LARS Technical Report 092377

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1977

STAR INFORMATION FORM

1. Report No. 092377	2. Government Accession No.	3. Recipient's Catalog No.
4. Title and Subtitle Soil Map Unit Composition Assessment by Digital Analysis of Landsat Data		5. Report Date September 23, 1977
		6. Performing Organization Code
7. Author(s) F. R. Kirschner, S. A. Kaminsky, R. A. Weismiller, H. R. Sinclair, E. J. Hinzel		8. Performing Organization Report No. 092377
		10. Work Unit No.
9. Performing Organization Name and Address Laboratory for Applications of Remote Sensing, Purdue University, 1220 Potter Drive, West Lafayette, Indiana 47906		11. Contract or Grant No. Grant No. NGL-15-005-186
		13. Type of Report and Period Covered
12. Sponsoring Agency Name and Address National Aeronautics and Space Administration, Office of University Affairs, Washington, D.C. 20546		14. Sponsoring Agency Code
15. Supplementary Notes		

16. Abstract

Digital Analysis of Landsat MSS data collected June 9, 1973 was used to prepare a spectral soil map of a 430-hectare area in Clinton County, Indiana. Spectral identification of soil drainage characteristics enabled soil map units, inclusions, and complexes to be readily identified and quantified.

17. Key Words (Suggested by Author(s))		18. Distribution Statement	
19. Security Classif. (of this report) Unclassified	20. Security Classif. (of this page) Unclassified	21. No. of Pages	22. Price*

*For sale by the National Technical Information Service, Springfield, Virginia 22161

NASA JSC

SOIL MAP UNIT COMPOSITION ASSESSMENT BY DIGITAL ANALYSIS OF LANDSAT DATA[1]

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ABSTRACT

Soil survey map units are designed such that the dominant soil represents the major proportion of the unit. At times, soil mapping delineations do not adequately represent conditions as stated in the map unit descriptions. Digital analysis of Landsat multispectral scanner (MSS) data provides a means of accurately describing and quantifying soil map unit composition.

Digital analysis of Landsat MSS data collected on June 9, 1973 was used to prepare a spectral soil map for a 430-hectare area in Clinton County, Indiana. Sixteen spectral classes were defined, representing 12 soil and 4 vegetation classes. The 12 soil classes were grouped into 4 drainage classes based upon their spectral responses; the 4 vegetation classes were grouped into one all-inclusive vegetation class.

The spectral soil map produced using these groupings was compared to a conventionally prepared soil map. Three map units were investigated in detail: a) Mahalasville silty clay loam, b) Reesville silt loam, 0 to 2 percent slopes, and c) Xenia silt loam, 2 to 6 percent slopes, eroded.

Results show that the percentage of soil map unit inclusions can be readily ascertained according to their soil drainage characteristics and that soil complexes can be easily quantified. Thus, the composition of soil map units can be accurately determined.

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[1]This work was accomplished under the National Aeronautics and Space Administration, Office of University Affairs, Grant No. NGL-15-005-186. Journal Paper No. 6690, Purdue University, Agricultural Experiment Station.

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INTRODUCTION

Soil maps depict soil conditions in a particular landscape with varying degrees of precision depending primarily upon the type of survey conducted, and the ability of the soil scientist to analyze the landscape and identify the components of the map units delineated. Due to the subjective nature of soil surveys and the vast areas of land involved, it is often difficult to evaluate the accuracy of the soil surveys. Currently, field methods such as spot checking and line and point intercept transects are used to evaluate the composition of map units (9). Various studies (1,6,8) to determine map unit composition suggest that many delineations do not adequately represent conditions as stated in the map unit descriptions. Also, many separations on a soil map often actually represent soil complexes rather than taxonomic units with minor inclusions.

A study was undertaken to determine the feasibility of using digital analysis of Landsat multispectral scanner (MSS) data as a means of accurately describing and quantifying soil map unit composition. This paper examines three distinctly different soil map units, comparing their compositions as described by conventional field mapping techniques and digital analysis of Landsat MSS data.

STUDY SITE

A 430 hectare tract located in Clinton County, Indiana (Sections 3, 4, 9, and 10 of T20N, R2W) was selected as the study site. Soils in this area are formed in glacial loess which was deposited over till, derived from the late Wisconsin glaciation, and localized lacustrine deposits. The slope of the surface topography ranges from 0-6 percent, but commonly is less than 2 percent.

Within the 430 hectare area, 112 hectares comprising three major mapping units, were selected for intensive investigation. However, the entire study site was analyzed in order to provide sufficient data points to statistically represent the spectral variability of the scene. The three map units selected for detailed analysis were: a) Mahalasville silty clay loam, occurring on nearly level or slightly depressed lake plains formed in calcareous stratified silts and sands; b) Xenia silt loam, 2 to 6 percent slopes, eroded, found on moraines and till plains of nearly level to gently sloping topography and formed in moderately thick loess deposits over calcareous loam till; and c) Reesville silt loam, 0 to 2 percent slopes, formed in loess on nearly level topography.

DATA

Landsat-1 MSS data collected on June 9, 1973 were used as the main data source for this study. This scene was selected because the data were: a) of high quality, b) acquired when most row crop cropland was in a bare soil state and c) free of interfering atmospheric and surface conditions (i.e., clouds, haze and standing water, although Clinton County had received approximately 2.90 inches of precipitation in the week prior to the Landsat overpass).

The Landsat MSS data were geometrically corrected (i.e., rotated, deskewed and rescaled) (2), and registered to ground control points selected from U.S. Geological Survey 7½ minute topographic quadrangle maps. These procedures produced a data set of a scale of 1:20,000 with points in the data registered to their exact ground position. A soil map of the study site had previously been prepared by soil scientists of the USDA/Soil Conservation Service (SCS) as an ongoing progressive survey in cooperation with the Purdue Agricultural Experiment Station. The aerial photography and field mapping sheets used by the USDA/SCS personnel were also at a scale of 1:20,000, allowing for convenient comparisons between the conventionally and computer prepared soil maps.

PROCEDURES

Landsat MSS data covering the study area were analyzed by a computer-implemented analysis package, LARSYS (7). Initially a clustering algorithm was used to arbitrarily divide the MSS data into groups of sample points of similar spectral characteristics by calculating the Euclidean distances between each sample and cluster class center and assigning each sample to the class with the minimum distance. After the initial clusters were formed from all data points, new cluster class centers were developed by considering the mean of each cluster. The process continued until the cluster centers did not change from one iteration to the next (3). Statistics consisting of the mean relative reflectance values and covariance matrices for each cluster grouping were determined and used in calculating the class divergences (a measure of the dissimilarity of two distributions) (4,5). A more reliable criterion for determining dissimilarity between distributions, termed transform divergence (D_T)

$$D_T = 2[1 - \exp(-D/8)],$$

where D is the original divergence, was actually used in this analysis (10). Based on results obtained from the transformed divergence, cluster groupings could either be deleted, retained, or combined based upon their statistical separability characteristics.

The clustering procedure indicated that there were 16 spectrally separable classes within the study area. A ratio A = V/IR,* calculated for each spectral class, was used to identify 12 soil and 4 vegetation classes within the 16 spectral classes.

The mean and covariance statistics developed for each of the 16 classes were used by computer-implemented pattern recognition techniques and a maximum likelihood Gaussian classifier (10) to assign each of the data points to one of the 16 spectrally separable classes. These classes were later grouped into four major soil classes and one all-inclusive vegetation class. Each major

*V is the relative intensity of the mean spectral responses of the visible wavelengths [(0.5 to 0.6μm) + (0.6 to 0.7μm)] and IR is the relative intensity of the mean spectral response of the reflective infrared wavelengths [(0.7 to 0.8μm) + (0.8 to 1.1μm)].

soil class was assigned to one of four drainage classes based upon the range of their total reflectances (i.e., the sum of the relative reflectance values from all four Landsat bands, Table 1). These groupings were verified by detailed field checking.

Mean reflectance values were calculated and plotted (Figure 1) for the major soil classes and vegetation. The separability of these grouped spectral classes is evident; however, the vegetation class does add some confusion to class distinctiveness. A one-way analysis of variance was performed on the mean reflectance values for each major class and showed significant differences for all groupings in all four channels. The Newman-Keuls multiple range test was used to indicate where these significant differences exist (Table 2). However, non-significant differences appeared between the vegetation and soil classes. Individual channel reflectance values indicate there is bare soil plus minor vegetation present in each soil class. Confusion, therefore, cannot be considered in error, but rather a true indication of the scene. Even within soil classes some overlapping distributions occur. Consideration of only the mean reflectance values (first order effects) for all 4 spectral channels shows all classes to be separable with the exception of the somewhat poorly and poorly drained soil classes. However, the maximum likelihood classifier uses not only the mean reflectance values but also the covariance matrices (second order effects) of the classes for classification. Thus, utilization of data from all four spectral channels (visible and infrared) and second order statistics contribute to the successful separation of the individual classes.

An alphanumeric spectral map delineating the 4 soil and 1 vegetation groupings was produced at a scale of 1:20,000. Field checks were conducted to evaluate the agreement between the conventionally developed soil map and the spectral soil map. Field observations included a) precise location of the three map units on both types of soil maps, b) notation of the various soils and their respective drainage classes and c) notation of the boundaries (agreements and disagreements) of the three map units and of their individual soil components.

RESULTS

The conventionally prepared soil map of the study area, and the enhanced boundaries of the 1) poorly drained Mahalasville, 2) moderately well drained Xenia and 3) somewhat poorly drained Reesville map units are shown in Figure 2. To allow for comparison, the boundaries of the three map units, as delineated on the conventional soils map, were superimposed upon the spectral soil map (Figure 3). As previously stated, the 12 spectral classes of soil were placed into 4 major soil groupings which were correlated with 4 soil drainage classes. It is clearly evident from Figure 3, that dissimilarities exist between the map unit boundaries as conventionally mapped and the boundaries suggested by the spectral map. Significant inclusions not delineated on the conventionally prepared soil map were noted on the spectral soil map, and in all cases, the inclusions identified different drainage characteristics than identified by the named map unit (Table 3). Field checking of these three map units and adjacent areas revealed the spectral classification to be correct.

Map Symbol	Drainage Class	Summed Reflectance
/	Moderately Well	184.47-215.13
+	Somewhat Poorly	162.47-176.20
X	Poorly	136.31-151.05
M	Very Poorly	118.78

Table 1. Correspondence Between the Spectral Reflectances and Drainage Characteristics of Soil Groupings.

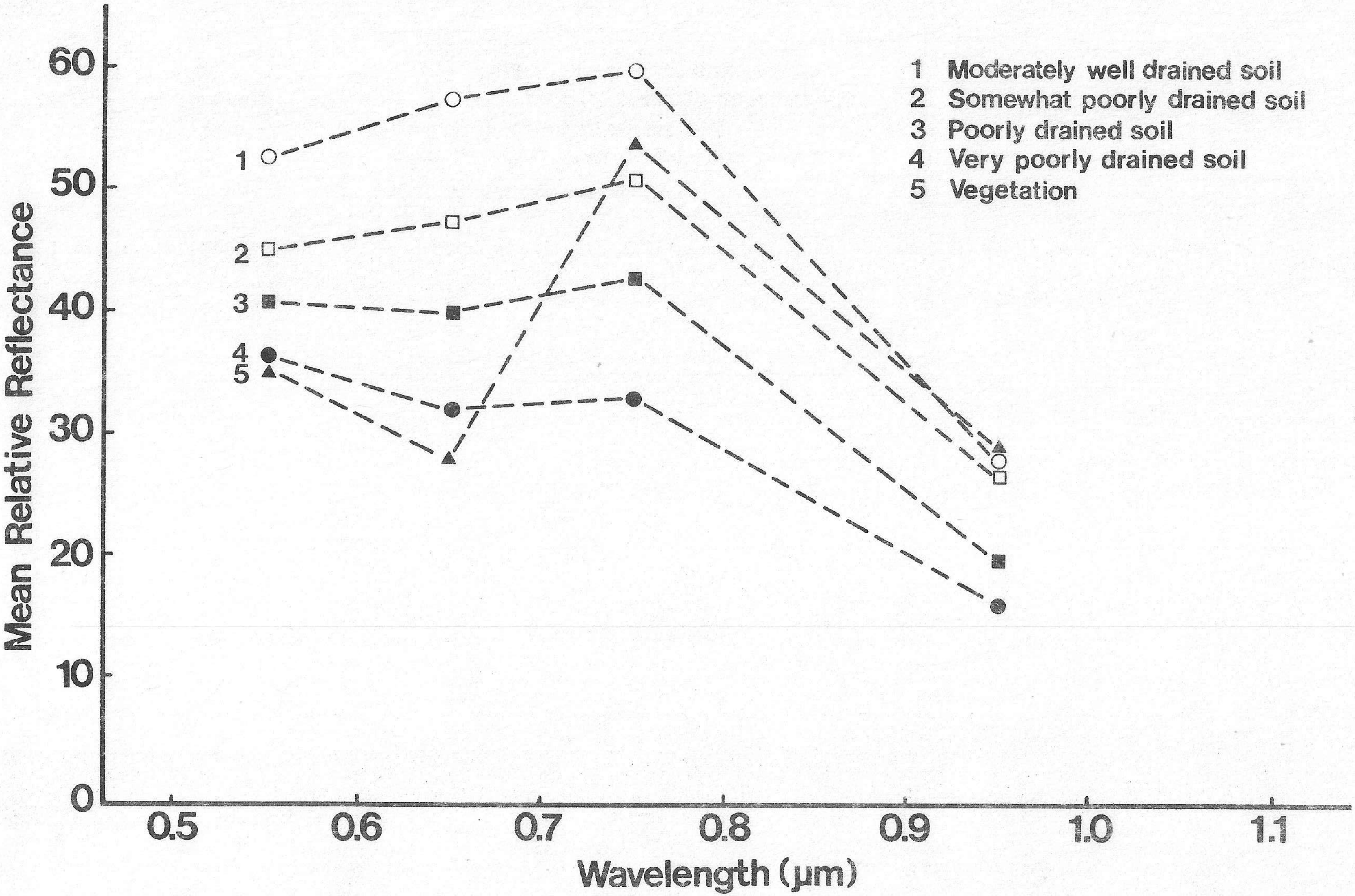

Figure 1. Landsat Relative Reflectance Values of Spectral Groupings

CHANNEL	MW*	SP*	P*	VP*	VEG*
1	52.68	44.38	41.13	36.56	34.9
2	57.31	44.9	40.4	32.96	27.09
3	60.53	52.3	43.4	33.7	53.4
4	27.46	24.73	20.16	15.78	28.9

Table 2. Significant Mean Spectral Class Values (Newman-Keuls)

*VP, P, SP, MW, VEG: very poorly, poorly, somewhat poorly, moderately well drainage classes and vegetation class, respectively.

**Bar indicates non significance .05 level

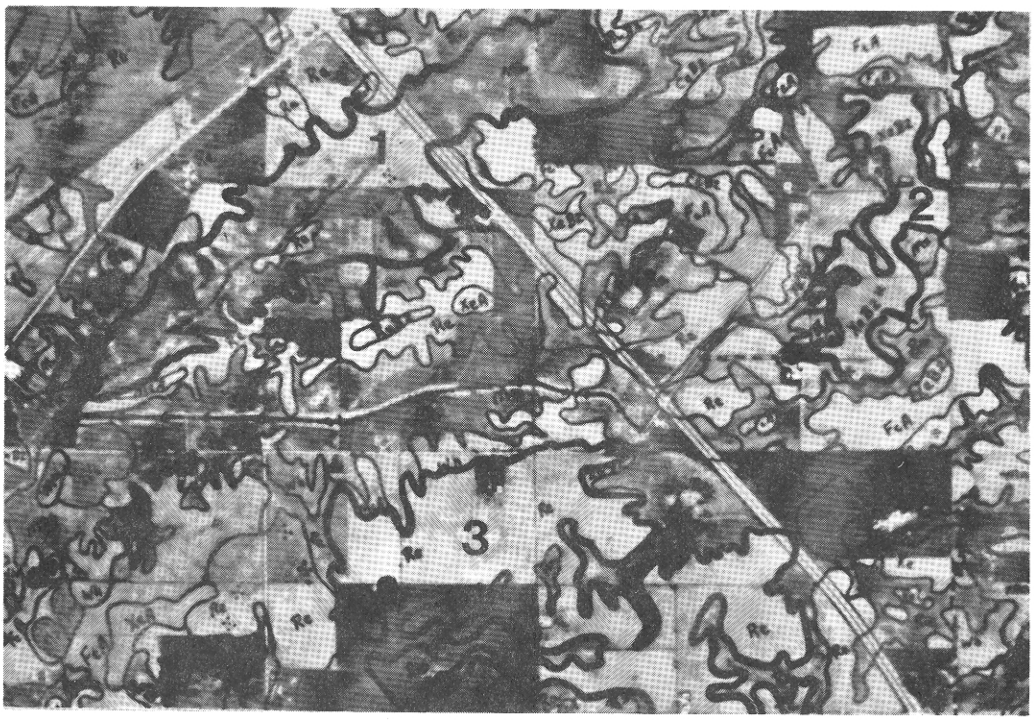

Figure 2. Conventional Soil Map Showing the (1) Mahalasville, (2) Xenia, and (3) Reesville map units.

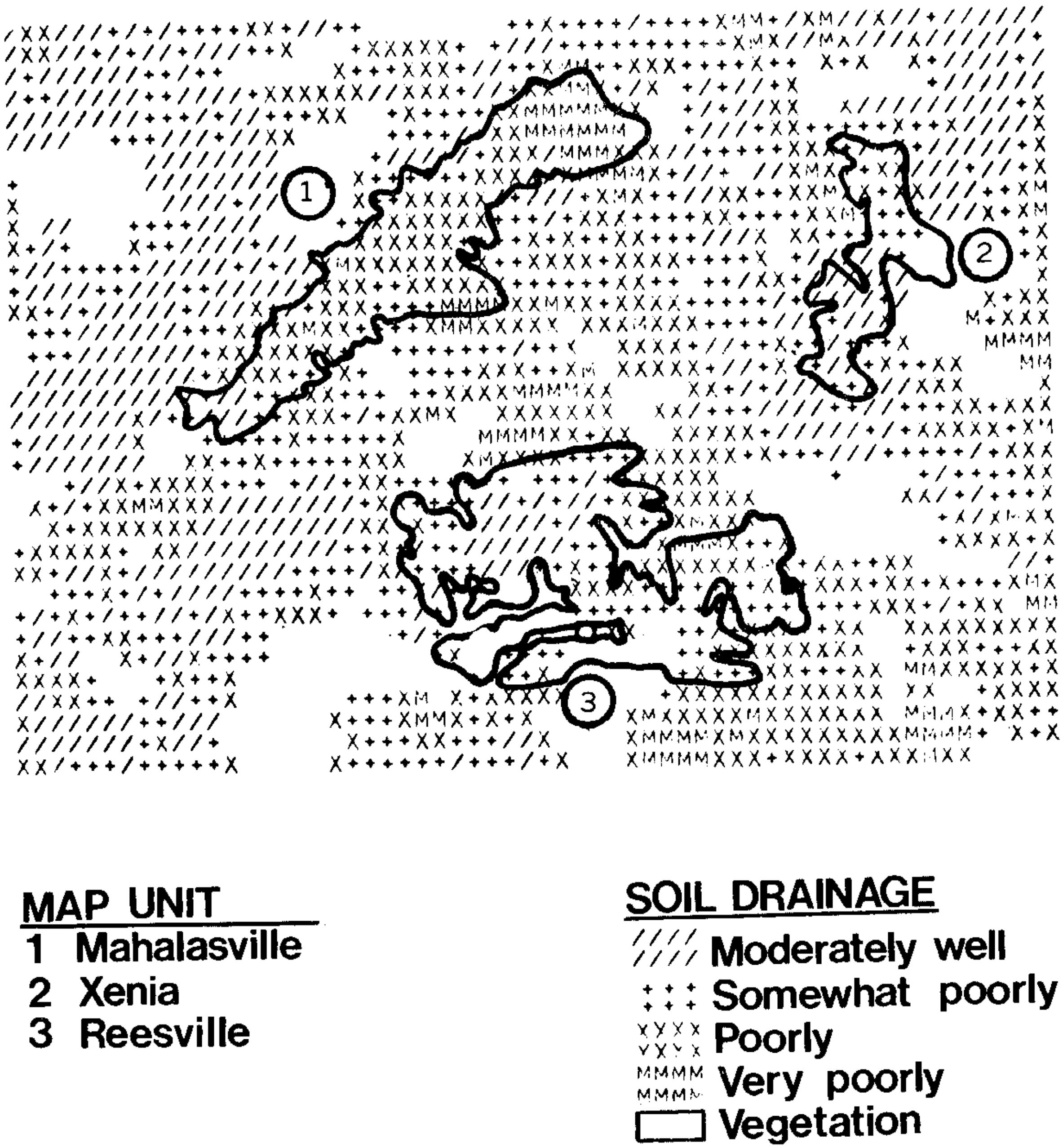

Figure 3. Conventionally Delineated Map Units Superimposed upon the Spectral Soil Map.

Map Unit	Size	Percent of Area Represented by Named Unit	Percent Inclusions Identified by Drainage Class
Mahalasville silty clay loam (poorly drained)	47.7ha	51.4	21.5%VP; 17.8%SP; 9.3%MW*,**
Reesville silt loam (somewhat poorly drained)	41.2ha	46.1	0.9%VP; 18.3%MW*,**
Xenia silt loam (moderately well drained)	13.4ha	30.0	16.7%P; 40.0%SP*,**

Table 3. Composition of Soil Map Units as Determined from Spectral Data.

*VP,P,SP,MW: very poorly, poorly, somewhat poorly and moderately well drainage classes, respectively.

**Remaining percentage of mapping unit was vegetated, and thus drainage classes could not be determined from spectral data.

Within the poorly drained Mahalasville map unit four drainage classes were delineated. A significant proportion of this map unit, 10.3 hectares, or 21.5 percent, was shown to be very poorly drained with small proportions of moderately well and somewhat poorly drained soils included (Table 3). The 10.3 hectares of very poorly drained soil, which also had a higher organic matter content, constitutes a large enough area that it could be mapped as a named series separately from the Mahalasville map unit. Likewise, many of the moderately well and somewhat poorly drained areas could be deleted from the Mahalasville map unit and combined with adjacent areas of similar drainage. Areas not large enough to map separately can be identified as either similar or contrasting inclusions. Also, the Mahalasville map unit boundary could be adjusted to include adjacent poorly drained areas which have similar characteristics.

Within the Reesville and Xenia map units, the named series represents only 46.1 and 30.0 percent of the respective map units. The remainder of the two map units are composed of soils with distinctively different drainage characteristics (Table 3). The boundaries of these map units could be adjusted to exclude the soils with different drainage characteristics or to include adjacent soils of similar drainage characteristics. Also since these areas have a very intricate soil pattern, the spectral data provides an excellent tool for evaluating the need for establishing a soil mapping unit complex.

CONCLUSIONS

Digital analysis of Landsat multispectral scanner data can provide the detail necessary to define soil features not readily discernible through visual interpretation of Landsat imagery or aerial photography. Capabilities inherent in this procedure allow for the differentiation of soil drainage characteristics which can be correlated with soil series being mapped in a given locale. The accurate identification of soil drainage characteristics and correlation of these classes with soil series will enable the soil scientists to readily ascertain soil map unit boundaries, inclusions and possible soil complexes. Also, the areal extent and relative proportions of these features are easily quantified. Thus, the composition and purity of soil map units can be accurately determined. In both the Reesville and Xenia map units, contrasting inclusions constituted a large enough percentage of the units to justify additional separations or the mapping of a soil complex.

Computer-aided Landsat data analysis can be utilized in numerous aspects of the soil survey. A spectral soil map based on drainage characteristics provides the soil scientist with a tool which can aid in the accurate delineation of map unit boundaries. It can aid the inexperienced soil scientist in the placement of soil borings by allowing him to avoid transition zones and to select areas most representative of the map unit. Using the quantitative data generated by digital analysis, it can readily be determined if inclusions exist within a map unit. These inclusions can be easily defined as being either similar or contrasting, and thus, the soil scientist can determine if a soil complex should be established. The determination and measurement of the presence of inclusion is quite important in the interpretation aspect of the survey. In urban areas the distribution of small contrasting inclusions (1 to 2 acres in size) must be recognized and accurately mapped to allow for appropriate land treatment which may be vastly different than specified for the map unit as a whole. Both the areal and quantitative nature of these data can serve as an aid in the quality control aspect of a soil survey by providing a priori knowledge of the soils.

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