Comparisons between Spectral Mapping Units Derived from SPOT Image Texture and Field Soil Map Units

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ABSTRACT: A spectral soil map, depicting map unit variability due to soil properties, would be a useful addition to field investigations in separating soil units in a soil survey program. This study was conducted to assess the usefulness of image texture features in discriminating among soil map units based on pertinent soil properties. SPOT satellite image texture data derived from transformation of the original image were classified for mapping unit separability in two 3108-ha areas in Ford County, Illinois. The image texture map units and field soil map units from a survey of the area were analyzed by discriminant analysis procedure to show how the depicted map units were separated based on variability of pertinent soil properties. Classification results showed percent overall agreement of discriminate map units from soil properties to be 61.01 for field soil map units and 46.61 for SPOT texture map units in the Mona Township area. The latter were 55.2 percent and 46.15 percent, respectively, for the Drummer Township area. A measure of the overall map agreement with the classification from soil properties, using the Kappa statistic, indicated that the field map was better than the SPOT texture map by a ratio of 0.5306:0.4035 in the Mona Township, and 0.5025:0.4291 in the Drummer Township. However, the Kappa statistic was not significantly different for the image texture and the field soil map units at the 0.05 level. The data demonstrate the inappropriacy of using only field soil maps as standards for judging the accuracy of spectral maps. It also underscores the potential for using image textural features for delineation of map units in the initial phases of detailed soil survey programs and land-use planning.

INTRODUCTION

REFLECTANCE PATTERNS depicted by spectral maps could portray the actual variability of soil map units due to soil properties and could be used in addition to field investigations to separate soil map units. The soil is a complex mixture of materials possessing various physical and chemical properties which can affect its absorptance and reflectance characteristics. Lund *et al.* (1980) and Harrison and Johnson (1982) have concluded that the use of spectral maps derived from Landsat data improved accuracy or quality of map unit delineations. Wright and Birnie (1986) studied the degree to which surface soil parameters could be detected and quantified on the basis of SPOT data, and they suggested that it would be possible to use SPOT data in a practical way to map within-field soil variations. The second-generation high resolution remote sensing satellites (e.g., Landsat TM and SPOT HRV) offer additional possibilities for mapping within-field variation of soil units (Agbu and Frank, 1988). In a study using high-resolution Landsat TM and SPOT satellite data to interpret detailed soil information at the consociation or complex mapping level for a rangeland in Kansas, Su *et al.* (1989) determined that the overall accuracy of soil spectral classes from TM and SPOT data was improved after digital elevation model data were merged with imagery data.

In analysis of remotely sensed data of the Earth and extraction of useful thematic information, data are transformed into information using various techniques and algorithms. Imhoff *et al.* (1982) employed image enhancement in addition to statistical classification techniques to create images more suitable for visual delineation of soil units. Principal components (PC) transformation is one of the most frequently used methods, and is based on the variance-covariance structure of the image, which produces new digital values that are linear combinations of the original digital numbers. Johnson and Wichern (1982) contend that the objective of PC transformation is two-fold, mainly, data reduction and image interpretation. The technique has been used in soil mapping on Arizona rangeland by Roudabush *et al.* (1985). Ratio transformations have been used (Friedman, 1980) to reduce the difference in digital numbers from similar surface materials caused by slope, shadows, or seasonal changes in sunlight illuminating angle and intensity. Satterwhite (1984) suggests that, in addition to the latter, ratios may also provide unique information not available in any single band that would be useful for discriminating between soils and vegetation. Frazier and Cheng (1989) investigated the Palouse region soils and determined that areas defined by amorphous Fe/C ratio, where topsoils have been thinned to the extent that paleosols are exposed, corresponded well with Landsat TM band ratios 3/4, 5/4, and 5/3 which are useful in mapping. They also suggested that the TM ratios 1/4, 3/4, 5/4 combination is a useful choice. SPOT ratio data were determined to be superior in discriminating different soil types of Henry County, Indiana (Venugopal and Gimblett, 1988). Principal component transformations were found to be less definitive than ratio transformation by Lee *et al.* (1988) in a study of Wisconsin soils. Other transformation techniques, using statistical divergence analysis to examine the separability of Landsat MSS and TM data, indicated that the use of a low-pass filter may increase class separability from Landsat TM data (Haack *et al.*, 1987), and soil features in Landsat imagery might be extracted by an intensity transformation (Mulders, 1987).

Another technique, the addition of image texture to spectral features in the analysis of imagery, for identification and classification of objects or regions of interest has been demonstrated. Statistical texture features generally allow users to measure the similarity between a central picture element in a subset of the image matrix and the block of surrounding elements. The addition of textural information to spectral reflectance information in Landsat MSS data (Shih and Schowengert, 1983) improved the statistical separability of otherwise similarly reflecting geomorphic surfaces in Arizona. Frank (1984) has assessed changes in the condition of semiarid geomorphic sur-

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faces using digital image processing techniques involving three texture measures: variance code, contrast code, and range code. His results suggest that albedo and texture measures are potentially viable indices of the condition of the geomorphic surfaces.

The results from an initial study (Agbu, 1989) indicate that using textural features from satellite digital data was superior to using principal components, ratioing, or original imagery data for characterizing spatial variability of soil properties. Because the goal in a soil survey is to group soils that are similar and to separate those that are different based on significant soil properties, spectral mapping units that maximize variation among mapping units while minimizing same within units is desired. The objectives of this investigation were (1) to derive spectral mapping units from classification of SPOT image textural features, and (2) to compare spectral map units from the image texture classification to the field soil map units using discriminant analysis of significant soil properties.

STUDY AREA

The study area for this investigation is located in Ford County, east-central Illinois and consists of two sites, each of 3108 ha with contrasting variability of map unit composition as indicated by a modern USDA soil survey map (Fehrenbacher, 1990). One of the areas, Mona Township, is located in the northern part of the county, and the other, Drummer Township, is in the southwest corner (Figure 1). The general area is part of the landscape developed during the Wisconsinan glacial period. The soils have developed in parent material of moderately thick to thin loess or silty material over different textured glacial till, outwash, and lacustrine sediments (Fehrenbacher *et al.*, 1984). In some parts the thin loess mantle is relatively unimportant as soil parent material because it has become mixed with other materials and cannot be identified as loess. Twenty mapping units were delineated in both study sites; the soils are all Mollisols and have a mesic temperature regime. Soil moisture regime is mainly aquic in major soils and udic in minor soils, and the mineralogy is mixed. Both areas are mostly cultivated to corn and soybeans. The Mona Township area lies between T 27 N and T 29 N; and within R.8E and R.10E. The study site is between section lines 1400E to 1700E and 3100N to 3500N. The second area is in Drummer Township (T 23 N to T24N), and lies between section lines 200E to 600E and 600N to 900N. A modern soil survey was recently completed in the county (Fehrenbacher, 1990), and a cloud-free satellite data set was successfully acquired on 26 April 1987. There was no precipitation event for two days preceding and including the image acquisition date, and most of the soil surface was fallow, except a small percent in permanent pasture and along the streams. The best period to acquire remote sensing data for this region for soil studies is from late April to mid-June (Kiefer, 1972) when the soil surface is predominantly fallow and the farmlands have been prepared for cropping.

FIG. 1. Location of the study areas in Ford County, Illinois.

SPOT DATA ANALYSIS

The SPOT data were read from the computer compatible tapes, using Earth Resources Data Analysis System (ERDAS) software, and the study area was extracted from the satellite scene. The data set for the study site was geometrically corrected by referencing it to the Universal Transverse Mercator (UTM) world coordinate system. Road intersections used as control points in the rectification of the image were picked from both the displayed image and a 7.5-minute quadrangle (USGS) map of the area. The data were resampled to a 20- by 20-metre cell size using the bilinear interpolation procedure. The effect, if any, of solar elevation in the image was not visible in the original imagery, and because both areas were extracted from the same scene, no correction was made for solar elevation. Of the various texture measures available for digital image transformation, Jensen (1979) showed that only a few statistical texture measures are necessary to characterize spatial relationships between picture elements. One such texture measure defined by Jensen (1979), the variance code (Equation 1), was selected for this study because it appears to represent the best surface variability measure for the kind of detail required: that is,

$$O = \text{SQRT}\left(\sum_{i=1}^{n}\sum_{j=1}^{n}(A(i,j) - \mu) ** 2\right) / (n**2) - 1. \qquad (1)$$

A 3- by-3 kernel size was used in calculating the transformed value, and all three bands (0.50 to 0.59 μm, 0.61 to 0.68 μm, and 0.79 to 0.89 μm) were used in the generation of the texture transformed image.

The data set was then classified by the unsupervised maximum likelihood algorithm to derive the spectral mapping units. Classification clusters were aggregated to form soil spectral classes. The precise positions of field sample points were located on the imagery by digitization of the points from the 7.5-minute quadrangle map of the area in UTM coordinates. These coordinates were then located on the geo-referenced satellite image, and the corresponding pixel in which the point occurred was subsequently identified. Soil spectral classes in the classified image were also identified in the same manner.

FIELD AND LABORATORY PROCEDURES

Observations were made on a systematic sampling grid spaced 402 m apart, with the first sample taken at the northwest corner of the site to coincide with the second diagonal pixel from the road intersection. This was located by pacing 40 m into the section and 40 m south from the corner. Subsequent observations were made with reference to the first one, and the soil was sampled to a depth of 1.2 m with a hand probe. A total of 221 observations were made. The systematic sampling procedure used provided even distribution of the observations (Yates, 1948); furthermore, it is reasonable to assume that the sampling scheme is independent of the distribution of soil properties because of the lack of apparent periodicity in landscape features (Quenouille, 1949). Soil morphological properties that were expected to genetically influence the surface section of the soil, and are pertinent in separation of soil map units (Table 1), were described according to procedures outlined in the Soil Survey Manual (Soil Survey Staff, 1981). The upper 50 cm of the B horizon were described as the upper B horizon and the lower part as the middle B horizon, because their influence is expected to differ in the surface control section. After the soil was described, samples of the A horizon and the upper 50 cm of the B horizon were collected in labeled soil bags and returned to the laboratory for analyses. Surface descriptive characteristics of the observation sites, mainly the landscape position (toeslope, footslope, sideslope, summit), slope form (convex, concave, linear, and level), and aspect were coded. The aspect codes ranged from 0 (level) to 8 (west, likely to be the brightest at time of satellite pass). The transformation for the Munsell color hue was used (ASTM, 1988). The qualitative soil variables were coded or transformed to facilitate analysis of the data (Horvath *et al.*, 1984; Agbu, 1989).

Soil samples were air dried, crushed, and passed through a 2-mm sieve prior to the various analyses. Particle size distribution of the A and the B horizons were determined by the modified pipet method of Kilmer and Alexander (1949). Soil reaction expressed as pH was measured in a 1:1 soil:water mixture using a pH meter and a glass electrode. Organic carbon content for the A horizon samples was determined by the loss-on-ignition method of Davies (1974).

TABLE 1. SIMPLE STATISTICS FOR SELECTED SOIL PROPERTIES OF SAMPLED SITES USED IN DISCRIMINANT ANALYSIS.

Variable	Mona Township			Drummer Township		
	Mean	SD	CV	Mean	SD	CV
			%			%
Landscape position	2.7	0.6	22.4	2.8	0.8	27.6
Percent slope	1.1	1.5	135.3	1.9	1.2	62.3
Slope form	2.2	1.1	48.2	2.8	0.9	34.0
Aspect	2.7	2.9	104.2	3.9	2.5	65.9
A horizon depth	35.8	10.2	28.4	40.3	15.6	38.8
A horizon color hue	20.7	1.8	8.9	20.1	0.8	3.9
A horizon color value	2.2	0.4	16.9	2.6	0.5	18.8
A horizon color chroma	1.0	0.3	34.1	1.2	0.4	36.0
Upper B horizon color hue	24.0	1.6	6.5	22.3	1.8	8.0
Upper B horizon color value	3.4	0.7	19.5	3.9	0.7	17.3
Upper B horizon color chroma	2.0	0.9	43.4	2.7	1.2	42.9
Middle B horizon color hue	24.2	1.2	5.1	23.3	2.2	9.4
Middle B horizon color value	4.5	0.7	15.4	4.6	0.6	13.9
Middle B horizon color chroma	3.1	1.0	33.4	3.4	1.0	30.4
Dominant mottle color hue	21.0	1.3	6.1	21.3	3.4	16.0
Dominant mottle color value	5.0	0.4	8.3	5.0	0.9	18.4
Dominant mottle color chroma	7.1	1.1	16.1	6.0	2.3	37.7
Depth (cm) to reduced colors	43.2	11.5	26.7	48.1	18.9	39.3
Depth (cm) to carbonates	92.4	31.1	33.7	104.8	22.6	21.6
Depth (cm) of loess over till/outwash	43.9	15.7	35.7	52.6	28.4	54.1
A horizon percent sand	27.2	14.7	53.9	10.0	4.9	48.8
A horizon percent silt	39.9	9.0	22.4	56.4	5.2	9.2
A horizon percent clay	32.9	9.7	29.4	33.6	5.4	16.1
A horizon percent organic carbon	2.1	0.3	14.2	2.1	0.3	15.7
B horizon percent sand	27.7	16.1	58.0	13.0	10.6	81.4
B horizon percent silt	38.0	8.7	22.8	50.0	7.5	15.0
B horizon percent clay	34.3	9.2	26.7	37.0	6.6	17.9
B horizon pH	7.2	0.5	7.3	6.7	0.7	10.1

STATISTICAL ANALYSIS

Descriptive statistics were computed by the elementary statistics procedure outlined in the Statistical Analysis System (SAS) computer software (SAS Institute Inc., 1985). The DISCRIM procedure in SAS was used to develop a discriminant function to classify each observation into one of the map units. Discriminant analysis as a predictive technique is based on classifying an observation into one of several populations based on a vector of variables for that observation. Distance functions between the observation and the centroid of each population are calculated, and each observation is placed in the class from which it has the smallest generalized squared distance, assuming that each class has a multivariate normal distribution. Pooled covariance matrices were used to calculate the discriminant functions because a test of homogeneity of within-group covariance matrices showed non significant chi-square at 0.05 probability level. In order to conserve space, individual covariance matrices are not presented. Both the Mona and Drummer Township areas were used to compare the use of this analysis for field soil and SPOT textural map units. A subset of soil variables derived from stepwise discriminant analysis failed to produce better discrimination models based on overall classification accuracies; therefore, all soil variables were used to produce the discriminant functions.

EVALUATION OF DISCRIMINATE MAP UNITS

Assessment of agreement between classification from discriminant analysis and the maps from both areas was conducted by comparing the predicted map unit classification against the SPOT texture map on the one hand, and the field soil map on the other. Observation site comparisons were made by calculating the frequency of coincident classes on the map and the classification, and reporting the coincident frequencies in an error matrix (not presented). Percent correct, percent omission error, percent commission error, and overall percent agreement (Equations 2 through 5) were calculated from the error matrices for all the map units as follows:

$$\text{Percent correct} = \frac{\text{Number of correct predictions for a map unit} \times 100}{\text{Total number of the map unit present in sample}} \tag{2}$$

$$\text{Percent commission error} = \frac{\text{Number predicted as other map units} \times 100}{\text{Total number of the map unit both correctly and erroneously classified}} \tag{3}$$

$$\text{Percent omission error} = \frac{\text{Number of incorrect predictions for a map unit} \times 100}{\text{Total number of the map units present in sample}} \tag{4}$$

$$\text{Overall agreement} = \frac{\text{Number of correct predictions for all map units}}{\text{Total number of observations}} \tag{5}$$

A better measure of overall agreement between the map and the classification was the Kappa statistic (Equation 6) calculated from the error matrix as follows:

$$K = \frac{N \sum_{i=1}^{r} X_{ii} - \sum_{i=1}^{r} (X_{i+} * X_{+i})}{N^2 - \sum_{i=1}^{r} (X_{i+} * X_{+i})} \qquad (6)$$

where

r = number of rows and columns in error matrix,

X_{ii} = number of observations in row i and column i,

X_{i+} = marginal total of row i,

X_{+i} = marginal total of column i, and

N = total number of observations.

The Kappa statistic is a non-parametric measure of agreement between the reference data (i.e., predicted units from soil properties) and SPOT texture or field soil map units (Congalton and Mead, 1983; Hudson and Ramm, 1987). It is the maximum-likelihood estimate from the multinomial distribution and a measure of the actual agreement of two classifications minus the chance agreement.

RESULTS AND DISCUSSION

Descriptive statistics for the selected soil properties, mainly, mean, standard deviation, and coefficient of variation, are shown in Table 1. These are indicative of the degree of variation shown by most of the selected soil properties, and compare well with what others have reported for other soils elsewhere (Wilding and Drees, 1983). The spatial pattern of soil variation, as delineated on the field soil map, shows broad areal map units for the Mona Township (Figure 2) but a smaller and more complex pattern in the Drummer Township (Figure 3). Only parts of the soil maps of the study areas with the superimposed sampling grid have been included to show the general pattern of soil distribution in the two areas. In the Drummer Township the field soil map shows 26 soil map unit delineations, out of which 14 occurred on the observation sites. Only 15 soil map units were delineated on the soil map in the Mona Township, and 11 of these occurred on the observation sites. These map units and their classification are documented in a soil survey report (Fehrenbacher, 1990). The spatial pattern of variation of spectral map units resulting from the SPOT texture classified image of the Mona Township is depicted in the spectral map shown in Plate 1, while that for the Drummer Township is shown in Plate 2. There were 15 spectral map units occurring on the observation sites in the Mona Township and 24 in the Drummer Township. The spectral map units were not characterized during this investigation; however, this would be a necessary next step before these mapping units would be useful for direct application in land use planning.

The results of the discriminant analysis (Table 2) show that Wilks' Lambda, which is a measure of how well the map units are separated, indicates slightly better separation of the units in the field soil map than the image texture map in the Mona Township area, whereas the opposite is the case for the Drummer Township. Average squared canonical correlation is another measure of separability of the map units; this showed that the field soil map had slightly better separation of map units than the image texture maps for both study areas.

The classification results in the Mona Township area show that two map units were completely and correctly predicted from both the field soil and the SPOT image texture maps (Table 3). Although the field soil map had two map units which were excluded from the discriminant error matrix, because they had one observation each, it generally had smaller errors of omission and commission for its units than the spectral map which did not have 100 percent omission error for any of its units. In the Drummer Township area two units of the field soil map and three of the spectral map were completely and correctly predicted (Table 4). The field soil map had one unit that had 100 percent omission errors, but the spectral map did not. However, it is pertinent to note that all the errors of total omission in both areas occurred with map units in which only one observation had been made in the sample. Generally, the spectral map units from both maps in both areas were more numerous than the field soil map units, and the commission and omission errors were lower in the field soil maps compared to the spectral maps. The more numerous map units in the spectral maps were

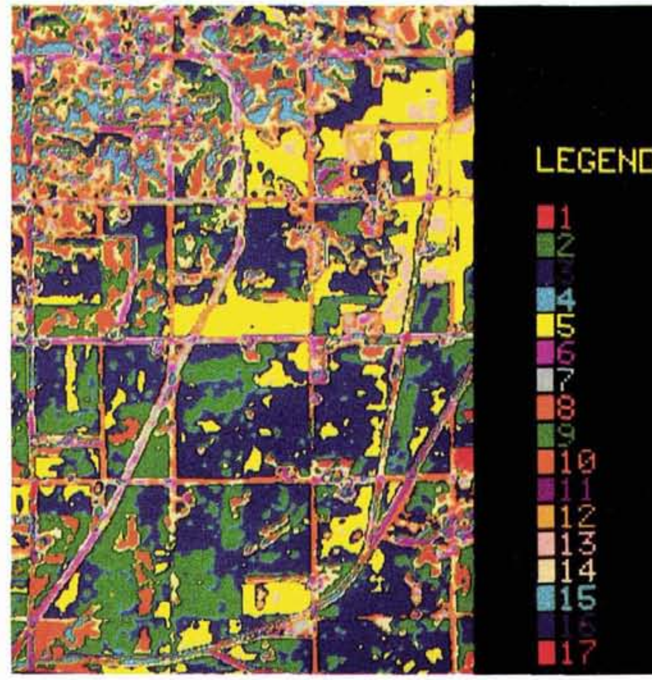

PLATE 1. SPOT image texture map of the Mona Township area.

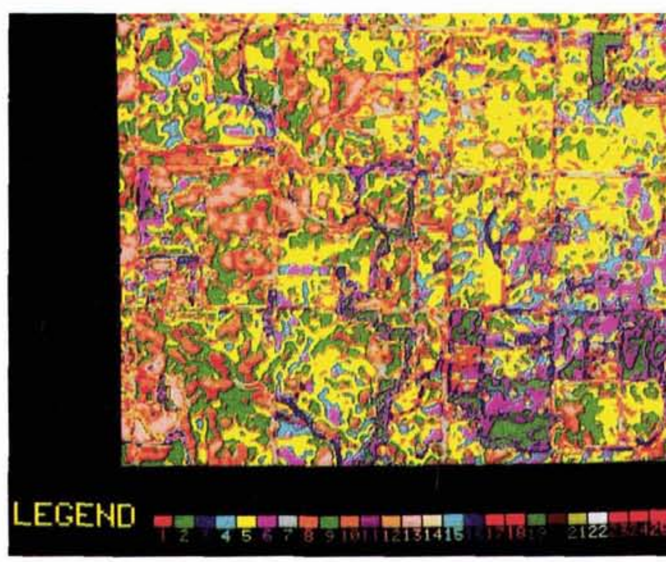

PLATE 2. SPOT image texture map of the Drummer Township area.

TABLE 2. MULTIVARIATE ANALYSIS OF VARIANCE OF SOIL PROPERTIES USED IN DISCRIMINATION OF FIELD SOIL AND IMAGE TEXTURE MAP UNITS.

Data source	Partial R**2	F Statistic	Prob. F	Wilks' Lambda*	Prob. Wilks'	ASCC**	Prob. ASCC
				Mona Township			
Field soil map	0.0077	2.239	0.0001	0.0558	0.0001	0.2180	0.0001
SPOT map	0.0251	1.397	0.0001	0.0682	0.0001	0.1657	0.0001
				Drummer Township			
Field soil map	0.0458	2.029	0.0001	0.0273	0.0001	0.2021	0.0001
SPOT map	0.0688	1.301	0.0001	0.0172	0.0001	0.1495	0.0001

* Wilks' lambda is close to 0 if the groups are well separated.
** Average squared canonical correlation (ASCC) is close to 1 if all groups are well separated.

TABLE 3. ACCURACY ASSESSMENT FOR FIELD SOIL AND SPOT IMAGE TEXTURE MAP UNITS IN MONA TOWNSHIP.

Field soil map units	Classification % Correct	% Commission	% Omission	Spectral map units	Classification % Correct	% Commission	% Omission
Ashkum	47.83	50.00	52.17	A1	34.78	63.64	65.22
Brenton	0.00	—	100.00	A10	38.46	61.54	61.54
Bryce	100.00	72.22	0.00	A11	100.00	33.33	0.00
Drummer	48.00	55.56	52.00	A13	50.00	60.00	50.00
Elliott	70.00	39.13	30.00	A14	46.15	62.50	53.85
Jasper	0.00	—	100.00	A15	75.00	62.50	25.00
La Hogue	100.00	42.86	0.00	A16	66.67	85.71	33.33
Milford	47.27	29.73	52.73	A17	100.00	25.00	0.00
Pella	70.00	18.33	30.00	A2	46.88	48.28	53.12
Rutland	100.00	50.00	0.00	A3	43.86	32.43	56.14
Selma	80.00	47.83	20.00	A4	55.56	58.33	44.44
				A5	36.67	50.00	63.33
				A6	80.00	60.00	20.00
Kappa = 0.5306				A7	71.43	50.00	28.57
% Overall agreement = 61.09				A8	35.71	61.54	64.29
					Kappa = 0.4035		
					% Overall agreement = 46.61		

TABLE 4. ACCURACY ASSESSMENT FOR FIELD SOIL AND SPOT IMAGE TEXTURE MAP UNITS IN DRUMMER TOWNSHIP.

Field soil map units	Classification % Correct	% Commission	% Omission	Spectral map units	Classification % Correct	% Commission	% Omission
Ashkum	44.44	55.56	55.56	B1	85.71	50.00	14.29
Brenton	75.00	40.00	25.00	B10	100.00	75.00	0.00
Bryce	25.93	53.33	74.07	B11	54.55	25.00	45.45
Corwin	0.00	—	100.00	B12	66.67	60.00	33.33
Dana	62.50	25.00	37.50	B13	75.00	25.00	25.00
Drummer	65.71	30.30	34.29	B14	80.00	50.00	20.00
Elliott	51.72	34.78	48.28	B15	62.50	54.55	37.50
Martinton	100.00	66.67	0.00	B16	75.00	57.14	25.00
Milford	66.67	55.56	33.33	B17	100.00	33.33	0.00
Proctor	100.00	58.33	0.00	B18	40.00	71.43	60.00
Raub	54.55	53.85	45.45	B19	100.00	60.00	0.00
Rutland	75.00	25.00	25.00	B2	21.74	66.67	78.26
Sawmill	57.14	20.00	42.86	B21	100.00	33.33	0.00
Swygert	60.00	50.00	40.00	B22	66.67	77.78	33.33
				B23	75.00	81.82	25.00
				B24	25.00	50.00	75.00
Kappa = 0.5025				B25	66.67	60.00	33.33
				B3	28.57	42.86	71.43
				B4	38.89	58.82	61.11
				B5	35.48	21.43	64.52
				B6	41.67	47.37	58.33
				B7	50.00	50.00	50.00
				B8	44.44	69.23	55.56
% Overall agreement = 55.20				B9	60.00	0.00	40.00
					Kappa = 0.4291		
					% Overall agreement = 46.15		

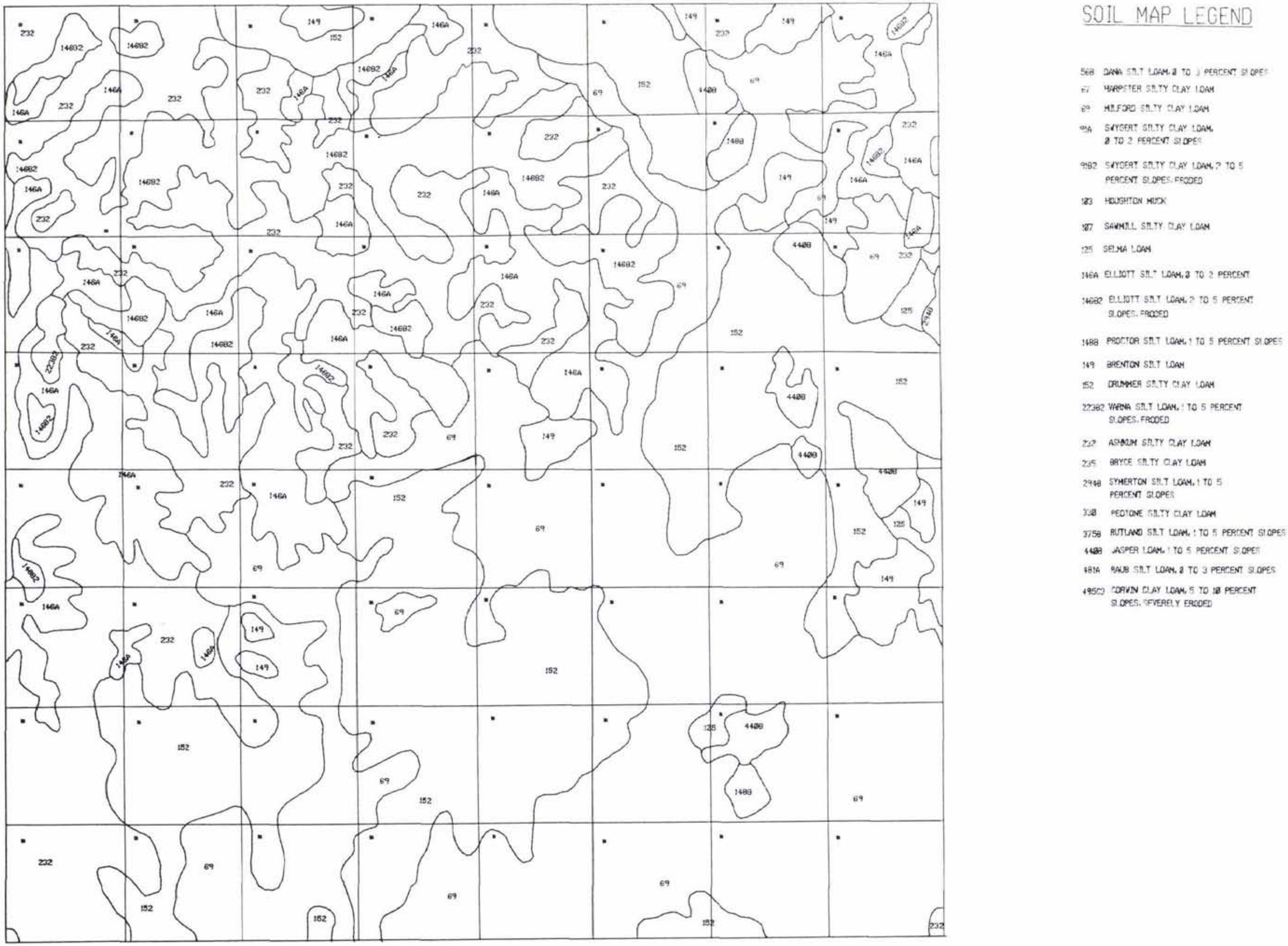

FIG. 2. Field soil map of part of the Mona Township area showing the general pattern of map unit distribution, the sampling grid, and the dots representing the sample sites.

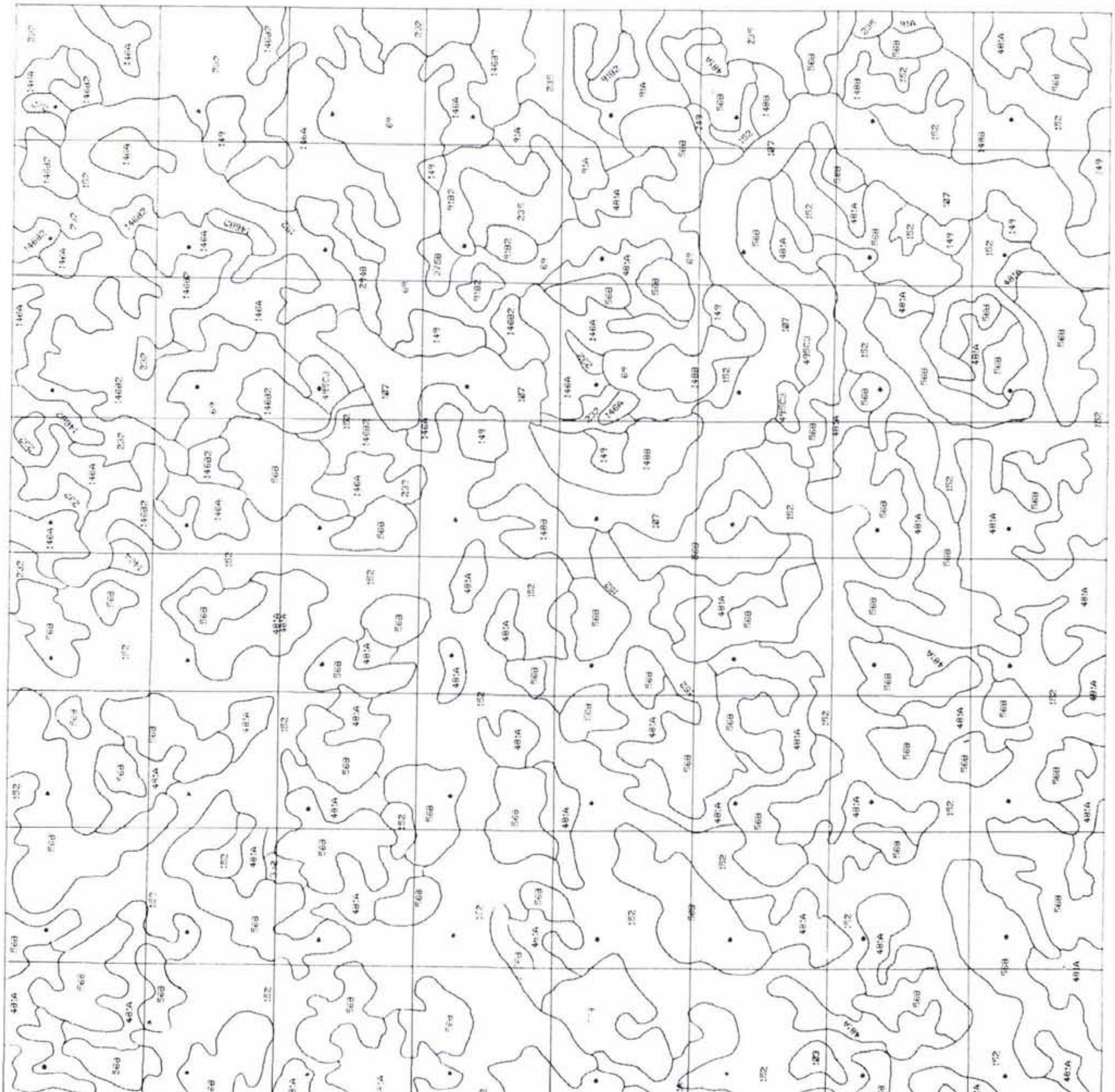

FIG. 3. Field soil map of part of the Drummer Township area showing the general pattern of map unit distribution, the sampling grid, and the dots representing the sample sites.

a consequence of allowing for more classes in the classification algorithm than were present in the field soil map during the imagery classification process. Also, the tendency for the spectral map to isolate small inclusions in the soil map unit due to spatial variations that are usually aggregated in the field soil map added to the greater number of spectral classes. There is reason to suggest that correlations exist between spectral classes and field soil map units because not only surface soil properties, but also some subsurface soil properties used in soil map unit delineation are related to spectral data. Agbu *et al.* (1990) have shown that a significant correlation exists among some pertinent subsurface soil properties and spectral data, suggesting that subsurface pedogenic processes in relatively stable landscapes influence soil surface properties including organic matter, amount and kind of clay, surface soil texture, etc., which are directly related to spectral reflectance.

The overall classification and map agreement was 61.1 percent for the field soil map and 46.6 percent for the spectral map in the Mona Township, while in the Drummer Township these were 55.2 percent and 46.2 percent, respectively. Adjusting the overall percent correct measure by subtracting the estimated chance contribution, using the Kappa statistic, the Mona Township shows actual agreement of the discriminant analysis classification to be 0.5306 with the field soil map and 0.4035 with the SPOT texture map (Table 3). In the Drummer Township the Kappa values were 0.5025 and 0.4291 for the field soil and SPOT texture maps, respectively. The ratios of the Kappa statistic for the different maps of an area could be used as a relative measure of the performance of one against the other, and this indicates that in the Mona Township the field soil map performed better than the SPOT image texture map by a factor of 1.32, while in the Drummer Township this factor was only 1.17, indicating that the two maps were comparable based on soil properties. These are not very wide margins and suggest that in these landscapes reasonably satisfactory map unit delineations could be made using image textural features in detailed soil surveys. Also, the Kappa coefficients of agreement for the spectral and the field soil maps were not significantly different from each other in both study areas at the 0.05 probability level, corroborating the comparability of the two maps for mapping unit separation. However, it should be acknowledged that the spectral texture map units must be characterized in terms of significant soil properties, and possible mergers determined before they can be useful in a soil survey or land use planning.

The classification accuracy of nearly 53 percent by the field soil map supports the contention that partition of soil variability, which is the basis of map unit separation, was not very effective. Therefore, the field soil map is an imperfect standard for judging the accuracy of a spectral map. Even if the field soil map were extremely accurate for detailed soil survey such as the one used in this study, which is a second-order survey (1:15,840), i.e., in minimizing soil property variability within map units and maximizing same among units, the particular pattern represented would be in part a function of the design of the mapping units, and hence not necessarily unique. The apparent divergence between the two maps could be a function of the properties emphasized and the way the respective mapping units were defined, rather than of differences in variability of soil properties which are usually reflected in delineated map units. Earlier work has indicated that some kind of transformation or classification of original imagery data is necessary for soil mapping unit discrimination. Therefore, the overall agreement shown by the texture image map, which is not significantly different from the field soil map based on variability of soil properties, suggests that textural transformation of original imagery data and its classification produces discriminate spectral mapping units which may be used as a basis for formulating and defining soil mapping units in a detailed soil survey program.

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BOOK REVIEWS

Geographic Information Systems: An Introduction by Jeffrey Starr and John Estes. Prentice Hall, Rt. 9 W, Englewood Cliffs, NJ 07632. 303 pages, 70 illustrations including 8 color plates. Hard cover. 1990. $44.20

WITHIN THE PAST FIVE YEARS, the field of geographic information systems (GIS) has mushroomed, as witnessed by the number of journals, conferences, and symposia devoted to the subject. The urgent demand for professionals trained in GIS has not gone unnoticed, with both graduate and undergraduate students showing an increasing interest and clamor for GIS instruction. Correspondingly, university departments nationwide are striving to meet that demand but have been hampered, especially at the introductory levels, by a lack of educational materials. *Geographic Information Systems: An Introduction* was written by the authors, Jeffrey Starr and John Estes, to help fill that void.

The first chapter introduces basic terminology and geographic/cartographic concepts important to understanding either manual or automated geographic information systems. The second chapter on background and history, though quite brief, helps put the present state GIS development into a much needed historical context. Importantly, the authors stress that the development of GIS, in terms of both the underlying concepts and the technology, is a product of many disciplines.

Starr and Estes take an all encompassing view of GIS, not necessarily to subsume other related disciplines but to link them. Data integration is viewed as the philosophical basis of GIS technology. GIS is seen as the correct tool for integrating the different technologies that are used in gathering, analyzing, and assessing spatial data. The authors define five essential elements that a GIS must contain: data acquisition, preprocessing, data management, manipulation and analysis, and product generation. A discussion of these five elements, along with data structures, form the core of the book with a chapter devoted to each.

A thorough grounding in data structures is crucial to stripping away the black-box image of GIS technology. The chapter does a reasonable job of introducing the various raster and vector data structures in common use: raster arrays, quad-trees, DIME files, DLGs, and arc-nodes. The authors rightly point out that geographic information systems should be able to work with both raster and vector data types and be able to readily convert from one data structure to the other. However, raster and vector systems are fundamentally different views of the underlying spatial information and the reader would have profited from expanded discussion on this and related topics (e.g., topological encoding).

Getting data into a GIS is one of the greatest operational headaches and costs involved in any GIS application. The two chapters on data acquisition and preprocessing provide an overview on developing a spatial database covering such topics as sampling, interpolation, photointerpretation, registration/rectification, digitizing/editing, inputting existing digital data sources, and data structure conversions. Once you have the data in, you have to manage it and make it available to users. Starr and Estes cover the basic principles of database management: efficiency, data retrieval/query, redundancy, integrity, security, and synchronization of multiple users. The discussion on spatial databases is framed in the context of two fundamental questions at the core of geographic analysis: (1) What is found at a given location?; and (2) Are there any examples of specified objects within a specified area?

Geoprocessing (manipulation and analysis of spatial data) is often the focus of attention when discussing GIS. Starr and Estes take a data structure independent approach in their overview of fundamental geoprocessing operations: reclassification and aggregation, connectivity and neighborhood operations, measurement, statistical analysis, and modeling. In comparison to the length of material presented on data preprocessing, this chapter receives short shrift, potentially disappointing readers