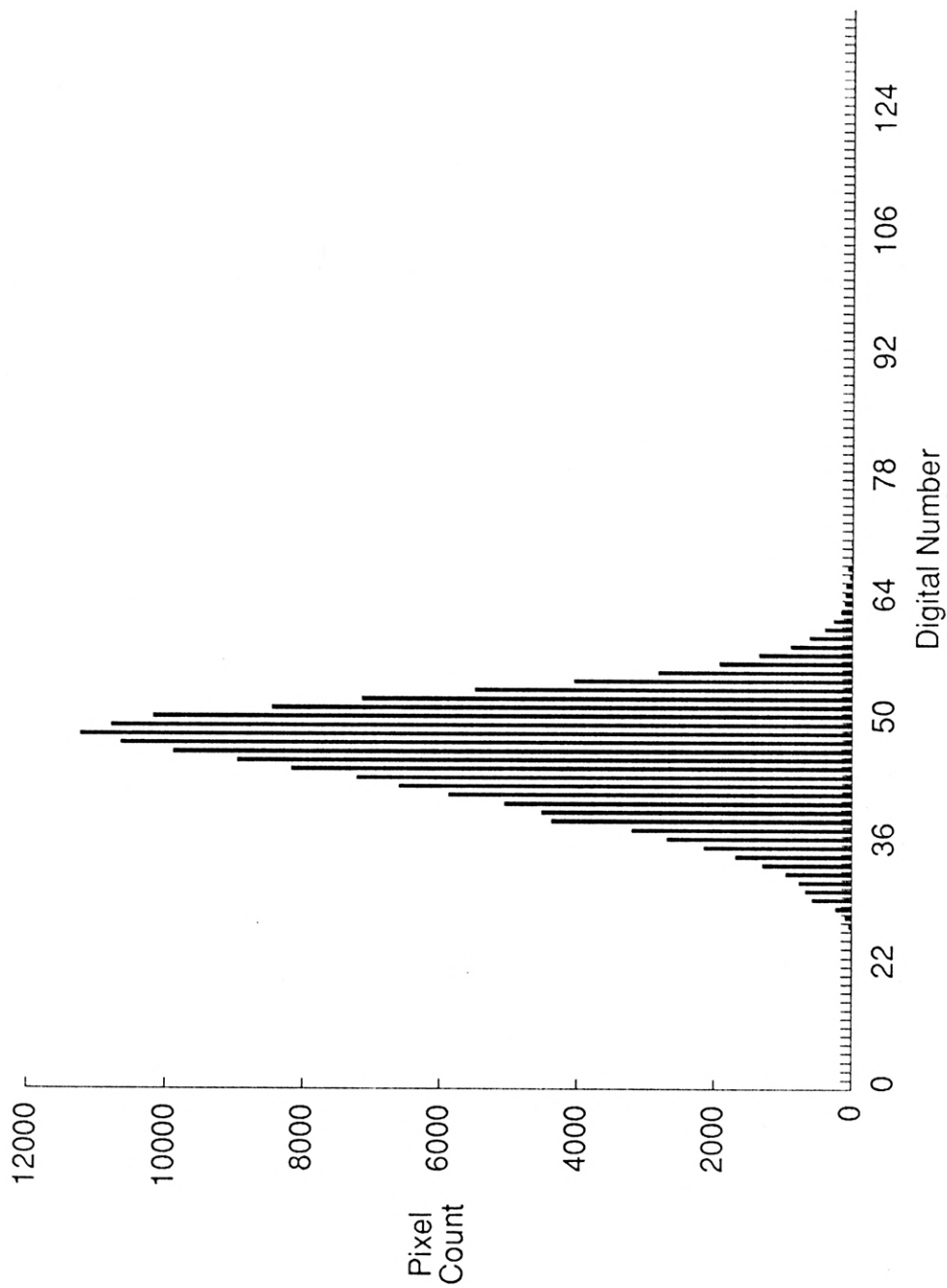


Fig. 22. Histogram of SPOT band 3 after low filtering was used.

Table 17. Statistical divergence for single band combination.

Combinations*	Transformed Divergence	
	No. (>1500)	Average
1	11	978
2	15	1034
3	8	903
A	2	424
E	27	1633
S	0	340

* E, S and A refer to digital elevation, slopes, and aspect data, respectively.

Table 18. Statistical divergence for 5 band combinations.

Combinations*	Transformed Divergence	
	No. (>1500)	Average
1,2,3,A,E	32	1871
1,2,3,A,S	25	1631
1,2,3,E,S	32	1877
1,2,A,E,S	32	1872
1,3,A,E,S	32	1869
2,3,A,E,S	32	1882

* E, S, and A refer to digital elevation, slopes, and aspect data, respectively.

matrix of DEM data merging is given in Table 19.

D. Overall Accuracy Assessment

The soil maps obtained from no transformed and transformed SPOT data were compared with the ground truth soil maps. Error matrices from the transformed data are given in Table 20, 21, 22, and 23. The highest average accuracy, 44.09%, was found from filtering transformation (Table 24). The similar tendency was also found from statistical divergence analysis (Table 16).

E. Differences Between dormant and Growing Seasons

The same procedures were used to process SPOT data, which were acquired on dormant season (March 20, 1987) and on growing season (June 26, 1987). A overall accuracy assessment was performed to compare the differences between dormant and growing seasons (Table 19 and 25). The accuracy from dormant season was higher than that from growing season.

**Table 19. Overall accuracy assessment
after DEM data were merged to SPOT multibands
in dormant season.**

True Classes	Interpreted Classes (pixel)					Total
	1	2	3	4	5	
1. Lo*	2421	1472	55	631	561	5140
2. St	355	1259	3	338	81	2036
3. Dr	16	60	270	62	719	1127
4. Cs	971	2869	244	4388	1372	9844
5. Bf	12	650	1129	1344	8548	11683
Total	3775	6310	1701	6763	11281	29830

Classes	Ommission Error(%)	Commission Error(%)	Accuracy(%)
1. Lo*	52.90	26.34	47.10
2. St	38.16	248.08	61.84
3. Dr	76.04	126.97	23.96
4. Cs	55.42	24.13	44.58
5. Bf	26.83	23.39	73.17
Average	49.87	89.78	50.13

* Lo includes all the soils in lowlands of the study area.
Overall accuracy = 56.61 %.

Table 20. Overall accuracy assessment of SPOT data.

True Classes	Interpreted Classes (pixel)					Total
	1	2	3	4	5	
1. Lo*	2228	974	192	555	1362	5311
2. Bf	1468	8626	2246	1223	1263	14826
3. Dr	354	737	494	25	47	1657
4. Cs	771	3557	341	2952	2378	9999
5. St	473	619	34	321	1296	2743
Total	5294	14513	3307	5076	6346	34560

Classes	Omission Error(%)	Commission Error(%)	Accuracy(%)
1. Lo*	58.05	57.73	41.95
2. Bf	41.82	39.71	58.18
3. Dr	70.19	169.76	29.81
4. Cs	70.48	21.24	29.52
5. St	52.75	184.10	47.25

* Lo includes all the soils in lowlands of the study area.

Table 21. Overall accuracy assessment of SPOT data after intensity transformation.

True Classes	Interpreted Classes (pixel)					Total
	1	2	3	4	5	
1. Lo*	1944	1020	360	580	1407	5311
2. Bf	635	9173	3209	1356	453	14826
3. Dr	164	771	674	35	13	1657
4. Cs	573	4153	669	3333	1271	9999
5. St	425	792	143	492	891	2743
Total	3741	15909	5055	5796	4035	34560

Classes	Ommission Error(%)	Commission Error(%)	Accuracy(%)
1. Lo*	63.40	33.84	36.60
2. Bf	38.13	45.43	61.87
3. Dr	59.32	264.39	40.68
4. Cs	66.67	24.63	33.33
5. St	67.52	114.62	32.48

* Lo includes all the soils in lowlands of the study area.

Table 22. Overall accuracy assessment of SPOT data after ratioing.

True Classes	Interpreted Classes (pixel)					Total
	1	2	3	4	5	
1. Lo*	2030	1002	447	469	1363	5311
2. Bf	601	8839	3925	1009	452	14826
3. Dr	132	690	793	25	17	1657
4. Cs	651	4455	809	2770	1314	9999
5. St	482	862	170	353	876	2743
Total	3896	15848	6144	4626	4022	34560

Classes	Omission Error(%)	Commission Error(%)	Accuracy(%)
1. Lo*	61.78	35.13	38.22
2. Bf	40.38	47.28	59.62
3. Dr	52.14	322.93	47.86
4. Cs	72.30	18.56	27.70
5. St	68.06	114.69	31.94

* Lo includes all the soils in lowlands of the study area.

Table 23. Overall accuracy assessment of SPOT data after low frequency filtering.

True Classes	Interpreted Classes (pixel)					Total
	1	2	3	4	5	
1. Lo*	2228	940	98	522	1523	5311
2. Bf	771	9366	1969	715	2005	14826
3. Dr	275	759	501	11	111	1657
4. Cs	536	3345	217	2636	3265	9999
5. St	377	516	7	232	1611	2743
Total	4187	14926	2792	4116	8515	34560

Classes	Omission Error(%)	Commission Error(%)	Accuracy(%)
1. Lo*	47.09	119.37	52.91
2. Bf	76.72	3.24	23.28
3. Dr	65.36	274.17	34.64
4. Cs	72.92	11.38	27.08
5. St	39.70	395.08	60.30

* Lo includes all the soils in lowlands of the study area.

**Table 24. Overall accuracy assessment
of supervised classification of SPOT data.**

Method	Accuracy(%)						
	Lo	Bf	Dr	Cs	St	Average	Overall
No transformed	41.95	58.18	29.81	29.52	47.25	41.34	45.13
Intensity	36.60	61.87	40.68	33.33	32.48	40.99	46.34
Ratioing	38.22	59.62	47.86	27.70	31.94	41.07	44.29
Filtering	41.95	63.17	30.24	26.36	58.73	44.09	47.29

**Table 25. Overall accuracy assessment
after DEM data were merged to SPOT multibands
in growing season.**

True Classes	Interpreted Classes (pixel)					Total
	1	2	3	4	5	
1. Lo*	1230	2849	192	667	202	5140
2. St	166	1512	37	312	9	2036
3. Dr	0	90	601	80	356	1127
4. Cs	218	4957	572	3936	161	9844
5. Bf	0	1439	3664	1587	4993	11683
Total	1614	10847	5066	6582	5721	29830

Classes	Omission Error(%)	Commission Error(%)	Accuracy(%)
1. Lo*	76.07	7.47	23.93
2. St	25.74	458.50	74.26
3. Dr	46.67	396.18	53.33
4. Cs	60.02	26.88	39.98
5. Bf	57.26	6.23	42.74
Average	53.15	179.05	46.85

* Lo includes all the soils in lowlands of the study area.

Overall accuracy = 41.14 %.

V. Discussion

A. Feature Selection From Landsat TM Data

The term feature was previously used in this thesis to refer to pattern measurements. In other words, feature can consist of a band in satellite data or an additional "band" in DEM data. The original measurements may contain excessive amounts of information which does not aid in the classification processing and may even hinder it. In order to select useful information for soil detection on this study, feature selection was used to extract useful soil information from Landsat TM and DEM data.

For the upland soil mapping units, the best separation among the training classes was obtained with Landsat TM band 5 (Fig. 3). Bands, 3, 4, and 7, also exhibited some separation, but bands 1 and 2 had very poor separation. Similar results were found by Thompson et al. (1984a). The reasons for the best separation of TM band 5 may be (1) the wide range of digital number in TM band 5 (Fig. 9) and (2) the sensitive spectral response of ground cover component (dried vegetation and soil) in TM band 5. However, soil properties, such as organic matter, mineralogy, could also be important to the separation among the soil mapping units. Results for the lowland mapping units were quite unstable (Fig. 4). Much variation of ground cover patterns for the lowland mapping units was identified during the training stage. For example, differing patterns of cropland and bare soils occurred in the stream valley. Consequently, the separation of soil mapping units was poor. However, the intent of this study was to concentrate on detecting soils information from upland positions, which are much more extensive than lowland positions in the study area.

The results from statistical divergence for the study area were similar to the graphic method. The highest average transformed divergence from the various band combinations was obtained with Landsat TM band 5. Bands 3 and 7 yielded higher average than those of bands 1, 2, and 3. For example, the average transformed divergence of three band combinations was $(5,E,A) > (7,E,A) > (3,E,A) > (2,E,A) > (1,E,A) > (4,E,A)$ (Table 8). Consequently, Landsat TM bands 3, 4, 5, and 7 were selected as the useful bands for supervised classification. By including three DEM "bands", at least 4 of 9 bands should be selected for band combinations.

B. Improvement of DEM Data Merging

From statistical divergence analysis, the digital elevation model (DEM) data were used as three additional "bands" that were merged to Landsat TM data using the same scale. A higher average transformed divergence was obtained when DEM data were combined with Landsat TM data, especially for the digital elevation data. The scattering plot of Fig. 14 shows a good separation of soil spectral classes of band 5 with DEM elevation, except for the Id and Cs classes. Consequently, Landsat TM data combined with DEM data were more efficient for soil interpretation than Landsat TM data used alone. This result agrees with the recent findings of Lee et al. (1987). They conducted an investigation in southwestern Wisconsin and found that the identification of soils was more accurate and efficient when TM and DEM data were combined.

Comparing slopes and aspects data from the DEM data merging, the lower relation tendency was found on the slopes, but better relation on the aspects. For example, the average transformed divergence of three band combinations was $(5,E,A) > (5,E,S)$ and $(7,E,A) > (7,E,S)$ (Table 8). The low tendency from

slopes may be influenced by the geomorphology of the terrain. The slopes of upland and lowland areas are not necessarily related to soils. For example, the Dwight-Irwin complex (Dr) in the upland area has the same slope (1 to 3 percent) as the Reading silt loam (Rd) mapping unit in the lowland area. Aspects data had a better relation with Landsat TM data, perhaps because of radiometric change in aspects. Landsat TM data had geometric correction in this study, but radiometric correction was not obtained.

DEM data merging was also used for SPOT data. A similar tendency of statistical divergence was obtained (Table 17 and 18). The most important DEM data found from the analysis was digital elevation data. Digital slopes and aspects were less significant for separating training class. The average divergences of slopes and aspects were 340 and 424, respectively (Table 17). For this study, only digital elevation and slopes of DEM data were selected as two merging "bands". The band combinations were digital elevation and slopes merging to three SPOT multibands.

C. The Improved Transformation in Supervised Classification

Maximum likelihood classification, an important supervised classification technique, was used for this study. However, the transformed satellite data for maximum likelihood classification may be better than original satellite data. Townshend (1980) reported that larger (coarse) spatial resolution for heterogeneous classes reduces scene variation and tends to increase classification accuracy. Recently, Haack et al. (1987) indicated that Landsat TM data have less separability than MSS data within heterogeneous cover types. These results suggest that the spatial filtering techniques may reduce the heterogeneous classes. In the study area, some subtle radiometric variation is partially

considered as noise. For smoothing this part of variation or noise, band ratioing, intensity transformation, and low filtering were used before supervised classification was conducted.

The statistical divergence resulting from these transformations indicated that the highest separability of soil mapping units was obtained with low frequency filtering (Table 16), which yielded the highest average accuracy, 44.09% (Table 24). The main reason of increasing separability and accuracy in filtering transformation was the reduction of spatial variation caused by the illumination of ground cover. In some cases, this low frequency filtering also reduced the noise for SPOT imagery. Unfortunately, a decrease in accuracy of mapping the Clime-Sogn complex (Cs) was observed because of useful data reduction. However, the average accuracy increased from 41.34% in no transformed to 44.09% in filtering. Reasons for the small percentage increase was the lack of sensitive transformation and/or the small area used for study. There was no increase in average accuracy from intensity and ratioing transformations, because the ratioing and intensity transformations are not sensitive to spatial variability.

Low frequency filtering had the highest overall accuracy, 47.29%. It increases about 2%, compared with the overall accuracy, 45.13%, of no transformation (Table 24). This result is similar to the average accuracy, but the very small differences were found from intensity transformation and ratioing. Based on this study, intensity transformation and ratioing may not necessarily improve the maximum likelihood classification. However, the increase of average accuracy and overall accuracy in low frequency filtering indicated that low frequency filtering can be used for maximum likelihood classification.

Table 26. Overall accuracy assessment in different seasons.

Sensor	Band	Overall Accuracy (%)		Increase (%)
		Dormant	Growing	
Landsat TM	4,5,A,E,S	54.57	48.68	5.89
	3,4,5,E,S	53.92	49.37	4.55
SPOT HRV	1,2,3,E,S	56.61	41.14	15.47

* E, S, and A refer to digital elevation, slopes, and aspects, respectively.

D. Satellite Data in The Dormant Season

The results of overall accuracy assessment of Landsat TM and SPOT data were obtained in dormant and growing seasons (Table 11, 12, 13, and 14). The overall accuracy derived from the dormant season data was increased about 4 - 6 % from Landsat TM data and about 15 % from SPOT data compared with the results obtained from imagery taken during the growing season (Table 26). These data indicate that the growing vegetation of this study area can mask the detection of soil information more serious ^{ly} than the ^{dead} died vegetation does. The variation of burned and unburned patterns in the image was significant in the growing season. However, the relationship between vegetation distribution and soil mapping units was not clearly shown on the spectral image data within the study area. Consequently, the satellite data acquired in dormant season of the prairie were more useful than that obtained in the growing season.

E. Relationship Between Conventional Soil Surveys and Resultant Soil Maps

For the purpose of comparing the conventional soil maps to the resultant soil map, Id, Ic, Tu, and Tv delineations were combined with Cs. Delineations of Id, Ic, Tu, and Tv were too small to reliably separate from Cs for the purpose of this investigation. All soil mapping units in lowland areas were grouped as a single complex (Lo). Consequently, only five soil mapping units were used on the resultant soil maps from satellite data. The soil maps derived from Landsat TM and SPOT data are given in Figs. 23 and 25. The visual interpreted soil maps are given in Figs. 24 and 26. The mapping unit, St was over-interpreted. The commission errors of St from Landsat TM and SPOT data were 209.68 % and 248.08 %, respectively (Table 14 and 19). If the mapping

unit St in the resultant soil maps (Figs. 23 and 25) is compared to St in the conventional soil map (Fig. 27), the most overinterpreted area of St in the resultant soil maps was designated Lo complex in conventional soil map. The similar image patterns of Lo and St were observed during data training stage. Brush and trees in many areas of St can also be observed in Lo areas. The mask of brush and trees is the most important reason for overinterpreting St in resultant soil maps. A very low accuracy was found for mapping unit Dr (Table 14 and 19) because delineations of Dr mapping unit are very small in the conventional soil survey.

The overall accuracy from SPOT data was not significantly different from Landsat TM data in spite of the higher resolution of the SPOT imagery. The overall accuracy with the same band combinations (TM 2, 3, and 4; SPOT 1, 2, and 3) was about 57 % from SPOT data and about 53 % from Landsat TM data (Table 15 and 19). The reasons for the small difference of accuracy are (1) SPOT data were resampled from 20 m to 30 m resolution, which could cause the soil information from the original SPOT data to be reduced and (2) different time of TM and SPOT data was used, which could cause some soil information to be affected by environmental conditions. However, the small difference of overall accuracy between resultant soil maps from TM and SPOT data could be caused by the different spectral resolution between TM and SPOT data. Consequently, SPOT data could be more useful than TM data for detailed soil information detection at the similar wavelength range.

The lower accuracy from the resultant soil maps was evaluated in overall accuracy, but the resultant soil maps still have potential for providing very useful soil information for field soil scientists, especially for delineating soil

boundaries in rangeland areas. On other hand, the conventional soil maps are known to contain inclusions of other soils (Jantz et al., 1975). For a soil complex, up to 25% of dissimilar soils may exist and also part of the remainder 75 % of the soil complex may include inclusions of similar soils. Hence, the total accuracy could be essentially as low as 60% or more. The overall accuracy from Landsat TM and SPOT data was about 55 - 57 %. Comparing the overall accuracy of the resultant maps to a conventional soil survey, there is not enough evidence to reject the resultant soil maps from Landsat TM and SPOT data. Consequently, the use of Landsat TM and SPOT data for making second order soil surveys should considered, especially for rangeland.

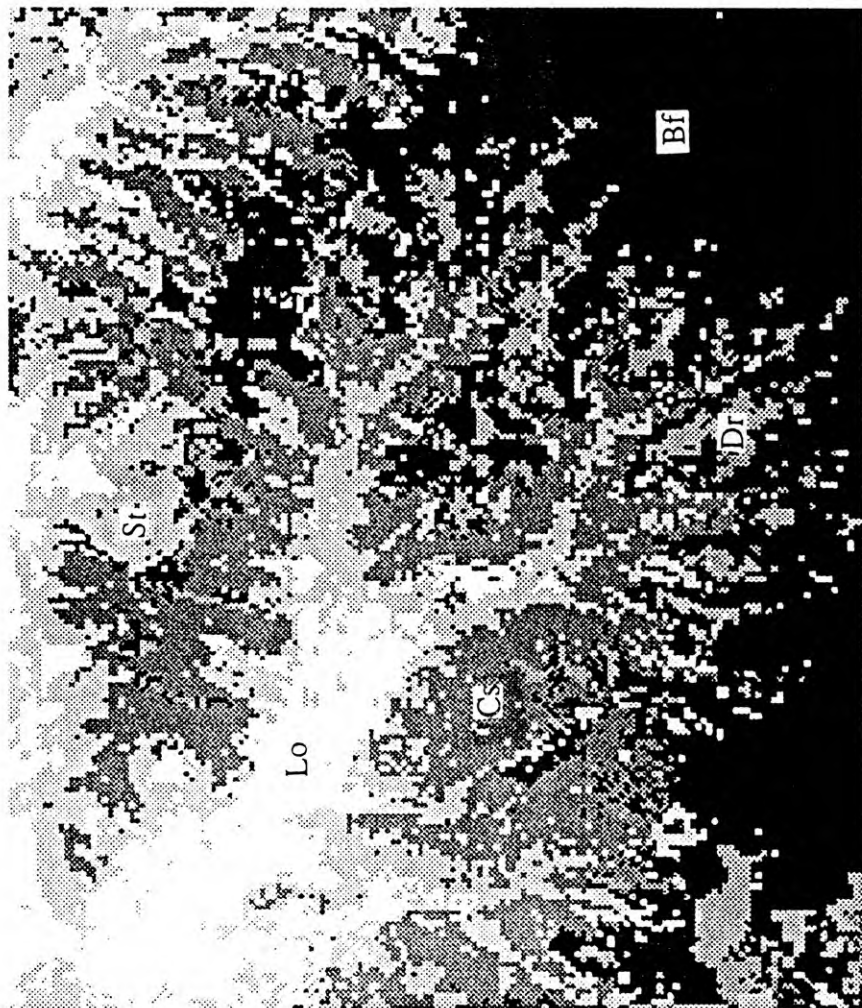


Fig. 23. Resultant soil map from Landsat TM data.

Print scale is 1:39 994.

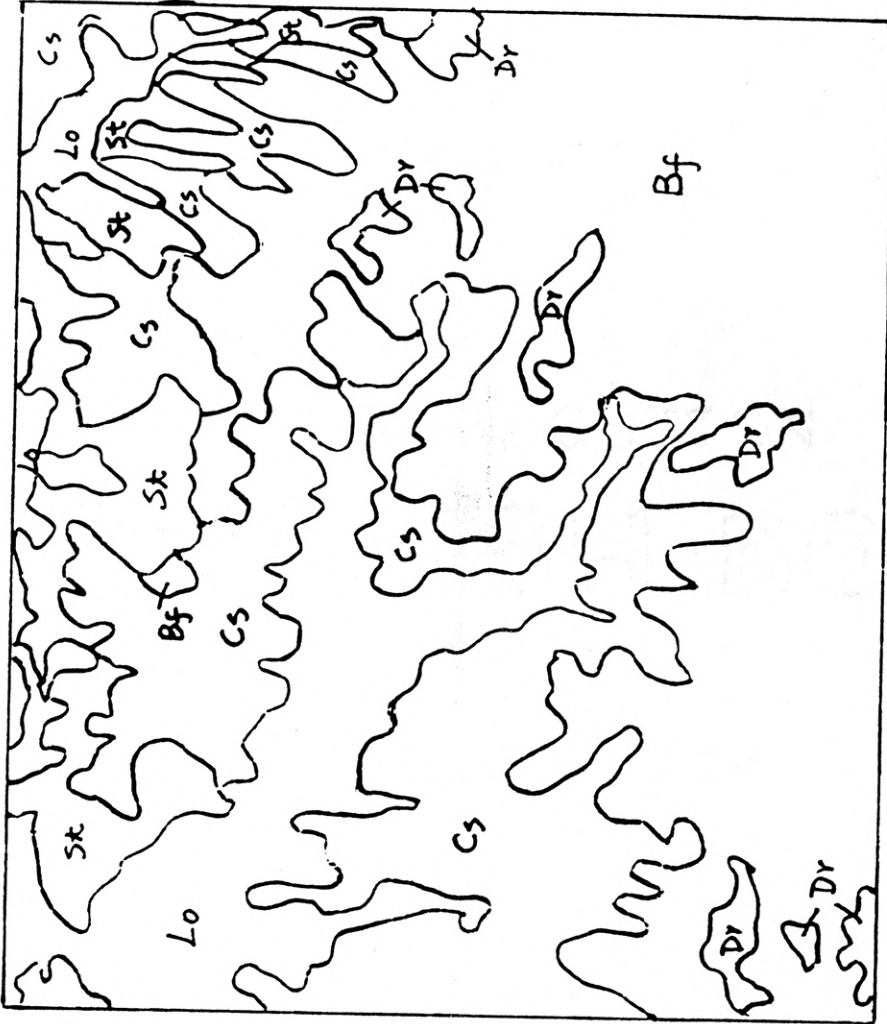


Fig. 24. Visual interpreted resultant soil map from Landsat TM
Print scale is 1:39 994.

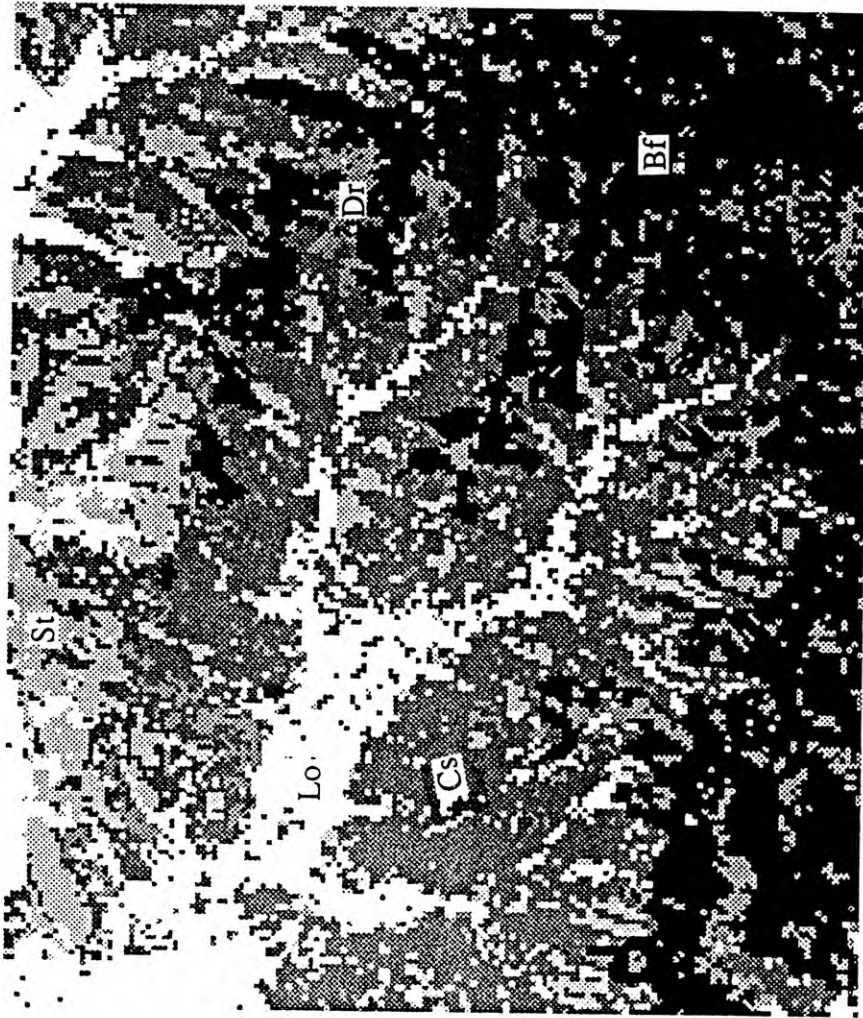


Fig. 25. Resultant soil map from SPOT data.

Print scale is 1:39 994.

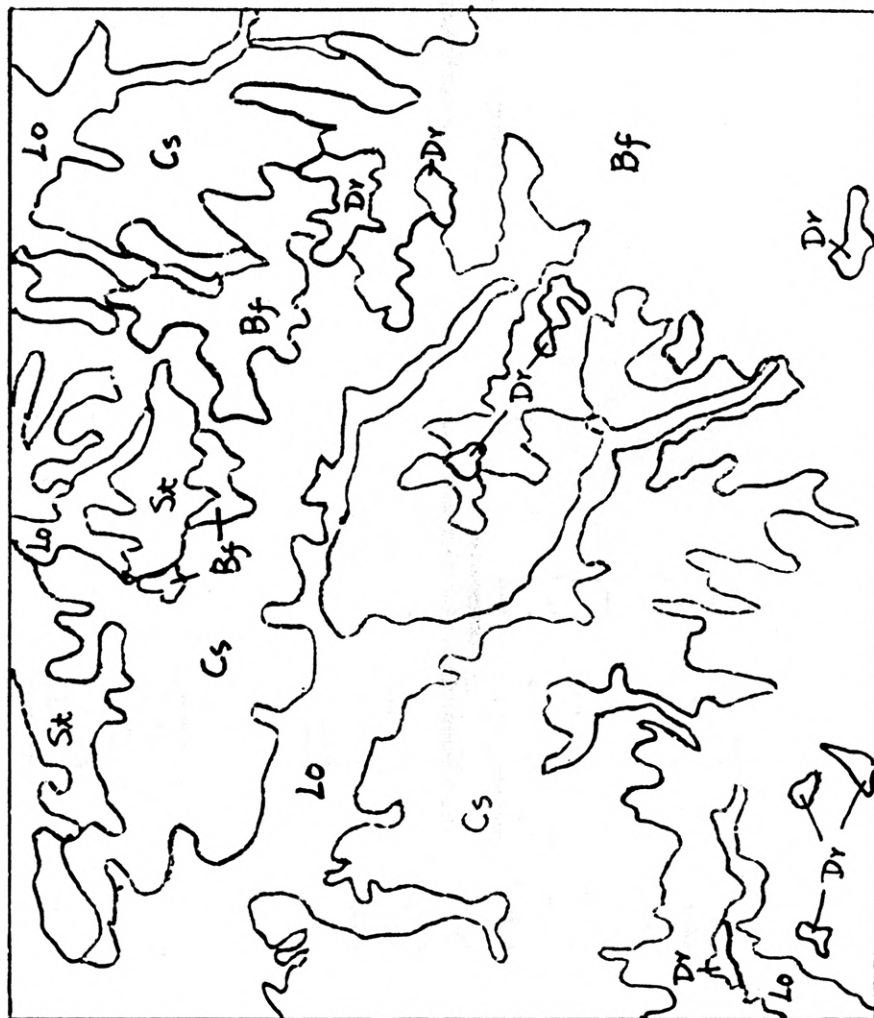


Fig. 26. Visual interpreted resultant soil map from SPOT

Print scale is 1:39 994.

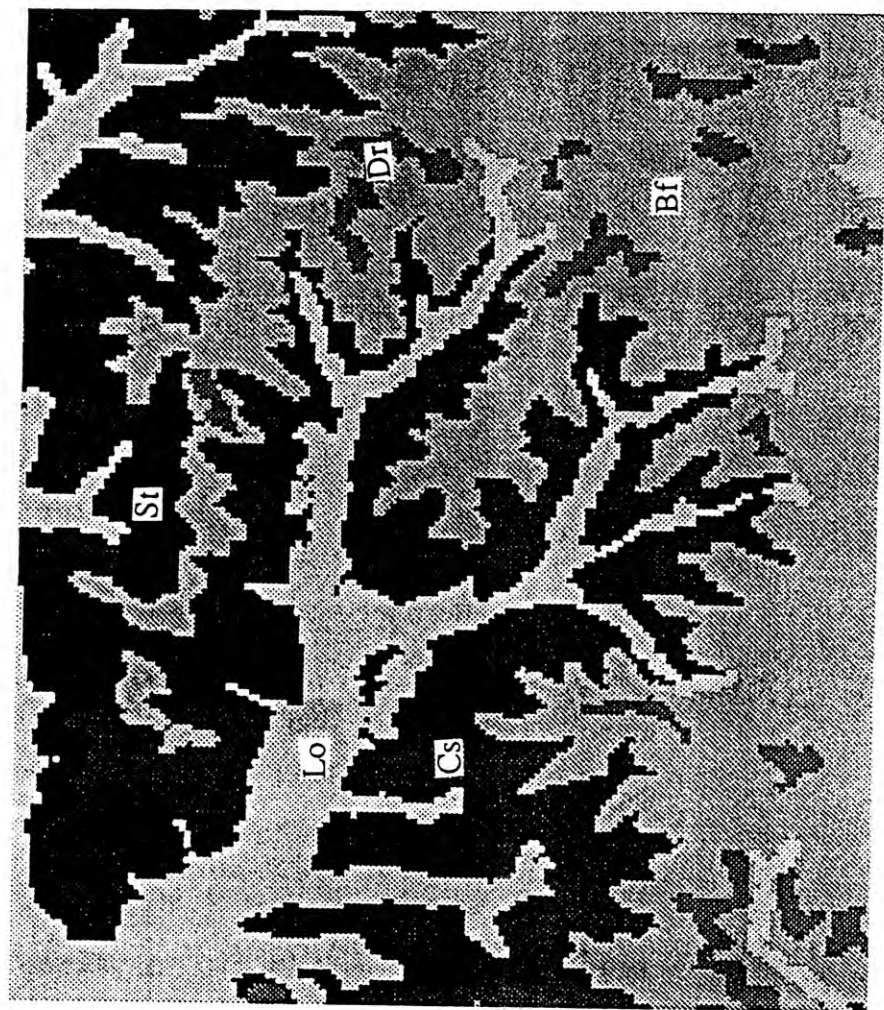


Fig. 27. Soil map of the study area. Lo is lowland complex.

Print scale is 1:39 994.

VI. Conclusions

For Landsat TM data, band 5 was most useful for soil information extraction on the upland areas of the Konza Prairie. Although the separation was not as good, TM bands 3 and 7 also provided useful soil information.

Landsat TM and SPOT data with Digital Elevation Model (DEM) data merging were highly related to soil information extraction. A better separation of soil mapping units was obtained in upland areas of the Konza prairie using statistical divergence analysis. The elevation data were most useful in DEM data merging. This suggests that the topography of the study area is related to soil development. However, elevation differences are difficult to detect from Landsat TM and SPOT data in detail unless DEM data are merged.

The separability and accuracy of soil mapping units from SPOT multiband data were improved after low frequency filtering by using supervised classification, but ratioing and intensity transformations did not result in a significant improvement in accuracy in this study. Consequently, low frequency filtering can be used to improve soil information extraction in supervised classification techniques. About 44% of average accuracy was obtained by low frequency filtering. DEM data merging was also performed for SPOT data. The overall accuracy (about 57 %) from SPOT data was not significantly different from Landsat TM data (about 55 %).

A better overall accuracy of Landsat TM data was found in the dormant season, since growing vegetation in the study area tended to mask soil information. Consequently, satellite data acquired in the dormant season may be more

useful for making detailed soil surveys of rangelands.

Compared with the conventional soil maps, the overall accuracy of Landsat TM and SPOT data were about 55 - 57 %. This result suggests that Landsat TM and SPOT data can be used to aid second order soil surveys where the dominant land use is rangeland.

VII. References

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Appendix A.
Maximum Likelihood Classification Program.

(* This is a maximum likelihood classifier program.
The program is to read mean data and covariance matrix
data of each class and to read image files (2-6, integer),
then to calculate the probability of each pixel on each
channel to classify the pixel to the class which has
maximum probability. The classes will be written to the
output file.
*)

```
program maxlike(input, output, file1, file2, file3, file4, file5, file6, file7);  
type
```

```
  str = packed array [1..20] of char;  
  files = array [1..6] of str;  
  line = array [1..6] of real;  
  linecl = array [1..30] of real;  
  matrix = array [1..6, 1..6] of real;  
  numvar = array [1..30] of matrix;  
  nummean = array [1..30] of line;
```

```
var
```

```
  imageout: integer;  
  covar: numvar;  
  Mean: nummean;  
  X: line;  
  class, channel, i, t, z: integer;  
  infile: files;  
  varfile, meanfile, outfile: str;  
  file1, file2, file3, file4, file5, file6, file7: text;
```

```
(***** call for file name *****)
```

```
#include 'usr/gold/usr2/iis/Hsulib/filename.h'
```

```
(*****)
```

```
  procedure getmean(var filexm: text; var meandata: nummean;  
    classlimit, channellimit: integer);
```

```
  var
```

```
    k, l: integer;
```

```
  begin
```

```
    for k := 1 to classlimit do begin
```

```
      for l := 1 to channellimit do begin
```

```
        read(filexm, meandata[k, l])
```

```
      end;
```

```
      readln(filexm)
```

```
    end
```

```
  end; { getmean }
```

```
(*****)
```

```
  procedure getcovar(var filexv: text;
```

```
    var covardata: numvar; classlimit, channellimit: integer);
```

```
  var
```

```
    k, l, s: integer;
```

```
  begin
```

```
    for k := 1 to classlimit do begin
```

```
    for l := 1 to channellimit do begin
        for s := 1 to channellimit do begin
            read(filexv, covardata[k, l, s])
        end;
        readln(filexv)
    end
end
end; { getcovar }
(***** call for determinant of n x n matrix ***)
#include 'usr/gold/usr2/iis/Hsulib/minvdet.h'
(*****)

procedure calculate(var datavar: numvar;
var datam: nummean; var dataX: line; var dataout: integer;
classlimit, channellimit: integer);
var
    k, l, s: integer;
    temp, M: line;
    p: linecl;
    pix, det: real;
    cvi, varx: matrix;
    max: real;
begin
    k := 1;
    max := -400000.0;
    while k <= classlimit do begin
        for l := 1 to channellimit do
            for s := 1 to channellimit do
                varx[l, s] := datavar[k, l, s];
            end;
        end;
        for l := 1 to channellimit do
            M[l] := datam[k, l];
        end;
        minvdet(varx, cvi, channellimit, det);
        pix := 0;
        l := 1;
        while l <= channellimit do begin
            temp[l] := 0;
            s := 1;
            while s <= channellimit do begin
                temp[l] := temp[l] + (dataX[s] - M[s]) * cvi[s, l];
                s := s + 1
            end;
            pix := pix + temp[l] * (dataX[l] - M[l]);
            l := l + 1
        end;
        p[k] := -0.5 * ln(det) - 0.5 * pix;
        if p[k] >= max then
            max := p[k];
        k := k + 1
    end;
    for k := 1 to class do begin
        if abs(p[k] - max) < 0.0000000001 then
```

```
        dataout := k
    end
end; { calculate }
(*****)

begin (*main*)
    writeln(' Input number of channels(2-6):');
    readln(channel);
    writeln(' Input number of classes(1-30):');
    readln(class);
    for i := 1 to channel do begin
        writeln('Input channel"s file', i: 2, ':');
        filename(infile[i])
    end;
    writeln('Input mean file:');
    filename(meanfile);
    reset(file1, meanfile);
    getmean(file1, Mean, class, channel);
    writeln('Input covar file:');
    filename(varfile);
    reset(file1, varfile);
    getcovar(file1, covar, class, channel);
    writeln('Output class file:');
    filename(outfile);
    case channel of
        2:
            begin
                writeln('Please wait .....');
                reset(file1, infile[1]);
                reset(file2, infile[2]);
                rewrite(file7, outfile);
                t := 1;
                while not (eof(file1) and eof(file2)) do begin
                    z := 1;
                    while not (eoln(file1) and eoln(file2)) do begin
                        read(file1, X[1]);
                        read(file2, X[2]);
                        calculate(covar, Mean, X, imageout, class, channel);
                        write(file7, imageout: 3);
                        z := z + 1
                    end;
                    readln(file1);
                    readln(file2);
                    writeln(file7);
                    t := t + 1
                end
            end;
        3:
            begin
                writeln('Please wait .....');
                reset(file1, infile[1]);
```

```
reset(file2, infile[2]);
reset(file3, infile[3]);
rewrite(file7, outfile);
t := 1;
while not (eof(file1) and eof(file2) and eof(file3)) do begin
    z := 1;
    while not (eoln(file1) and eoln(file2) and eoln(file3)) do begin
        read(file1, X[1]);
        read(file2, X[2]);
        read(file3, X[3]);
        calculate(covar, Mean, X, imageout, class, channel);
        write(file7, imageout: 3);
        z := z + 1
    end;
    readln(file1);
    readln(file2);
    readln(file3);
    writeln(file7);
    t := t + 1
end
end;
4:
begin
    writeln('Please wait .....');
    reset(file1, infile[1]);
    reset(file2, infile[2]);
    reset(file3, infile[3]);
    reset(file4, infile[4]);
    rewrite(file7, outfile);
    t := 1;
    while not (eof(file1) and eof(file2) and
eof(file3) and eof(file4)) do begin
        z := 1;
        while not (eoln(file1) and eoln(file2) and
eoln(file3) and eoln(file4)) do begin
            read(file1, X[1]);
            read(file2, X[2]);
            read(file3, X[3]);
            read(file4, X[4]);
            calculate(covar, Mean, X, imageout, class, channel);
            write(file7, imageout: 3);
            z := z + 1
        end;
        readln(file1);
        readln(file2);
        readln(file3);
        readln(file4);
        writeln(file7);
        t := t + 1
    end
end
end;
```

5:

```
begin
  writeln('Please wait .....');
  reset(file1, infile[1]);
  reset(file2, infile[2]);
  reset(file3, infile[3]);
  reset(file4, infile[4]);
  reset(file5, infile[5]);
  rewrite(file7, outfile);
  t := 1;
  while not (eof(file1) and eof(file2) and
eof(file3) and eof(file4) and
eof(file5)) do begin
    z := 1;
    while not (eoln(file1) and eoln(file2)
and eoln(file3) and eoln(file4) and
eoln(file5)) do begin
      read(file1, X[1]);
      read(file2, X[2]);
      read(file3, X[3]);
      read(file4, X[4]);
      read(file5, X[5]);
      calculate(covar, Mean, X, imageout, class, channel);
      write(file7, imageout: 3);
      z := z + 1
    end;
    readln(file1);
    readln(file2);
    readln(file3);
    readln(file4);
    readln(file5);
    writeln(file7);
    t := t + 1
  end
end;
```

6:

```
begin
  writeln('Please wait .....');
  reset(file1, infile[1]);
  reset(file2, infile[2]);
  reset(file3, infile[3]);
  reset(file4, infile[4]);
  reset(file5, infile[5]);
  reset(file6, infile[6]);
  rewrite(file7, outfile);
  t := 1;
  while not (eof(file1) and eof(file2) and
eof(file3) and eof(file4) and eof(file5)
and eof(file6)) do begin
    z := 1;
    while not (eoln(file1) and eoln(file2) and
```

```
eoln(file3) and eoln(file4) and
eoln(file5) and eoln(file6)) do begin
  read(file1, X[1]);
  read(file2, X[2]);
  read(file3, X[3]);
  read(file4, X[4]);
  read(file5, X[5]);
  read(file6, X[6]);
  calculate(covar, Mean, X, imageout, class, channel);
  write(file7, imageout: 3);
  z := z + 1
end;
readln(file1);
readln(file2);
readln(file3);
readln(file4);
readln(file5);
readln(file6);
writeln(file7);
t := t + 1
end
end
end
end. { maxlike }
```

Appendix B.
Statistical Analysis for Five Training Classes.

Table 27. Statistical analysis for soil mapping unit-Bf.

Univariate Statistics						
Band	1	2	3	4	5	7
Mean	57.28	19.91	25.25	28.26	71.99	32.28
Std.Dev.	1.92	0.96	1.53	1.98	6.53	5.98
Variance	3.69	0.91	2.33	3.91	42.69	35.82
Min.	52	17	21	21	48	20
Max.	62	23	30	34	94	64

Variance-Covariance Matrix						
Band	1	2	3	4	5	7
1	3.69					
2	0.84	0.91				
3	1.35	0.81	2.33			
4	1.28	1.03	2.16	3.91		
5	5.63	3.23	6.99	8.62	42.69	
7	3.75	2.16	4.48	5.19	26.26	35.82

Correlation Matrix						
Band	1	2	3	4	5	7
1	1.00					
2	0.46	1.00				
3	0.46	0.56	1.00			
4	0.34	0.54	0.72	1.00		
5	0.45	0.52	0.70	0.67	1.00	
7	0.33	0.38	0.49	0.44	0.67	1.00

Table 28. Statistical analysis for soil mapping unit-St.

Univariate Statistics						
Band	1	2	3	4	5	7
Mean	52.95	16.89	19.02	22.52	45.44	20.09
Std.Dev.	2.58	1.27	2.22	4.69	9.58	4.41
Variance	6.64	1.62	4.93	21.95	91.86	19.44
Min.	47	13	13	14	24	9
Max.	60	21	25	64	66	32

Variance-Covariance Matrix						
Band	1	2	3	4	5	7
1	6.64					
2	1.67	1.62				
3	4.05	1.96	4.93			
4	5.78	3.21	6.53	21.95		
5	14.99	7.43	15.57	27.82	91.86	
7	5.87	2.74	5.87	9.04	27.04	19.44

Correlation Matrix						
Band	1	2	3	4	5	7
1	1.00					
2	0.51	1.00				
3	0.71	0.69	1.00			
4	0.48	0.54	0.63	1.00		
5	0.61	0.61	0.73	0.62	1.00	
7	0.52	0.49	0.60	0.44	0.64	1.00

Table 29. Statistical analysis for soil mapping unit-Cs.

Univariate Statistics						
Band	1	2	3	4	5	7
Mean	57.21	19.53	23.60	25.88	60.59	26.78
Std.Dev.	2.06	1.09	1.80	2.16	6.20	3.38
Variance	4.23	1.20	3.25	4.66	38.39	11.45
Min.	50	16	18	21	45	19
Max.	62	22	28	39	73	34

Variance-Covariance Matrix						
Band	1	2	3	4	5	7
1	4.23					
2	1.27	1.20				
3	2.19	1.37	3.25			
4	1.45	1.15	1.69	4.66		
5	7.34	4.69	9.40	6.56	38.39	
7	3.85	2.42	4.88	2.63	19.37	11.45

Correlation Matrix						
Band	1	2	3	4	5	7
1	1.00					
2	0.56	1.00				
3	0.59	0.70	1.00			
4	0.33	0.49	0.43	1.00		
5	0.58	0.69	0.84	0.49	1.00	
7	0.55	0.65	0.80	0.36	0.92	1.00

Table 30. Statistical analysis for soil mapping unit-Lo.

Univariate Statistics						
Band	1	2	3	4	5	7
Mean	53.58	17.30	19.71	24.24	46.04	19.99
Std.Dev.	2.03	1.08	1.79	3.28	7.56	3.01
Variance	4.11	1.18	3.21	10.76	57.11	9.07
Min.	48	15	16	18	29	13
Max.	58	21	24	32	64	26

Variance-Covariance Matrix						
Band	1	2	3	4	5	7
1	4.11					
2	0.92	1.18				
3	1.98	1.21	3.21			
4	3.15	1.90	4.44	10.76		
5	6.21	4.34	8.66	19.03	57.11	
7	3.08	1.90	4.24	7.92	18.87	9.07

Correlation Matrix						
Band	1	2	3	4	5	7
1	1.00					
2	0.42	1.00				
3	0.54	0.62	1.00			
4	0.47	0.53	0.76	1.00		
5	0.41	0.53	0.64	0.77	1.00	
7	0.50	0.58	0.79	0.80	0.83	1.00

Table 31. Statistical analysis for soil mapping unit-Dr.

Univariate Statistics						
Band	1	2	3	4	5	7
Mean	60.21	21.76	27.83	34.31	84.10	41.19
Std.Dev.	3.31	1.49	2.71	8.84	9.01	10.32
Variance	10.95	2.23	7.36	78.17	81.11	106.40
Min.	52	18	21	25	62	26
Max.	68	25	33	64	101	64

Variance-Covariance Matrix						
Band	1	2	3	4	5	7
1	10.95					
2	4.13	2.23				
3	7.94	3.64	7.36			
4	15.64	7.98	11.93	78.17		
5	20.66	10.58	19.77	47.51	81.11	
7	10.42	4.73	9.15	15.01	28.27	106.40

Correlation Matrix						
Band	1	2	3	4	5	7
1	1.00					
2	0.83	1.00				
3	0.88	0.90	1.00			
4	0.53	0.60	0.50	1.00		
5	0.69	0.79	0.81	0.60	1.00	
7	0.31	0.31	0.33	0.16	0.30	1.00

Appendix C.
Pedon Descriptions and Characterization Data.

NARRATIVE PEDON DESCRIPTION

Pedon: Clime taxajunct

NSSL Pedon Number: 87P0448

Soil Survey Number: S87-KS-161-001

Location: 400 ft. east and 600 ft. south of the northwest corner of section 19. T. 11 S. R.

8 E. Riley Co., KS.

Physiography: Upland slope in level or undulating uplands

Geomorphic Position: backslope sideslope

Slope: 10% plan east facing

Drainage: Well drained

Land Use: Rangeland not grazed

Runoff: Very rapid

Parent Material:

Colluvium from limestone-cherty material over residuum from limestone-shale material.

Classification: Fine, mixed, mesic Udorthentic Haplustoll

Described by: F. Minzenmayer and Haiping Su

Sample Date: 05/87

A1 -- 0 to 15 cm; very dark gray(10YR 3/1) cherty silty clay loam; black (10YR 2/1), moist; strong medium granular structure; firm; many fine discontinuous tubular roots and opal crystals; 15 percent pebbles sedimentary rocks; clear wavy boundary.

A2 -- 15 to 41 cm; dark grayish brown(10YR 4/2) very cherty silty clay loam; very dark grayish brown (10YR 3/2), moist; moderate medium granular structure; firm; many fine discontinuous tubular roots; 60 percent pebbles sedimentary rocks; clear wavy boundary.

Bt1 -- 41 to 62 cm; brown (7.5YR 5/4) very cherty silty clay; brown to dark brown (7.5YR 4/4), moist; moderate fine subangular blocky structure; firm; common fine roots; continuous distinct dark brown (7.5YR 3/2) clay films on vertical and horizontal faces of peds; 50 percent pebbles sedimentary rocks; gradual wavy boundary.

2Bt2 -- 62 to 78 cm; light yellowish brown (10YR 6/4) silty clay loam; yellowish brown (10YR 5/4), moist; moderate fine subangular blocky structure; firm; few fine roots; patchy distinct dark brown (7.5YR 3/2) clay films on vertical and horizontal faces of peds; common medium soft masses of carbonate; strongly effervescent continuous; 5 percent pebbles shale; gradual wavy boundary.

2BC -- 78 to 100 cm; light yellowish brown (2.5YR 6/4) shaly silty clay loam; light olive brown (2.5YR 5/4), moist; massive; firm; few fine roots; many coarse soft masses of carbonate; violently effervescent continuous; 30 percent pebbles shale; gradual wavy boundary.

2C -- 100 to 120 cm; light yellowish brown (2.5YR 6/4) very shaly silty clay loam; light olive brown (2.5YR 6/4), moist; massive; firm; many coarse soft masses of carbonate and few coarse carbonate concretions; violently effervescent continuous; 75 percent pebbles shale.

Table 32. Characterization data for Clime taxajunct*.

S87KS-161-001 (RILEY COUNTY, KANSAS)
 SAMPLED AS : CLIME TAX.; FINE, MIXED MESIC UDORTHENTIC HAPLUSTOLL
 NSSL - PROJECT 87P 102, RILEY CO.
 - PEDON 87P 448, SAMPLES 87P2327-2333
 - GENERAL METHODS 1B1A, 2A1, 2B

DEPTH (CM)	HORIZON	TOTAL			ORGANIC C 6A1C					
		CLAY < .002	SILT .002 - .05	SAND .05 - 2						
		PERCENT of <2MM(3A1)				PERCENT				
0- 15	A1	46.7	45.9	7.4	4.82					
15- 41	A2	59.4	32.7	7.9	2.50					
41- 62	Bt1	65.9	30.8	3.3	1.52					
62- 78	2Bt2	33.4	59.3	7.3	0.73					
78-100	2BC	26.1	63.1	10.8	0.47					
100-120	2C	26.1	63.1	10.8	0.27					
120-160	2Cr	28.9	66.6	4.5	0.12					
DEPTH (CM)	NH ₄ OAC EXTRACTABLE BASES					ACIDITY	CEC	BASE SAT.		CO ₃ AS CaCO ₃ <2mm 6E1G
	Ca 5B5A 6N2E	Mg 5B5A 6O2D	Na 5B5A 6P2B	K 5B5A 6Q2B	SUM BASES		SUM CATS 5A3A	SUM 5C3	NH ₄ OAC 5C1	
	MEQ/100G					6H5A		PERCENT		
0- 15	32.6	4.0	TR	1.3	37.9	10.6	48.5	78	91	25 27 16
15- 41	34.3	4.0	0.1	0.8	39.2	10.9	50.1	78	87	
41- 62	45.7	2.6	0.1	0.7	49.1	8.4	57.5	85	100	
62- 78		1.0	TR	0.2					22	
78- 100		1.0	TR	0.1						
100-120		1.0	0.1	0.1						
120-160		1.6	0.1	0.2						

*Analyses conducted by National Soil Survey Laboratory, USDA-SCS, Lincoln, Nebraska 68508. Method codes refer to methods described by Soil Conservation Service (1982).

NARRATIVE PEDON DESCRIPTION

Pedon: Dwight

NSSL Pedon Number: 87P0450

Soil Survey Number: S87-KS-161-003

Location: 2200 ft. south and 700 ft. west of the northwest corner of section 20. T. 11 S. R.8 E. Riley Co., KS.

Physiography: Upland slope in level or undulating uplands

Geomorphic Position: summit interfluvium

Slope: 1% convex

Drainage: Moderately well drained

Land Use: Rangeland not grazed

Parent Material:

Loess from mixed material over loess from mixed material over residuum from limestone-cherty material over residuum from shale-calcareous material

Classification: Fine, montmorillonitic, mesic Typic Natrustoll

Described by: W. Wehmueller and M. Ransom

Sample Date: 05/87

A -- 0 to 15 cm; very dark gray (10YR 3/1) silt loam; black (10YR 2/1), moist; moderate medium granular structure; slightly hard, friable; many fine discontinuous tubular roots; abrupt smooth boundary.

Bt1 -- 15 to 42 cm; dark gray (10YR 4/1) silty clay; very dark grayish brown (10YR 3/2), moist; moderate medium columnar structure parting to moderate medium angular blocky; very hard, very firm; many fine roots; continuous faint very dark gray (10YR 3/1) skeletalans over cutans on vertical and horizontal faces of peds; clear smooth boundary. Cracks 2 to 3 cm wide filled with (10YR 2/1) between columnar structural units.

Bt2 -- 42 to 54 cm; dark grayish brown (10YR 4/2) silty clay; very dark grayish brown (10YR 3/2) and dark brown (10YR 3/3), moist; weak medium prismatic structure parting to moderate medium subangular blocky; very hard, very firm; common fine roots; patchy faint vertical and horizontal faces of peds; clear smooth boundary. Cracks 2 to 3 wide filled with (10YR 2/1) between some of the structural units.

Bt3 -- 54 to 72 cm; brown to dark brown (10YR 4/3) silty clay loam; dark brown (10YR 3/3), moist; common medium distinct strong brown (7.5YR 4/6) and common medium distinct dark gray (10YR 4/1) mottles; weak medium prismatic structure parting to moderate medium subangular blocky; hard, firm; common fine roots; patchy faint black (10YR 2/1) organic coats on vertical faces of peds and patchy faint very dark grayish brown (10YR 3/2) skeletalans over cutans on vertical and horizontal faces of peds; few fine rounded carbonate concretions and few fine rounded iron-manganese concretions; clear wavy boundary.

2Bt4 -- 72 to 87 cm; brown (10YR 5/3) silty clay loam; brown to dark brown (10YR 4/3), moist; common medium distinct strong brown (7.5YR 4/6) and common medium distinct dark gray (10YR 4/1) mottles; weak medium prismatic structure parting to moderate medium subangular blocky; slightly hard, firm; common fine roots; common very fine discontinuous tubular pores; discontinuous distinct dark yellowish brown (10YR 4/4) clay films on vertical and horizontal faces of peds and discontinuous distinct lime or carbonate coats in root channels and/or pores; common medium irregular carbonate nodules and few fine rounded iron-manganese concretions; slightly effervescent discontinuous; clear wavy boundary. Weakly

calcareous around pores. Soil matrix is noncalcareous.

2Bt5 -- 87 to 107 cm; silt loam; brown to dark brown (7.5YR 4/4); common medium distinct dark grayish brown (10YR 4/2) and common medium faint reddish brown (5YR 4/4) mottles; weak medium prismatic structure parting to moderate medium subangular blocky; friable, brittle; few fine roots; common very fine discontinuous tubular pores; discontinuous faint dark brown (7.5YR 3/4) clay films on vertical and horizontal faces of peds and discontinuous faint lime or carbonate coats in root channels and/or pores; few medium irregular carbonate nodules and few fine rounded iron-manganese concretions; slightly effervescent discontinuous; clear wavy boundary. Weakly calcareous around pores.

2Bt6 -- 107 to 122 cm; silty clay loam; brown to dark brown (7.5YR 4/4); common distinct dark grayish brown (10YR 4/2) mottles; weak medium prismatic structure parting to moderate medium subangular blocky; firm, brittle; few fine roots; common very fine discontinuous tubular pores; continuous faint reddish brown (5YR 4/4) clay films on vertical and horizontal faces of peds and nodules and few fine rounded iron-manganese concretions and; slightly effervescent discontinuous; 4 percent pebbles sedimentary. Weakly calcareous around pores.

3Bt7 -- 122 to 160 cm; very cherty clay loam; yellowish red (5YR 4/6); common medium distinct dark grayish brown (10YR 4/2) mottles; moderate fine subangular blocky structure; firm; few fine roots; continuous distinct dark reddish brown (5YR 3/3) clay films on vertical and horizontal faces of peds and continuous distinct dark reddish brown (5YR 3/3) clay films on rock fragments; few fine rounded iron-manganese concretions and silica concretions; 35 percent pebbles sedimentary rocks; abrupt wavy boundary. Continuous lens of bedded chert from 135 to 144 cm.

4Cr -- 160 to 180 cm; extremely shaly silty clay loam; pale yellow (2.5YR 7/4) and dark reddish brown (5YR 3/3) and; violently effervescent continuous; 75 percent pebbles shale.

Table 33. Characterization data for Dwight.

S87KS-161-003

(RILEY COUNTY, KANSAS)

SAMPLED AS : DWIGHT; FINE, MIXED MESIC PACHIC ARGISTOLL

NSSL - PROJECT 87P 102, RILEY CO.

- PEDON 87P 450, SAMPLES 87P2343-2351

- GENERAL METHODS 1B1A, 2A1, 2B

DEPTH (CM)	HORIZON	TOTAL			ORGANIC C 6A1C					
		CLAY .<.002	SILT .002 - .05	SAND .05 - 2						
		PERCENT OF <2MM(3A1)			PERCENT					
0- 15	A	26.8	64.8	8.4	3.89					
15- 42	Bt1	50.5	46.8	2.7	1.62					
42- 54	Bt2	44.2	53.2	2.6	1.07					
54- 72	Bt3	37.3	58.4	4.3	0.62					
72- 87	2Bt4	28.8	63.2	8.0	0.24					
87-107	2Bt5	30.1	60.4	9.5	0.22					
107-122	2Bt6	42.1	47.1	10.8	0.22					
122-160	3Bt7	59.4	29.6	11.0	0.20					
160-180	4Cr	16.9	55.9	27.2	0.09					
DEPTH (CM)	NH ₄ OAC EXTRACTABLE BASES					ACIDITY	CEC	BASE SAT.		CO ₃ AS
	Ca 5B5A 6N2E	Mg 5B5A 6O2D	Na 5B5A 6P2B	K 5B5A 6Q2B	SUM BASES		SUM CATS 5A3A	SUM 5C3	NH ₄ OAC 5C1	
	MEQ/100G					6H5A	5A3A	5C3	5C1	CaCO ₃ <2MM 6E1G
							PERCENT			
0- 15	17.2	4.8	0.4	1.1	23.5	8.4	31.9	74	92	1 TR TR TR -- 67
15- 42	22.0	10.1	1.6	1.1	34.8	8.3	43.1	81	89	
42- 54	24.1	10.7	2.8	0.6	38.2	3.3	41.5	92	98	
54- 72	39.1	10.3	3.8	0.4	53.6	2.0	55.6	96	100	
72- 87	23.2	7.6	4.9	0.2	35.9	1.2	37.1	97	100	
87-107	18.6	6.3	4.8	0.2	29.9	1.8	31.7	94	100	
107-122	17.4	7.9	5.1	0.3	30.7	2.0	32.7	94	100	
122-160	27.7	10.7	6.5	0.5	45.4	2.9	48.3	94	100	
160-180	37.4	2.2	1.4	TR	41.0	--	41.0	100	100	

NARRATIVE PEDON DESCRIPTION

Pedon: Benfield

NSSL Pedon Number: 87P0452

Soil Survey Number: S87-KS-161-005

Location: 2000 ft. north and 400 ft. west of the southeast corner of section 17. T. 11 S. R.8 E. Riley Co., KS.

Physiography: Upland slope in level or undulating uplands

Geomorphic Position: backslope sideslope

Slope: 10% concave west facing

Drainage: Well drained

Land Use: Rangeland not grazed

Parent Material:

Local colluvium from limestone-cherty material over residuum from shale-calcareous material

Classification: Fine, mixed, mesic Udic Argiustoll

Described by: M. Ransom and H. Campbell

Sample Date: 05/87

A -- 0 to 10 cm; dark gray (10YR 4/1) silt loam; very dark gray (10YR 3/1), moist; moderate medium granular structure; slightly hard, friable; many discontinuous tubular roots; 5 percent pebbles sedimentary rocks; clear smooth boundary.

AB -- 10 to 35 cm; dark gray (10YR 4/1) very cherty silty clay loam; very dark gray (10YR 3/1) and brown to dark brown (10YR 4/3), moist; moderate medium granular structure; slightly hard, friable; many fine discontinuous tubular and few medium discontinuous tubular roots and 60 percent pebbles sedimentary rocks; gradual wavy boundary.

Bt1 -- 35 to 63 cm; silty clay; brown to dark brown (10YR 4/3); moderate fine subangular blocky structure; hard, firm; common fine discontinuous tubular roots; continuous distinct brown to dark brown (7.5YR 4/4) clay films on vertical and horizontal faces of peds; common fine rounded iron-manganese concretions and few medium irregular clay bodies; 5 percent pebbles shale; clear wavy boundary.

Bt2 -- 63 to 74 cm; shaly silty clay; light yellowish brown (2.5Y 6/4); weak medium subangular blocky structure; hard, firm; few fine discontinuous tubular roots; discontinuous distinct dark yellowish brown (10YR 4/4) clay films on vertical and horizontal faces of peds; common medium irregular clay bodies and salt masses; strongly effervescent continuous; 20 percent pebbles shale; clear wavy boundary. Coarse fragments are mostly shale with lesser amounts of highly weathered chert.

BC -- 74 to 92 cm; very shaly silty clay loam; yellowish brown (10YR 5/4) and dark yellowish brown (10YR 4/4); weak medium subangular blocky structure; hard, firm; few fine discontinuous tubular roots; common medium irregular clay bodies and; violently effervescent continuous; 50 percent pebbles shale; clear wavy boundary. Clay flows are (10YR 4/3), coarse fragments are equal amounts of shale and highly weathered chert.

Cr -- 92 to 110 cm; weathered bedrock; light yellowish brown (2.5Y 6/4) and brownish yellow (10YR 6/6); massive; very hard, very firm; violently effervescent continuous.

Table 34. Characterization data for Benfield.

S87KS-161-005

(RILEY COUNTY, KANSAS)

SAMPLED AS : BENFIELD; FINE, MIXED MESIC UDIC AGRIUSTOLL

NSSL - PROJECT 87P 102, RILEY CO.

- PEDON 87P 452, SAMPLES 87P2358-2363

- GENERAL METHODS 1B1A, 2A1, 2B

DEPTH (CM)	HORIZON	TOTAL			ORGANIC C 6A1C
		CLAY <.002	SILT .002 - .05	SAND .05 - 2	
		PERCENT OF <2MM(3A1)			PERCENT
0- 10	A	37.6	52.8	9.6	2.48
10- 35	AB	48.0	43.8	8.2	1.52
35- 63	BT1	73.9	23.7	2.4	1.53
63- 74	BT2	46.8	36.6	16.6	0.91
74- 92	BC	24.4	59.9	15.7	0.58
92-110	CR	17.6	44.4	38.0	0.19

DEPTH (CM)	NH ₄ OAC EXTRACTABLE BASES					ACIDITY	CEC	BASE SAT.		CO ₃ AS
	Ca 5B5A 6N2E	Mg 5B5A 6O2D	Na 5B5A 6P2B	K 5B5A 6Q2B	SUM BASES		SUM CATS 5A3A	SUM 5C3	NH ₄ OAC 5C1	CaCO ₃ <2MM 6E1G
	MEQ/100G						PERCENT			
0- 10	28.7	3.8	0.1	1.2	33.8	9.4	43.2	78	100	
10- 35	29.0	4.0	0.1	0.7	33.8				96	--
35- 63		2.7	0.1	0.8						1
63- 74		1.3	0.1	0.3						28
74- 92		0.7	0.1	0.2						65
92-110		0.5	TR	0.1						69

NARRATIVE PEDON DESCRIPTION

Pedon: Florence

NSSL Pedon Number: 87P0451

Soil Survey Number: S87-KS-161-004

Location: 400 ft. north and 400 ft. west of the center of section 18. T. 11 S. R.8 E. Riley Co., KS.

Physiography: Upland slope in level or undulating uplands

Geomorphic Position: shoulder headslope

Slope: 2% concave northeast facing

Drainage: Well drained

Land Use: Rangeland not grazed

Parent Material:

Residuum from limestone-cherty material over residuum from shale-calcareous material

Classification: Clayey-skeletal, montmorillonitic, mesic Udic Argilustoll

Described by: W. Wehmüller and H. Campbell

Sample Date: 05/87

A1 -- 0 to 10 cm; dark gray (10YR 4/1) silt loam; black (10YR 2/1), moist; moderate medium granular structure; friable; many fine discontinuous tubular roots; clear smooth boundary.

A2 -- 10 to 30 cm; dark gray (10YR 4/1) very cherty silt loam; very dark gray (10YR 3/1), moist; moderate medium granular structure; friable; many fine discontinuous tubular roots; 60 percent pebbles sedimentary rocks; abrupt wavy boundary.

Bt1 -- 30 to 65 cm; brown to dark brown (7.5YR 4/4) extremely cherty silty clay; dark brown (7.5YR 3/4), moist; moderate fine subangular blocky structure; firm; common fine roots; continuous faint dark reddish brown (5YR 3/4) clay films on rock fragments and continuous faint dark reddish brown (5YR 3/4) clay films on faces of peds; few fine irregular iron-manganese concretions; 90 percent bedded chert 5 to 25 cm in diameter. 75% of fragments are greater than 8 cm.

Bt2 -- 65 to 80 cm; reddish brown (5YR 4/3) very cherty silty clay; dark reddish brown (5YR 3/3), moist; moderate fine subangular blocky structure; firm; common fine roots; continuous faint dark reddish brown (5YR 3/3) clay films on faces of peds and continuous faint dark reddish brown (5YR 3/3) clay films on rock fragments; few fine irregular iron-manganese concretions and durinodes; 40 percent cobbles sedimentary rocks; abrupt wavy boundary. Chert fragments are 1 cm to 5 cm in diameter, some is soft and highly weathered.

Bt3 -- 80 to 103 cm; extremely cherty silty clay; dark brown (7.5YR 3/4) and reddish brown (5YR 3/3), moist; moderate fine subangular blocky structure; firm; common fine roots; continuous faint dark reddish brown (5YR 3/4) clay films on rock fragments; few fine irregular iron-manganese concretions; 90 percent cobbles sedimentary rocks; abrupt wavy boundary. 90 percent bedded chert, 75 percent is larger than 8 cm in diameter.

2Cr -- 103 to 150 cm; extremely shaly silty clay loam; light yellowish brown (2.5YR 6/4); common fine distinct strong brown (7.5YR 5/6) mottles; massive; common medium irregular clay bodies; strongly effervescent continuous. Clay flows are (5YR 3/4), 5 to 10 percent weathered chert.

Table 35. Characterization data for Florence.

S87KS-161-004

(RILEY COUNTY, KANSAS)

SAMPLED AS : FLORENCE; CLAYEY-SKELETAL, MONTMORILLONITIC, MESIC UDIC AGRUSTOLL

NSSL - PROJECT 87P 102, RILEY CO.

- PEDON 87P 451, SAMPLES 87P2352-2357

- GENERAL METHODS 1B1A, 2A1, 2B

DEPTH (CM)	HORIZON	TOTAL			ORGANIC C 6A1C					
		CLAY <.002	SILT .002 - .05	SAND .05 - 2						
		PERCENT OF <2MM(3A1)			PERCENT					
0- 10	A1	30.6	56.0	13.4	5.80					
10- 30	A2	36.0	50.9	13.1	4.47					
30- 65	BT1	68.2	18.3	13.5	2.56					
65- 80	BT2	73.5	16.9	9.6	1.21					
80-103	BT3	33.6	58.4	8.0	0.38					
103-150	2CR	22.9	59.6	17.5	0.22					
DEPTH (CM)	NH ₄ OAC EXTRACTABLE BASES					ACIDITY	CEC	BASE SAT.		CO ₃ AS CaCO ₃ <2MM 6E1G
	Ca 5B5A 6N2E	Mg 5B5A 6O2D	Na 5B5A 6P2B	K 5B5A 6Q2B	SUM BASES		SUM CATS 5A3A	SUM 5C3	NH ₄ OAC 5C1	
	MEQ/100G						PERCENT			
	0- 10	22.5	4.1	TR	1.7	28.3	10.9	39.2	72	88
10- 30	21.5	3.9	TR	1.2	26.6	11.2	37.8	70	86	
30- 65	35.6	5.6	0.1	1.0	42.3	13.3	55.6	76	82	
65- 80	49.7	4.0	0.3	0.9	54.9	8.9	63.8	86	100	
80- 103		1.4	TR	0.2						
103-150		3.2	TR	0.1						

NARRATIVE PEDON DESCRIPTION

Pedon: Tully

NSSL Pedon Number: 87P0453

Soil Survey Number: S87-KS-161-006

Location: 1900 ft. east and 850 ft. south of the northwest corner of section 18. T. 11 S. R.8 E. Riley Co., KS.

Physiography: Upland slope in level or undulating uplands

Geomorphic Position: footslope sideslope

Slope: 7% concave west facing

Drainage: Well drained

Land Use: Pasture land and native pasture

Parent Material:

Local colluvium from limestone-shale material

Classification: Fine, mixed, mesic Pachic Agriustoll

Described by: W. Wehmueller and M. Ransom

Sample Date: 05/87

Ap -- 0 to 16 cm; dark gray (10YR 4/1) silty clay loam; very dark gray (10YR 3/1), moist; moderate fine granular structure; slightly hard, friable; many fine discontinuous tubular roots; abrupt smooth boundary.

A -- 16 to 33 cm; very dark gray (10YR 3/1) silty clay loam; black (10YR 2/1), moist; moderate medium granular structure; slightly hard, friable; many fine discontinuous tubular roots; 1 percent pebbles; clear wavy boundary.

BA -- 33 to 59 cm; dark grayish brown (10YR 4/2) silty clay loam; very dark grayish brown (10YR 3/2), moist; moderate fine subangular blocky structure; hard, friable; many fine discontinuous tubular roots and; 1 percent pebbles; gradual wavy boundary.

Bt1 -- 59 to 90 cm; dark grayish brown (10YR 4/2) silty clay; very dark grayish brown (10YR 3/2), moist; moderate medium subangular blocky structure; very hard, firm; common fine discontinuous tubular roots; patchy faint very dark brown (10YR 2/2) clay films on vertical and horizontal faces of peds and patchy faint very dark grayish brown (10YR 3/2) nonintersecting slickensides throughout; few fine irregular iron-manganese concretions; 1 percent pebbles; gradual wavy boundary.

Bt2 -- 90 to 114 cm; dark grayish brown (10YR 4/2) silty clay; very dark grayish brown (10YR 3/2), moist; common fine distinct yellowish brown (10YR 5/6) mottles; weak medium prismatic structure parting to moderate subangular blocky; very hard, firm; common fine discontinuous tubular roots; discontinuous faint very dark grayish brown (10YR 3/2) clay films on vertical and horizontal faces of peds and discontinuous faint dark brown (10YR 3/3) nonintersecting slickensides throughout; few fine irregular iron-manganese concretions; 1 percent pebbles; clear wavy boundary. 1% chert fragments.

BC -- 114 to 132 cm; yellowish brown (10YR 5/4) silty clay; dark yellowish brown (10YR 4/4), moist; common fine distinct yellowish brown (10YR 5/6) mottles; weak medium subangular blocky structure; very hard, firm; few fine discontinuous tubular roots; faint dark yellowish brown (10YR 4/4) nonintersecting slickensides throughout; common fine irregular iron-manganese concretions; 2 percent pebbles; clear wavy boundary. 2% chert fragments.

C1 -- 132 to 151 cm; brown (10YR 5/3) silty clay; brown to dark brown (10YR 4/3), moist; massive; very hard, very firm; few fine discontinuous tubular roots; faint brown to dark brown (10YR 4/3) nonintersecting slickensides throughout; common fine irregular iron-manganese concretions and few fine irregular lime concretions; 4 percent pebbles; abrupt wavy boundary.

Table 36. Characterization data for Tully.

S87KS-161-006

(RILEY COUNTY, KANSAS)

SAMPLED AS : TULLY; FINE, MIXED MESIC PACIFIC ARGISTOLL

NSSL - PROJECT 87P 102, RILEY CO.

- PEDON 87P 453, SAMPLES 87P2364-2371

- GENERAL METHODS 1B1A, 2A1, 2B

DEPTH (CM)	HORIZON		TOTAL					ORGANIC C 6A1C			
			CLAY .<.002		SILT .002 - .05		SAND .05 - 2				
			PERCENT OF <2MM(3A1)					PERCENT			
0- 16	AP	35.2		54.7		10.1		2.91			
16- 33	A	40.5		50.9		8.6		2.08			
33- 59	BA	46.7		46.7		6.6		1.33			
59- 90	BT1	44.8		49.2		6.0		0.82			
90-114	BT2	43.4		49.7		6.9		0.55			
114-132	BC	41.8		49.8		8.4		0.38			
132-151	C1	43.0		49.5		7.5		0.36			
151-185	2C2	29.7		55.3		15.0		0.21			
DEPTH (CM)	NH ₄ OAC EXTRACTABLE BASES					ACIDITY	CEC	BASE SAT.		CO ₃ AS	
	Ca 5B5A 6N2E	Mg 5B5A 602D	Na 5B5A 6P2B	K 5B5A 6Q2B	SUM BASES		SUM CATS 5A3A	SUM 5C3	NH ₄ OAC 5C1		CaCO ₃ <2MM 6E1G
	MEQ/100G						PERCENT				
	0- 16	19.6	4.1	TR	0.9	24.6	9.0	33.6	73	88	1 1 31
	16- 33	19.8	5.3	0.1	0.6	25.8	7.8	33.6	77	87	
33- 59	21.8	7.3	0.1	0.6	29.8	7.4	37.2	80	90		
59- 90	20.7	8.3	0.2	0.6	29.8	5.3	35.1	85	94		
90-114	20.5	8.3	0.2	0.6	29.6	3.6	33.2	89	96		
114-132		8.5	0.3	0.5			30.3				
132-151		9.6	0.3	0.6			31.2				
151-185		5.9	0.2	0.3			21.5				

**DETECTING SOIL INFORMATION ON THE KONZA PRAIRIE
USING HIGH RESOLUTION SATELLITE DATA**

by

Haiping Su

B.S., Zhejiang Agricultural University, 1982

AN ABSTRACT OF A MASTER'S THESIS

submitted in partial fulfillment of the

requirements for the degree

MASTER OF SCIENCE

Department of Agronomy

KANSAS STATE UNIVERSITY
Manhattan, Kansas

1988

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ABSTRACT

Detecting Soil Information on The Konza Prairie Using High Resolution Satellite Data

Computer pattern recognition techniques were used to discriminate soil information from Landsat TM and French SPOT satellite data on the Konza prairie near Manhattan, Kansas. Digital Elevation Model (DEM) data were merged to Landsat TM and SPOT data to delineate soil mapping units within the study area. Soil mapping units from a digitized soil map were compared with a classified soil spectral map obtained from Landsat TM or SPOT, and DEM derived elevation, slope, and aspect data using an overall accuracy assessment. The overall accuracy of soil spectral classes from TM and SPOT data was improved after DEM data were merged. Higher separability of soil mapping units derived from Landsat TM and DEM data on upland positions of the study area was obtained using statistical divergence analysis. Ratioing, intensity transformation, and low frequency filtering were performed before supervised classification was used. A better average accuracy of soil mapping units was found from low frequency filtering. A higher overall accuracy derived from TM data in the dormant season was obtained compared with the accuracy in the growing season. This result indicates that satellite data acquired in dormant season are more useful for soil information detection. The overall accuracy from Landsat TM and SPOT data was not significantly different because of scale reduction of SPOT data. The overall accuracy from Landsat TM and SPOT data was about 55 to 57 %. This study demonstrates that high resolution Landsat TM and SPOT satellite data can be used to aid soil consociation delineation at the second order level in areas where the dominant land use is rangeland.