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Utilizing Remote Multispectral Scanner Data and Computer Analysis Techniques

Philip N. LeBlanc

Christian J. Johannsen

Joseph E. Yanner

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LAND USE CLASSIFICATION UTILIZING REMOTE MULTISPECTRAL SCANNER DATA AND COMPUTER ANALYSIS TECHNIQUES

P. N. LeBlanc, C. J. Johannsen
and J. E. Yanner

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ABSTRACT

LeBlanc, Philip Norman. M.S. Purdue University, August, 1972. Land Use Classification Utilizing Remote Multispectral Scanner Data and Computer Analysis Techniques. Major Professors: Christian J. Johannsen and Joseph E. Yahner.

This research was designed to study the ability of present automatic computer analysis techniques with the use of multispectral scanner data to differentiate land use categories represented in a complex urban scene and in a selected flightline. An airborne multispectral scanner was used to collect the visible and reflective infrared data.

A small subdivision near Lafayette, Indiana was selected as the test site for the urban land use study. Multispectral scanner data were collected over the subdivision on May 1, 1970 from an altitude of 915 meters. The data were collected in twelve wavelength bands from 0.40 to 1.00 micrometers by the scanner.

The results indicated that computer analysis of multispectral data can be very accurate in classifying and estimating the natural and man-made materials that characterize land uses in an urban scene.

A 1.6 km. wide and 16 km. long flightline located in Sullivan County, Indiana, which represented most major land use categories, was selected for analysis. Multispectral scanner data were collected on three flights from

an altitude of 1,500 meters. Energy in twelve wavelength bands from 0.46 to 11.70 micrometers was recored by the scanner.

A new, more objective approach to computer training was developed for analysis of the three dates of data. Emphasis was placed on the standardization of a procedure for analysis of data. The procedure offered faster and consistantly good duplication of attained results.

The results indicated an ability for automatic computer analysis of remotely sensed multispectral scanner data to characterize and map land use categories within the test area. Additionally, results indicated an alteration of the data analysis procedure and land use classification scheme.

INTRODUCTION

The need for current information on major land use, acreage, and distribution of crops is essential for efficient management of resources in both the developed and developing countries of the world. Historically, the collection, compilation and interpretation of data on use of land in the United States has proved invaluable in the study of present land-resource problems.

In the past, land use data have been compiled by census interview or by field mapping. In some countries, major classes of land use are mapped in the field and published, usually on a small scale. For most countries, land use inventory data consist of data compiled by census from personal interview, mail questionnaires, study of sample areas, or some combination of these means. Generally, these methods take a relatively long time because the number of trained scientists and workers are limited. These factors account for the relatively long intervals between census projects in many countries.

The increasing need for land use inventory in many developed and some of the developing countries has already pressed the use of one method of remote sensing. This familiar technique is the use of black and white aerial photography. Airphotos have been used to make maps showing the distribution of major land uses and specific crops in many countries. Measurements from these airphoto maps provide data on acreage of categories of land use. Comparison between recent and older photos can provide information regarding change such as expansion of urban development, revision of farmland to forest, or development of new farmland by clearing, drainage, or irrigation.

Currently, the competition for use of land is becoming more intense. Urban development, need for more recreation areas (particularly near large urban areas) and the preservation of wildlife habitats are matters of great interest to those concerned with land resources. In the future, it is clear that current, accurate and concise information will be of great importance and need in the careful examination and utilization of our resources.

Newer, more sophisticated remote sensing systems have the potential to offer significant improvement in rural and urban land use evaluation. Computer analysis of multispectral scanner data is one such new arm in the field of remote sensing. This project is concerned with determining the ability of present automatic computer techniques employing multispectral scanner data to obtain useable land use information.

The first study is a preliminary investigation into the uses of remote sensing techniques for the identification of land uses that characterize an urban scene. The second study involves the use of a new multispectral analysis technique for the identification of land use classes in an agricultural scene. The results from this project should further define the role of remote sensing as a tool in resource evaluation.

CHAPTER 1

LITERATURE REVIEW

The Role of Remote Sensing in Land Use Classification

The concept of multispectral remote sensing is that "plants and materials located at the surface of the earth possess the fundamental property of reflecting or emitting electromagnetic energy differentially over the spectrum" (Tanguay, 1969a). In the visible portion of the electromagnetic spectrum these particular properties are seen in the form of color. These properties appear to be characteristic of each material and are due to the fundamental properties of energy absorption, emission and surface reflectance. These characteristics will be further discussed in following sections.

Hoffer (1967a) has defined multispectral remote sensing as:

> "...the detection and recording, from a distance or remote location, of reflected or emitted electromagnetic radiation in many discrete relatively narrow spectral bands between 0.3 to 14 micrometers wavelength..."

Remote sensing information can be collected by a variety of instruments mounted near or above the surface of the earth in airplanes and satellites. With these instruments, energy reflected from a "target" can be collected and recorded for processing and analysis. Holter (1970) and LARS (1968) have described in detail the instrumentation, data collection and data processing systems currently used in the field of remote sensing with multispectral scanner data.

The merits of remote sensing as a potentially valuable tool in gathering and updating land use and resource information has been reported by Shelton (1967) and Johannsen and Baumgardner (1968). Aside from its data acquisition and handling characteristics, the value of remote sensing in a land use classification system depends on its ability to accurately differentiate materials such as rock, bare soil, crop species, trees, grass, and water. The basic assumption underlying this project is that remote sensing, utilizing multispectral scanner data and automatic computer analysis techniques, has achieved sufficient accuracy and reliability in the identification of land surface materials to warrant its application to land use classification. The literature reports successful application of remote sensing in the areas of vegetation mapping, soils mapping and geologic studies.

In soils mapping, studies by Kristof and Zachary (1971), Stoner and Horvath (1971), and West (1972), have shown that spectral maps of surface soils can be produced using multispectral data and automatic computer analysis techniques which compared favorably with soils maps prepared by conventional soil survey techniques. Mathews et al. (1971), using multispectral data, were able to classify soil parent materials that compared well with the boundaries identifiable on aerial photography. It has been shown (Al-Abbas et al., 1972) that gross textural differences in surface soils can be mapped using remote sensing techniques.

Tanguay (1969b), in research studying the feasibility of engineering soils mapping, reported identifying and mapping areas that indicated "the distribution of main soils classes, drainage features, wet zones, muck pockets, and bare rock areas." In another study, Baumgardner et al. (1970) have shown that computer analysis techniques can differentiate five different ranges of organic matter content for mineral soils.

Recent geologic studies have reported classifying various geologic materials. Smedes et al. (1969) have reported using multispectral data and automatic computer analysis techniques to map terrain in Yellowstone National Park. They showed that nine classes (bedrock exposures, talus, vegetated rock rubble, glacial kame, glacial till, forest, bog, surface water and shadows) could be mapped with good accuracy. Using multispectral scanner data collected between 6.7 and 13.4 micrometers and computer analysis techniques; Lyon et al. (1969) were able to identify quartz beach sand at a Texas site and recognize and map granite and andesite rock at a California test site. In preliminary work with resource inventory and survey, Mallon (1971), using scanner data collected in the 8 to 14 micrometer range of the electromagnetic spectrum, investigated automatic computer mapping of manganese, bauxite and chromate ore materials. He reported that his studies show "an appearance of a family of spectral curves" associated with each material.

In vegetation mapping studies, correct identification of 81 to 99 percent were reported in mapping six cover-type classes (row crops, wheat, oats, pasture, hay and trees) using multispectral scanner data (LARS, 1970). Hoffer (1967b) reported good results in classifying land surfaces into three basic categories of green vegetation, bare soil and water.

The literature indicates that basic land cover mapping utilizing multispectral scanner data and presently developed computer analysis techniques is sufficiently advanced to provide accurate identification and mapping of land use characteristics. It is with this assumption that this study was undertaken.

Energy Phenomena

The electromagnetic spectrum has no definite upper or lower limit; it can be stated, however, that it extends from radio frequencies, less than one Hertz (cycles per second) to cosmic rays greater than 10^{26} Hertz (Halliday and Resnick, 1962). Hoffer and Johannsen (1969) illustrated a portion of the electromagnetic spectrum which is of importance to remote sensing (Figure 1) and reviewed various types of sensors used in the different wavelength regions.

Optical-mechanical scanner systems effectively operate within the electromagnetic spectrum from approximately 0.3 to 15.0 micrometers. This portion of the spectrum can be divided essentially into two parts: the reflective and the emissive regions (approximately 0.3 to 3.0, and 3.0 to 15.0 micrometers, respectively). The reflective region can be further subdivided into the ultraviolet, visible and infrared regions (approximately 0.004 to 0.38, 0.38 to 0.68, and 0.68 to 3.0 micrometers, respectively).

A remote sensor receives energy emanating from a target as a function of the illumination and the reflective and emissive properties of the target. The illumination source for the earth is primarily the sun; although, illumination may be received from the moon, stars, or

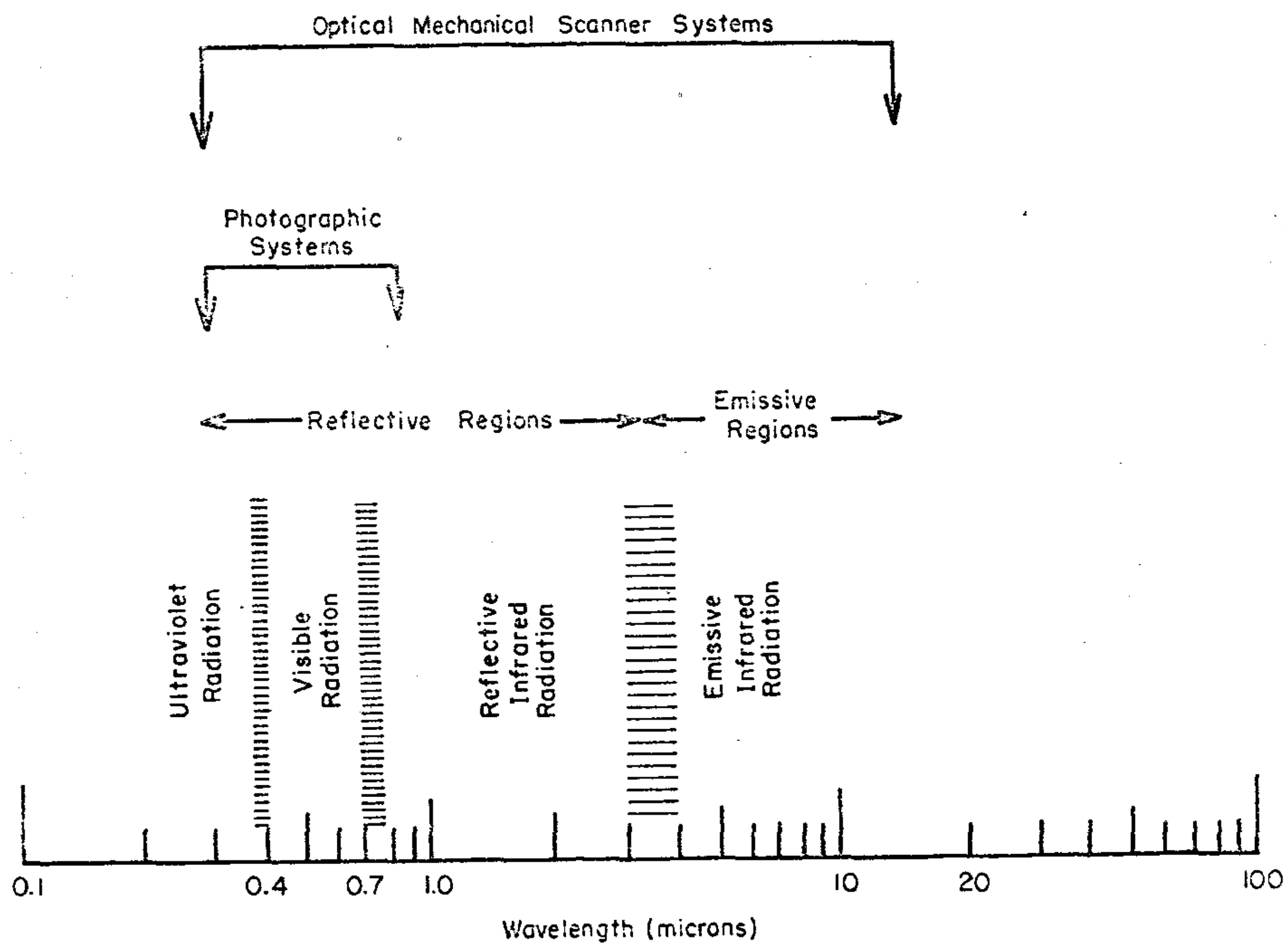


Figure 1. Portion of the electromagnetic spectrum (after Hoffer and Johannsen, 1969).

intense artificial sources such as a laser or mercury-arc lamp. The earth's atmosphere and local weather changes can adversely affect the spectral character of the sunlight (Gates, 1965; and Johannsen, 1969). The attenuation effects by the atmosphere on the sun's energy profile must be considered not only from the source to the target, but also the energy returning from the target to the remote sensor. Within the electromagnetic spectrum there are regions or "windows" where the attenuating effects of the atmosphere are relatively hindered. Within these regions spectral channels are selected for energy measurements from a target to a remote sensor.

Radiated energy is emitted by all objects above the temperature of absolute zero as a function of their temperature and emissivity (Gates, 1962). Basic data on emissivity are given by Myers and Allen (1968) and Kumar (1972). Various factors influence soils and plant temperatures. Gates (1963), Waggoner and Shaw (1951), Ansari and Loomis (1959) and Kryuchkow (1961) discussed the factors of solar radiation, air temperature, humidity, wind speed, available soils moisture, leaf structure and differences in plant species as the important factors which affect plant temperature. The primary factors relating to soil temperature are soil particle size, soil moisture, soil air humidity and soil porosity (Myers, 1970).

The reflectance function varies considerably from one object to another and for each object within a specific category. Gates (1970), Gausman et al. (1969) and McClure (1969) discussed many of the physical and physiological properties of plants which explain some of their reflectance characteristics. The properties mentioned were leaf geometry, morphology, physiology, chemistry, soil site and climate. Soil reflectance characteristics are influenced by moisture content, particle size, structure, surface roughness and organic matter content (Bowers and Hanks, 1965).

From this discussion it can be seen that objects reflect and emit energy differentially over the electromagnetic spectrum. It is the concept of multispectral analysis that in some channel or channels in the electromagnetic spectrum classes or categories of materials will be distinguishable and will be detectable with multispectral analysis techniques. It must be kept in mind that each factor mentioned that influences the reflectivity, emissivity or illumination of an object can also contribute considerable variability to the response of a given material. It is for this reason that frequently there will exist several spectral subclasses to characterize one class of material.

Land Use Classification Schemes

Because there are several concepts about what "land" is (Barlowe, 1958), there exists a similar range in ideas about the concept of "land use." In an effort to reach a general understanding of the definition of the term "land use" the Committee on Land Use Statistics grappled at length with this problem (Clawson and Stewart, 1965). The committee concluded that the term "land use" should refer "to man's activities on land which are directly related to the land." It was further noted that phrases such as "human uses of land" or "human activity on land" might help in the clarifying of the concept of land use; it is the activity dimension that constitutes the central focus in defining land use.

The purpose of this section is to review some of the presently accepted land use schemes in an effort to select or formulate a suitable scheme that would be compatible with remote multispectrally sensed scanner data. Four land use schemes from the Conference on Land Use Information and Classification (1971) were selected for review; a more detailed outline format of each scheme is included in the Appendix, Table B.

Three of these classification schemes, the Standard Land Use Coding Manual, the Canadian Land Inventory, and a scheme developed by the Association of American Geographers, were developed for use on a country-wide or national basis, while the fourth scheme, the New York State Land Use scheme, was devised for use only in the state of New York.

The three national schemes differ significantly in the level of inventory detail contemplated in their use. The Standard Land Use Coding Manual ("A Standard System for Identifying and Coding Land Use Activities," 1965) provided a four-digit categorization of land use which was developed mainly for identifying and coding (rather than mapping) urban land use activities and adjacent situations in the United States. This classification scheme was not designed specifically for use with air photo-interpretation or other remote sensing technques. Ground observations and enumeration must provide much of the information necessary to classify land use with this scheme when used in urban areas. The scheme has nine first-order categories and ninety-nine second-order categories.

The Canadian Land Inventory ("A Guide to the Classification of Land Use," 1970) employed essentially a two-digit or two level land use classification scheme for use throughout the more densely populated portions of

Canada. Maps of present land use were compiled at a scale of 1:50,000 using this scheme, which has six major or first-order categories, twelve second-order categories, and two third-order categories. The scope and objectives of the Canadian inventory necessitated a much more generalized scheme for classifying land use than the situations for which the Standard Land Use Coding Manual was primarily prepared.

The third national scheme was developed from a study by the Association of American Geographers (Anderson, 1971 a) for use with orbital imagery for making land use maps ranging in scale from 1:250,000 to 1:2,500,000. This classification scheme was developed and used in a pilot study in the Phoenix, Arizona area to test the capabilities of the devised scheme for use with conventional color and color infrared imagery taken from the Apollo 9 satellite and from high altitude aircraft (50,000 to 60,000 feet). The imagery was supplemented by black and white photo mosaics at a scale of 1:62,000. The scheme has seven first-order categories and twenty third-order categories. Fourth or even fifth-order categories can be added for use with larger scale imagery or for use with ground observations and enumeration.

The fourth scheme developed specifically for the state of New York is quite adaptable for use elsewhere. The New York land inventory classification scheme ("A Review of the New York State Land Use and Natural Resource Inventory," 1970) employed essentially a three-digit classification scheme which was developed to accomodate the recognition of areal and point data, i.e., cropland and farmsteads. The scheme has eleven first-order categories, forty-eight second-order categories and seventy-five third-order "point data" categories. Aerial photography at a scale

1:24,000 constituted the main land use information source for the New York state inventory.

A set of working criteria against which to evaluate land use classification schemes for use with orbital and other high altitude imagery was presented by Anderson (1971b). It proved to be valuable in the final evaluation of the selected classification scheme used in this study. These criteria are:

(1) A minimum level of accuracy of about 85 to 90 percent or better should be approached in the interpretation of the imagery being used.

(2) A well-balanced reliability of interpretation for the several categories included in the classification scheme should be attained. Closely related to the requirement of a minimum overall level of accuracy is the matter of varying levels of accuracy which can be attained for the several categories of the classification being used.

(3) Repeatable or repetitive results should be obtainable from one interpreter to another and from one time of sensing to another.

(4) The classification scheme should be useable or adaptable for use over an extensive area.

(5) The categorization used in the classification scheme should permit vegetative and other cover types to be used as surrogates for activity-oriented categories wherever possible.

(6) The classification scheme should be suitable for use with imagery taken at different times during the year.

(7) The classification scheme should permit effective use of sub-categories that can be obtained from ground surveys or from the use of imagery available at a larger scale or with the use of color photography.

(8) A need to collapse the categories of the classification scheme into a smaller number of categories must be recognized.

(9) The classification scheme should recognize the multiple use aspects of land use whenever possible.

The above outlined criteria could not be met by the classification scheme developed for use in this study. As Anderson (1971) has stated, even some of the presently used classification schemes do not meet satisfactorily the above criteria. In the future, it may be desirable to augment these criteria as the role of remote sensing in a land classification system is more fully defined.

CHAPTER II

TRAINING FIELD APPROACH TO CLASSIFYING AN URBAN SCENE -- A PRELIMINARY STUDY

Introduction

The use of remote sensing techniques in the rapid gathering, processing and interpretation of data obtained over an urban area is of interest to many people. Quantitative information from a remote sensing system would have a broad spectrum of applications to urban planning. This study is concerned with the determination of the accuracy with which an urban area can be categorized, evaluation of the classification procedure for this purpose, and further definition of investigations which should be conducted.

The multispectral data analysis techniques used in this study were developed at the Laboratory for Applications of Remote Sensing and followed a standard computer training procedure utilizing manually selected training fields. This preliminary study served to familiarize the researcher with the LARS's data analysis procedures and helped to formulate a revised data analysis technique used in the second study, "Spectrally separable training class approach to land use mapping" (Chapter 3).

Experimental Methodology

Description of Test Site

The 26.3 ha (65 acre) Meadowbrook subdivision (Figure 2) is located 4 km. (2 1/2 miles) east of Lafayette, Indiana, on State Route 26 (SE 1/4 of SW 1/4 of SE 1/4 of Sec. 23; Range 4W, Township 23N). The subdivision contains 68 moderately priced homes which are predominantly 2 to 3 bedrooms, single level with attached garage.

The subdivision is bounded on the north and west by woods and with cultivated fields to the south and east. Roads in the subdivision are asphalt with surface color from light grey to nearly black; driveways are generally concrete with some being asphalt or gravel. All lots have good grass cover and are minimally landscaped with only a few lots having trees or shrub plantings. The roofing materials are asphalt shingles, and their colors are predominantly light green, or blue and grey with several roofs being black.

Data Collection

The remote multispectral scanner data for this study were collected by the Willow Run Laboratory, University of Michigan, using a multispectral optical-mehcanical scanner mounted in a C-47 aircraft. The overflight of the test site was made on May 6, 1970 at 10:30 A.M. from an altitude of 915 meters (3,000 feet). The data were collected in 12 discrete channels of the spectrum (six in the visible and six in the reflective and emissive infrared). A detailed description of the scanner system is given by Holter (1967).

Figure 2. Black and white aerial photograph of the Meadowbrook Subdivision.

Data Organization and Registration

Analog-Digital Data conversion. The raw data from the overflight was in analog form and was first transformed to a digital format compatible for the LARS digital computer and multivariate pattern recognition programs. Each analog scan line was sampled at twice the normal digitization rate (440 points instead of 220) as a means of increasing the amount of information gained from materials on the ground. Because of a machine limitation bounded by the maximum rate of digitization in the analog to digital conversion system, doubling the number of points sampled per scan line meant halving the number of channels of data from twelve to six (Table 1). Each data point, or remote sensing unit (RSU) is given a unique address in a two-dimensional coordinate system composed of scan line numbers and data points within a scan line. Each RSU is designated to represent a unit of area on the ground. Since these data were collected at an altitude of 915 meters (3,000 ft.), each RSU, directly below the aircraft, represents about 9 square meters on the ground.

Data Registration. Because the scanner data were collected with a three aperture scanner, one for the visible, reflective infrared, and emissive infrared portions of the spectrum, the respective sets of channels of data had to be aligned such that all data points would coincide. This process, called "Data Registration," is accomplished by locating check points on grey scale computer printouts (to be described below) of the channels of data, such as road intersections or corners of fields. After an array of such points are established throughout the flightlines, the data are aligned with these points by the computer. A complete description of this procedure is given by Anuta (1970).

Table 1. Re-digitized multispectral data channels used for collection of data over test site on May 6, 1970.

Channel	Wavelength (micrometers)	Spectral Description
1	.40 - .44	violet
*2	.50 - .52	blue-green
3	.55 - .58	green
*4	.58 - .62	yellow
5	.66 - .72	red
*6	.80 - 1.00	Reflective IR

*Channels selected by $DIVERG for the classification of the test site.

LARS Data Analysis

The computer programs used at LARS to analyze multispectral scanner data were developed at LARS under a NASA grant; their functions and sequential steps involved in the analysis procedure are indicated in Table 2 .

Computer grey-scale printouts, which are digital, spatial displays of the spectral responses of the data, were first obtained in several channels. From ground observation collected at the test site on the day of the flight, computer training samples were selected from areas of known materials such as trees, grass, roads, driveways, and rooftops, located on the grey scale printouts. For this study, 14.1 percent of the total data points were used in computer training. The procedure is referred to as a "supervised" approach to computer training because the researcher selects only training samples of materials he desires the computer to recognize for the classification.

After training samples were selected, another program, $NSCLAS, was used to determine spectral separability or uniformity between and among training classes. Often classes of materials, which were not spectrally separable were merged to speed computer classification time, and subclasses of materials, which were spectrally separable, were found that could greatly increase the detail of the classification.

The next step in the analysis procedure was to obtain statistical information concerning the spectral responses of each class or subclass of materials. This was accomplished by the program, $STAT for which the output consists of class means and covariance matrices for the responses in each wavelength band for each computer training class. Another program called $DIVERG selected those channels which allowed the greatest

Table 2 . Computer programs used for classification of multispectral scanner data (after West, 1972).

ANALYSIS STEPS	PROGRAM NAME	PROGRAM DESCRIPTION
1	LARSPLAY	
	$PIC	Obtain grey scale printouts of each spectral band desired using alphanumeric symbols. Primary purpose to select training samples from known areas based on "ground observations."
2	$NSCLAS	Obtain spectral groupings or clusters of the data based on reflectance values from selected spectral bands without supervision or prior ground truth designations.
3	LARSYSAA	
	$STAT	Statistical analysis of reflectance data from training fields and classes - histograms, spectral curves, mean vector, covariance and correlation matrices are generated.
	$DIVERG	Selection of best subset of available spectral bands for classification; obtain indication of separability of proposed classes.
	$CLASSIFY	Classification of each remote sensing unit in designated area.
	$DISPLAY	Display of classification by alphanumeric symbols with the use of threshold levels. Evaluate classification performance.

separation between all combinations of desired classes (Table 2). Wacker (1971) found that the accuracy of classification is not greatly increased beyond the use of four to five channels for agricultural materials.

Next, the training field statistics were used as classification criteria by a classifier program called $CLASSIFY. The computer classifies each data point or RSU based on maximum likelihood criteria (Landgrebe, et al., 1968).

The final step is to display the classified area, using the program, $DISPLAY. Any alphanumeric character can be used to display a particular class. This program also offers an option for testing the accuracy of the classification. The user inputs the coordinates of test fields for which the ground truth is known. On call, the computer will note the accuracy on the test fields and calculate the percent accuracy.

Results and Discussion

The final classification of the subdivision (Figure 3) is displayed in two categories: man-made, containing the classes of roof and street-driveways (Figure 4), and naturally occurring materials containing the classes trees-shrubs and grass (Figure 5). The class "streets-driveways" in the category of man-made materials is further subdivided into asphalt and concrete materials (Figure 6).

Tabular comparisons between the computer classification results and an estimate of the actual area covered by each category (Table 3) were obtained by overlaying a photograph of the test area with a dot grid. The dots in each category were counted and divided by the total

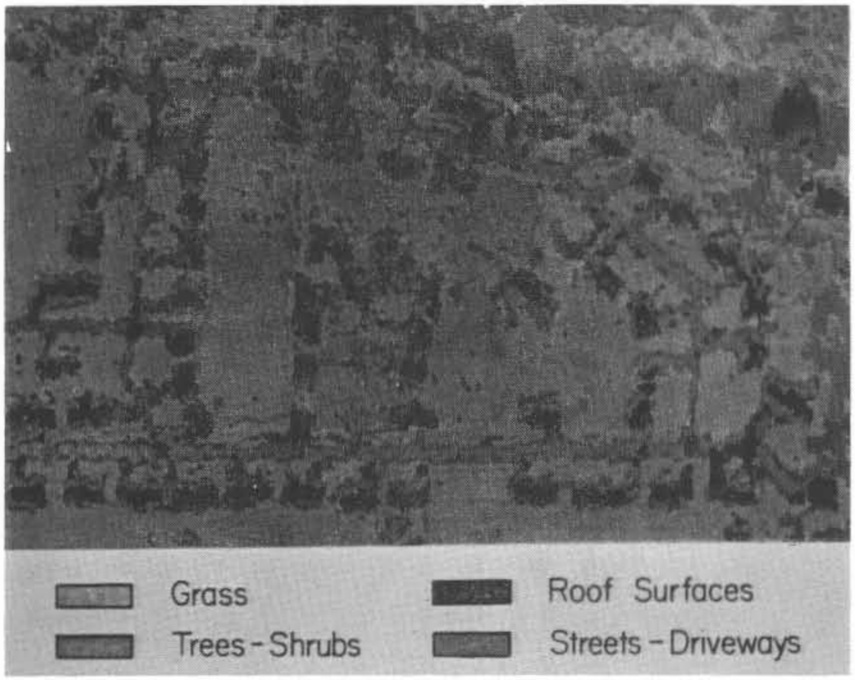


Figure 3. Computer classification display of man-made and natural features of the test site.

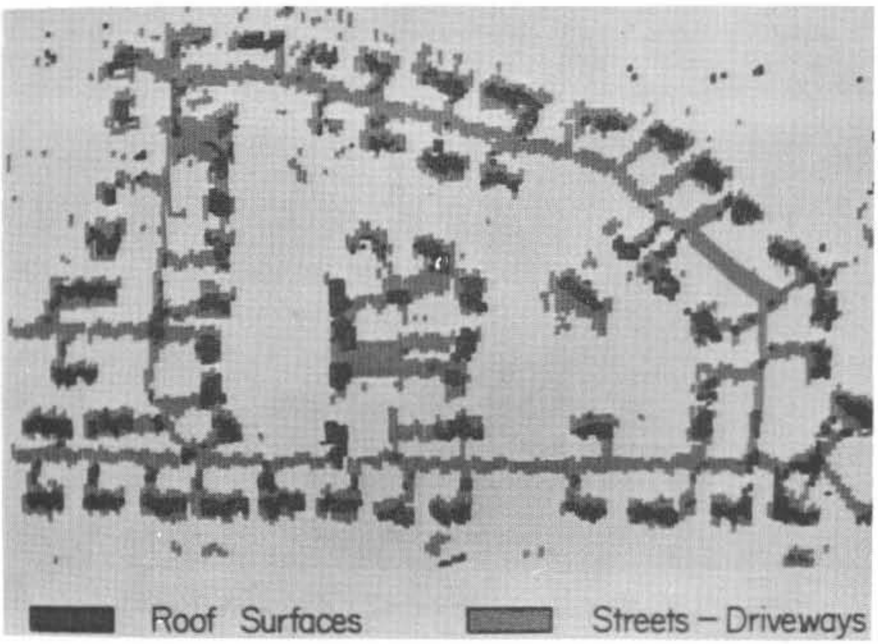


Figure 4. Computer classification display of the man-made materials present in the test site.

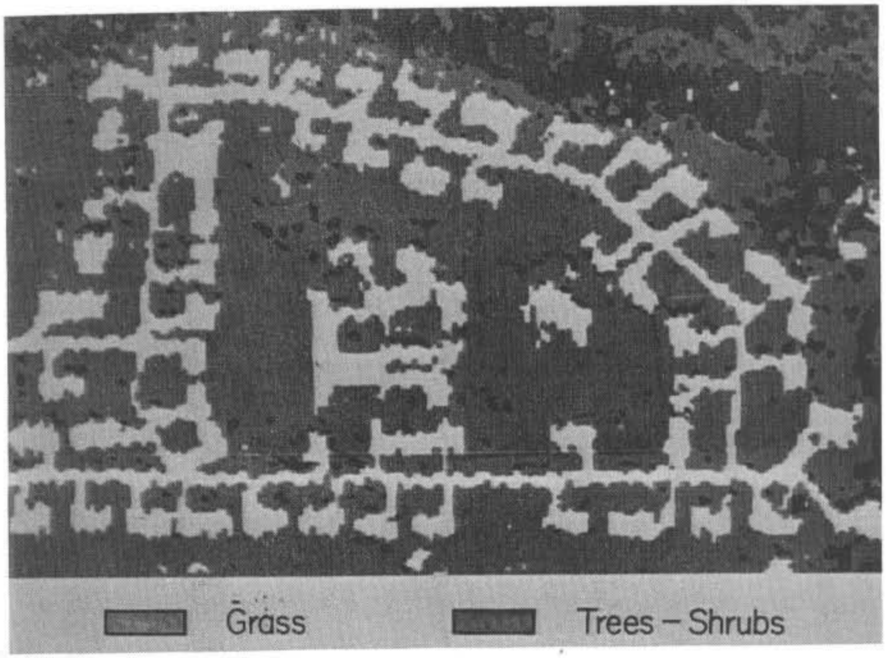


Figure 5. Computer classification display of the natural materials present in the test site.

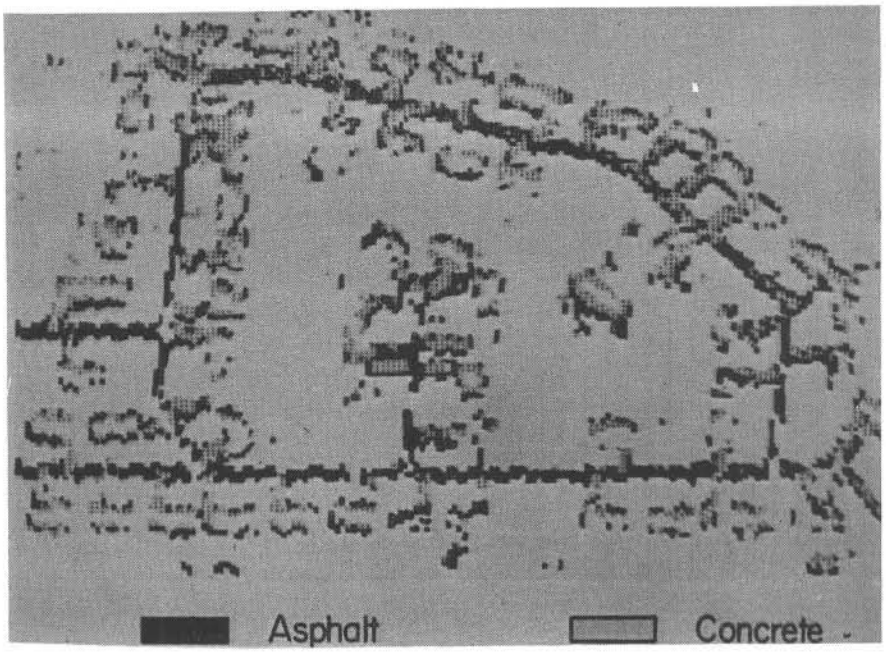


Figure 6. Computer classification display of the category "streets-driveways" subdivided into asphalt and concrete materials present in the test site.

Table 3. Computer classification results compred to a dot-grid estimate of the different categories of material present in the test site (all numbers represent percent in the total area).

Material	Computer Results	Dot-grid Estimate
	Man-Made	
Roof	5.1	8.2
Streets-Driveways	17.3	13.3
Subtotal	22.4	21.5
	Naturally Occurring	
Trees and Shrubs	15.2	20.6
Grass	62.1	57.9
Subtotal	77.3	78.5
Grand Total	99.7	100.0

dots in the scene. The computer classification results were automatically calculated by the computer. A total of 99.7 percent of the data points in the test area (Table 3) are actually classified by the computer. The remainder of the data points were not classified because an insufficient number of computer training classes were present to adequately represent these data points. These points are considered "thresholded" points.

The classification results (Table 3) reflect the percent of the total area occupied by a mapped category. The results do not indicate the spatial accuracy of the classification. Comparison of the photography (Figure 2) to the classification displays, shows that the spatial accuracy is good and that most of the misclassifiction occurs near class boundaries.

The computer classification results align themselves will with the estimated actual percentages of each category as shown in Table 3 . The results show that the computer classification slightly over-estimates the percent area occupied by the category "man-made" (22.4 versus 21.5 percent of the area as calculated by the actual) and only slightly under-estimates the area occupied by the category "naturally occurring" material (77.3 versus 78.5 by the actual).

Within the category "man-made," Table 3 shows the percent area classified as roof material as 5.1 and the percent area classified as streets-driveways as 17.3. The estimated actual percent of these materials in the total area are 8.2 for roof and 13.3 for streets and driveways. With closer examination of the photography (Figure 2), concrete sidewalks and patios were visible around many of the homes, but not to the extent shown by the computer classification of this material in Figure 6 . Much of the misclassification may be explained by shadows, and the large variation in roof size, color and surface orientation with respect to the scanner.

Some difficulty was experienced in differentiating roofs from dark vegetation in some of the preliminary classifications, but was overcome by introducing a reflective infrared channel (0.8 to 1.0 micrometers) in the classification procedure. This channel was quite valuable in mapping man-made materials from naturally occurring because the responses were largely independent of color.

Within the category "naturally occurring," the computer estimate of the percent of the total areas occupied by trees and shrubs and by grass were 15.2 and 62.1, respectively. The actual percentages of the total area for these two classes of material were 20.6 and 57.9, respectively. Comparison of the photography (Figure 2) with the classification display (Figure 5) indicated that much of the underestimation of trees and shrubs and over-estimation of grass may be due to difficulty in discriminating between shrubs and grass materials.

Considerable spectral variability existed within both the natural and man-made materials; therefore, a large number of samples were required to represent single classes of materials. This is especially true in categories dealing with materials of small area. A possible explanation of the variability in these smaller areas is in the registration of the data channels. By overlaying each individual channel of data (in the form of grey scale printouts of the data) on a light table, it is found that registration is generally within one or two data points between channels. For large area analysis, this degree of registration accuracy would not generally present any problems, but for small areas this degree of error can be critical. Considering the ground area occupied by some of the materials such as rooftops, streets and driveways, it is very important that each data point in each data channel characterize the same exact spot on the ground.

A possible improvement in classification accuracies especially with materials of limited ground area could be obtained if the number of data points for training could be increased. This could be accomplished by either collecting the data at a lower altitude or increasing the resolution of the scanner. If the data were collected at a lower altitude, then the area represented by a single data point could decrease. This would decrease the effective coverage of the scanner but would also increase the resolution of the data. It would be most advantageous to mechanically increase the resolution of the scanner through increased scanner technology and increase the effective coverage of the scanner. This would allow improved scanner resolution for more detailed studies and increase the ground area over which data could be collected, thus increasing the economy of the scanner system.

Conclusions

Much more work must be done with multispectral analysis of urban land use before exact procedures and spectral bands most useful to this type of analysis can be made. However, from this limited study the following conclusions can be drawn.

(1) Computer analysis of multispectral data has shown to be accurate in characterizing and estimating a limited number of land use categories in a small urban scene when compared to conventionally accepted methods such as photointerpretation.

(2) The use of the reflective infrared channels was very valuable in differentiating the man-made materials from naturally occurring materials.

(3) More accurate data registration would be recommended for this type of analysis.

(4) Better resolution of the scanner would be desirable.

Further studies using present state-of-the-arts multispectral scanner and computer analysis techniques should involve investigation into the following:

(1) The reflective and emissive portions of the spectrum in an effort to further classify man-made materials.

(2) A more complex urban scene for the benefit of further testing of the multispectral approach to urban information gathering.

(3) Studies into urban-suburban relationships over time.

CHAPTER 3

SPECTRALLY SEPARABLE TRAINING CLASS APPROACH TO LAND USE MAPPING

Introduction

Every year land use changes occur on millions of acres in the United States. The greatest portion of these changes occur when agricultural and forest lands are diverted to housing, industry, highways, public buildings, and parks. The effects associated with these changes are numerous and far reaching.

To the present, most interpretation, monitoring, and land use evaluation has involved the utilization of aerial photography. Because of its utilitarian value as a base for most resource surveys, aerial photography will continue to be the basic tool available to the planner, but as the scope of planning activities continue to expand, new means of data collection, handling and interpretation must become available. Computer analysis of multispectral scanner data is one such new technique.

This study is concerned with determining the ability of automatic computer techniques in employing multispectral scanner data to obtain land use information. Emphasis is placed on the standardization of a procedure for the analysis of data with accurate repeatability of classification results. Three overflight dates of data are classified and evaluated in an effort to (1) determine the accuracy of the classification results as a predictor of land use, (2) find a suitable land use classification scheme for use with multispectral data and (3) determine the best date or combination of dates that will return the largest and most accurate land use information.

Experimental Methodology

Selection of Flightline for Analysis

The data selected for this study was collected during the 1971 Corn Blight Watch Experiment over the intensive study area located in western Indiana. The intensive study area was composed of thirty north-south oriented flightlines that extended from the northwest to the southwest portions of the state. Each flightline was 1.6 km. (1 mile) wide and ranged 12.7 to 19.2 km. (8 to 12 miles) in length.

Because multispectral scanner data were collected over each flightline at two-week intervals (when weather permitted) from the middle of May to late September, it offered ideal coverage of a flightline for this study.

The selection of a suitable flightline was made primarily on the basis of the diversity of land uses present. Flightline 219 located in Sullivan County, Indiana, was selected because it represented four main land use categories: agricultural, forest, urban, and water. Other factors considered in its selection was its relative closeness to LARS facilities and the researcher's familiarity with this flightline from previous analysis during the Corn Blight Watch Experiment (Bauer, 1972; Phillips, 1972; Johannsen and Bauer, 1972).

Physiographic Sketch of Flightline 219. Flightline 219 is located in the northeastern portion of Sullivan County (Figure 7); it is 1.6 km. (1 mile) wide, approximately 16 km. (10 miles) long and is oriented in a north-south direction. Sullivan County is located on the west, south-central portion of Indiana and is bounded by Vigo County to the north, Greene and Clay Counties to the east, Knox County to the south and the Wabash River to the west.

The topography of the north and central portions of the flightline is level to gently undulating with some surface drainage into small ponds in the northern sector. The southern portion of the flightline is characterized by greater relief that contains several small west-to-east draining creeks. The flightline elevation ranges from 165 meters (550 feet) in the northern section to 138 meters (460 feet) in the south.

The underlying bedrock of the area is Pennsylvanian age sandstone and shale of the Covemaugh series. These units are underlain by Mississippian age sedimentaries in which extensive strip coal mine operation has been active to the east of the flightline (Bieberman, 1949).

The soils present in the flightline were formed under forest conditions in Illinoian and Wisconsinan age loess underlain by Illinoian age glacial till. The two soil associations present in the flightline are the somewhat poorly drained Reesville-Iva present in the northern third and the southern third of the flightline and the moderately well drained Cincinnati-Ava-Alford present in the middle third and some of the southern portions of the flightline. Both soil associations have deeply developed profiles that are deeply leached, acid, and a lack of good fertility (Sullivan County Soil Survey, 1971).

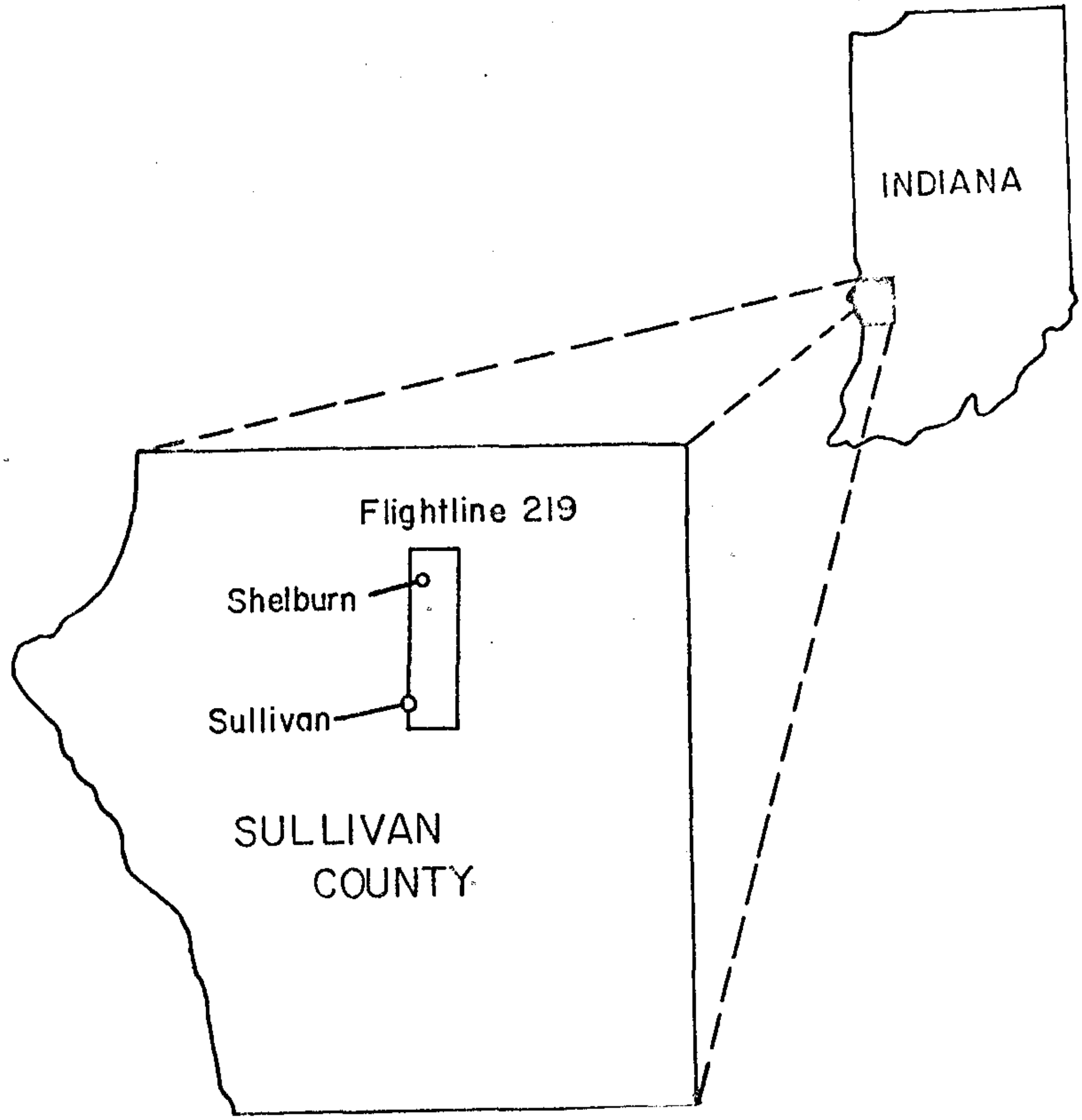


Figure 7. The location of flightline 219 in Sullivan County, Indiana.

Climate for the area is midcontinental characterized by wide ranges in temperature from summer to winter. The mean daily maximum temperature in July is 88°F, and the average minimum in January is 22°F. Average rainfall is 96.5 cm. (38 inches) annually and is well distributed throughout the year, but is slightly heavier in the spring and summer than fall and winter (Sullivan County Soil Survey, 1971).

The soils in the flightline are used primarily for cropland, pasture, and woodland with cropland predominating. The poorly drained areas are usually in woodland-forest. The main agricultural crops are corn, soybeans, small grains, hay and pasture.

Selection of Data Dates to be Analyzed

Data from three overflight dates of flightline 219 were chosen from a possible eight flights made during the summer of 1971. The eight sets of data were collected on May 21 and at two week intervals from June 27 through September 28 inclusive by the University of Michigan aircraft. Data for analysis were selected on the basis of data quality, channels of data available for analysis, altitude, field conditions, availability of photographic data for overflight, and time of day data were collected. A summary of data overflight information for the selected dates of analysis are found in Table 4.

All dates were first examined for uniformity of data and collection procedure. This included selection of those dates with the same number of channels of data available for analysis; those dates where the data were collected near the same time of day, at same altitude and same aircraft heading; and those dates with the same data preprocessing (i.e., analog to digital processing) procedure. Those selected dates were then

Table 4 . Summary by date of data information for Flightline 219 for the three flights selected for analysis.

Mission No.	Date Flown	Run No.	Data Tape No.	Channels of data avail.	Altitude in meters	Time of Flight	Plane Heading
38	5/21/71	71017100	502	13	1,500	1224	180°
41	7/21/71	71039800	511	12	1,500	1050	180°
45	9/15/71	71070500	529	12	1,500	1145	180°

examined for overall data quality and for the availability of photographic coverage for that date. This included dates with cloud free data, and dates with the same flightline coverage. Finally, dates were selected that provided the greatest range in field conditions for the land use classes and were most evenly spaced over the summer data collection period. The three dates selected and meeting the above criteria were: May 21, July 21 and September 15 (Missions 38, 41 and 45, respectively).

Description of Flightline for the Three Data Collection Dates

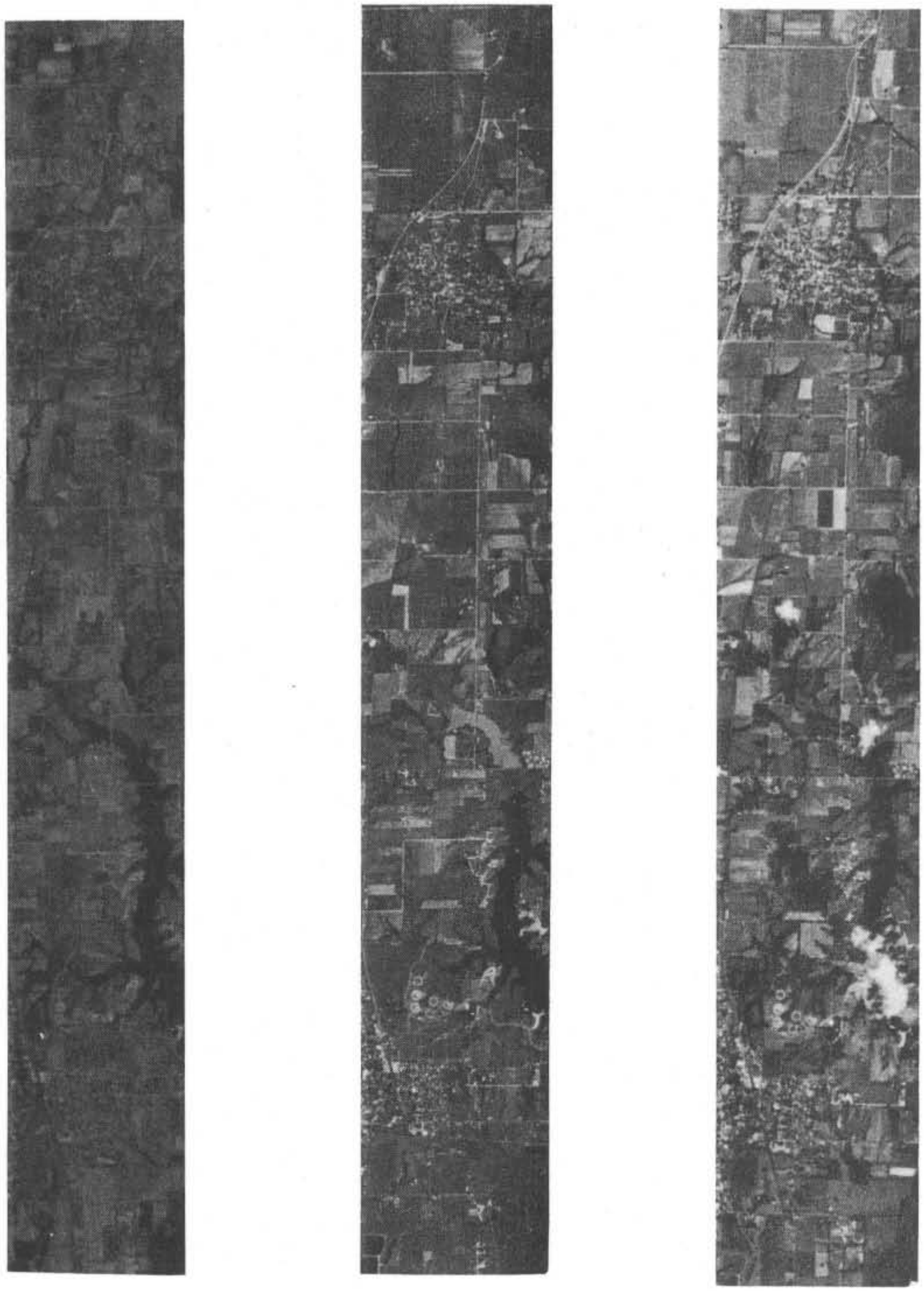
Color infrared photography (CIR) was used in Figures 8a,b and c for the flightline description because it was felt that it could supply more information than conventional black and white or color photography. Also it was used because complete flightline coverage was available for the dates needed, and its collection dates came closest to all the dates of the actual scanner data collection than any other photographic data available. Although the dates of the CIR photography do not coincide exactly with the actual scanner dates, the photographs provide basic flightline information at near flight conditions. To interpret CIR photography, one must remember that these materials appear near these colors on the CIR: vegetation, red; bare soils, green; and water, blue to black. These figures are summarized as follows.

May (Figure 8a). Agricultural cropland is represented in the flightline for this date as bare soil (plowed) and last year's crop residue (sometimes weedy); it is seen on the CIR as green. Winter wheat is the only agricultural crop that is present in the flightline for this date and is red on the CIR photography. Pasture and hay appear

Figure 8. Color IR photographs of Flightline 219 for the three data collection dates. (Scale 1:75,000)

Legend

Photograph	Date Flown	Roll Number	Frame Number	Mission Number
a	5/13/71	99RF710004	7907	165
b	7/12/71	99RF710045	8432	175
c	9/21/71	99RF710097	103	180



(a) May (b) July (c) September

Figure 8.

to be at the lush green stage (very bright red on the CIR photograph) and appear very similar in color to winter wheat. Trees and bushes are also red but are not completely leafed out; areas around the lake and other low wet areas are lined with vegetation. The urban areas where trees are present are most clearly visible because trees have not yet hidden many of the streets, sidewalks, driveways, and roofs. Highway and railroad right-of-ways are lined with vegetation and are clearly visible.

July (Figure 8b). All agricultural cropland has been planted by this date. Corn fields are uniformly red in the photograph and are not yet tasseled. Soybean fields show early and late planting dates: relatively young soybeans characterized by very low ground cover, and fields of older beans with heavy ground cover which are very difficult to differentiate at this stage from corn. Winter wheat fields are either mature (brown color on CIR) or harvested. Some harvested winter wheat fields have been apparently replanted with a short cover crop and appear redish brown on the CIR photo. Individual roofs and other hard surfaced materials are hard to see in the urban areas where there is now heavy tree cover.

September (Figure 8c). Agricultural land for this date is characterized by mostly mature crops and vegetation. Only a few corn and soybean fields have been harvested. The only fields still red on the photograph are late planted soybeans, pasture and hay. Tree vegetation is still quite red especially near the edges of the lake. Near the center of the photography are several clouds and cloud shadows. (These clouds and shadows appear only on the photography and not in the scanner data.)

Collection of Ground Observations

Black and white base line photography at a scale of 1:20,000 was collected along the flightline in April, 1971 for use in the location and coding of fields in the flightline. Ground conditions information was then collected by Agricultural Stablizations and Conservation Service personnel from Sullivan County A.S.C.S. office on the ground for the entire flightline near the time of the flight. These data included field information concerning location, size, identification of cropland, pastureland, forestland, idleland (land not presently engaged in production) and non-farm areas (urban, water areas, transportation, and extraction). This information was made available on computer printouts and was updated (for randomly selected corn fields) on a biweekly basis during the period from June 15 to September 30, 1971.

High altitude (18,000 meters or 60,000 feet) CIR photography (shown in Figures 8a, b, and c) flown on dates within two weeks of the scanner data collection was also available for general ground observation information. These photographs, used in conjunction with a "VARISCAN," a film projection device that provided the viewer with four levels of film magnification (3.00X, 5.00X, 12.10X, and 28.68X), were extremely valuable in verification of field boundaries and ground observation information and in various other phases of the data analysis.

Black and white photography collected at 5,000 feet was available for most scanner flights used in the analysis. This photography allowed a field by field cross-check of the scanner data for the presence of clouds and offered supplementary point data information for the ground observation data. It was especially useful in evaluating the different scanner data flights for data quality during the selection of data to be used in the analysis.

Selection of a Suitable Land Use Classification Scheme

Remote multispectral scanner data relates the physical scene only as a function of the reflectance and emittance properties of the scene. The data and the LARS programs relate in no way to the spatial characteristics of the scene, in other words, to the size and shape of objects, as does photography. Therefore, a land use classification scheme could only be based on land uses that have spectrally unique characteristics by virtue of a particular vegetation cover or material associated with a land use.

The land use classification scheme was selected for use with the collected multispectral scanner data. The selection of the scheme was accomplished by incorporating sections from the classification schemes of the Association of American Geographers and the Canadian Land Inventory with additional categories not specifically outlined in either of the four schemes reviewed (see Chapter 1, pages 9 to 13). All land use categories were selected on the basis of their presence within the flightline. The detail of the land use scheme was determined by the resolving power of the scanner, in other words, its ability, to "see" that category on the ground. As previously determined (Chapter 1), the resolution of the scanner at 1,600 meters (5,000 feet) is 5 meters by 5 meters square. A material with an area smaller than 25 square meters that falls within a data point cannot be purely characterized spectrally in a single data point. For example, a small road would not contribute enough spectral information to characterize a single resolution element as "road." It was found that the Standard Land Use Coding Manual and the New York State schemes were usually too detailed in their first and second digit levels to be compatible with the collected data (see Appendix, Table B). Those categories that were not too detailed were also found in the two more general schemes, the Association of American Geographers and the Canadian Land Inventory (see Appendix, Table B).

The final land use scheme then, reflects those categories of land use, in theory, that can be "seen" in the data based on the resolution of the apparatus. Table 5 shows the selected land use scheme with the associated land use code, the ground observation information and the materials (components) that would comprise the land use category. The derived land use scheme has four first-order categories, nine second-order categories, six third-order categories and four fourth-order categories. Like the four schemes reviewed, other second, third, fourth and fifth-order categories can be added to the scheme if needed. Point data, as in the New York State scheme, can also be implemented into the selected scheme.

Analysis of Data Procedure

The previously described "training field" or "supervised" computer training procedure (see Chapter 2, page 19) has several limitations when more than one set of data are evaluated for spectral information. Standardizing the training procedure from one set of data to another is difficult because the procedure is very subjective. The computer training phase continues until the desired classification results have been obtained, or the "best" classification of the data has been reached. The training phase of the analysis is usually the more laborious; therefore, the time aspect is a second consideration.

Table 5. Selected land use classification scheme and related ground observations and scene components.

LAND USE CLASSIFICATION SCHEME	LAND USE CODE	GROUND OBSERVATIONS	SCENE COMPONENTS
I. Resource Production			
A. Agriculture			
1. crop production			
a. row crop	A	-Harvested land -Plowed land -Row crops corn soybeans sorghum	-Crop residues -Bare soil -Specific, uniform crop types
b. small grain	B	-Harvested land -Plowed land -Non-row crops rye winter wheat	-Crop residues -Bare soil -Specific, uniform crop types
2. forage production			
a. hay	C	-Hay crops	-Mostly uniform, short, green vegetation
b. pasture	D	-Pasture land	-Non uniform, short, green vegetation
B. Forest			
1. continuous	E	-Forest (dense)	-Mostly uniform tall, green vegetation
2. discontinuous	F	-Mixed trees, shrubs, and grasses	-Non uniform mixed green vegetation
C. Extraction	G	-Stripmine -Stone quarry	-Overburden -Mixed green vegetation -Small ponded areas

Table 5 , cont.

LAND USE CLASSIFICATION SCHEME	LAND USE CODE	GROUND OBSERVATIONS	SCENE COMPONENTS
II. Water Resource			
A. Ponded and Lake			
1. fresh water	H	-Lakes -Ponds -Streams	-Water
2. waste treatment	I	-Waste treatment -Lagoons	-Effluent
B. Marshland	J	-Marshland	-Mixed short and tall green vegetation -Shallow water areas
III. Urban			
A. Urban core	K	-Hard surface material	-Roofs, streets, sidewalks, parking lots
B. Suburban	L	-Hard surface material -Trees, shrubs, grass	-Roofs, streets, sidewalks -Mixed short and tall green vegetation
IV. Transportation			
A. Motoring	M	-Highways -Highway right-of-way	-Hard surface materials -Mixed short and tall green vegetation
B. Railroad	N	-Railroad right-of-way	-Mixed short and tall green vegetation

Anticipating these handicaps of the "supervised" computer training procedure, a more objective method of training was selected. The concept of determining spectrally separable classes within a set of data was decided as the objective approach to be taken in evaluating the three sets of data. Ideally, if the maximum number of spectrally separable classes for a set of data could be determined, then the maximum amount of information could be obtained from a set of multispectral data. The LARS program $NSCLAS (Wacker, 1969) was selected as the most suitable program to analyze a set of data for spectrally separable classes.

The analysis of data procedure (Table 6) was identical to that described in the preliminary study (see Chapter 2, page 19) with the exception of the substitution of a "non-supervised" classifier program, $NSCLAS, for the "supervised" selection of training fields. The $NSCLAS program essentially "provides the user with the capability of classifying a limited number of data points on a nonsupervised basis" (Wacker and Landgrebe, 1971). It is nonsupervised in that the researcher is not involved in the process of selection of computer training classes. The user must identify the classes <u>after</u> clustering is completed.

To cluster (or classify) a set of data points, the user must first select the desired number of classes to be found in the data. The points from the specified area of data are read from Aircraft Data Storage Tapes into the computer for processing. After the desired number of classes are found in the data a map displaying the clustered area can be displayed on the line printer. Tables containing the means and variances of each class as well as the pairwise separability values between all class pairs are listed on the printer output.

Table 6 . Analysis of data procedure.
(with program options used)

Step	Program or Procedure	Options
1	$NSCLAS	MAX. CLASS = 35 CONVERGENCE = 100% MIN. POINTS = 2
2	Regroup $NS classes	SEPARABILITY ≤ 1.0
3	$STAT	
4	$DIVERG	BEST 4 CHANNELS
5	$CLASS	
6	$DISPLAY	
7	Assignment of classified classes to land use categories	

$NSCLAS Procedure

All twelve data channels were used in the $NSCLAS analysis in order to maximize the use of all the available information collected. By knowing the program requirements for computer core (Wacker, 1969), using all twelve channels of data, it was calculated that about 4,200 data points could be sampled from the flightline. Assuming that the flightline is 180 columns wide[1] and 1000 lines in length, the sampling rate is equal to 2.5 percent.

The program options used in the data analysis were selected for ease of data handling and conservation of computer time. Two of the three options used were "MAX. CLASS" equal to 35 classes and "CONV" (convergence) equal to 100 percent. "MAX. CLASS" simply directs the program to find 35 spectral classes (or clusters) within the data. "CONV" is an option for the percent of data points that must meet program requirements to be used in a class assignment within the program. It was felt that the extra information that may be gained by using the maximum number of classes available in the program, which is 40 classes, with the same convergence or less (100 percent or less) would not justify the increased computer time that would be required.

Because of a limitation in the LARS program $DIVERG it was required to reduce the number of classes to a maximum of 18 classes or less for classification. With the use of the class separability information produced by the $NSCLAS program a procedure was established to reduce the

[1] The width of the flightline was reduced by 20 columns on each side because of errors that may be encountered due to scanner "look angle" effect (Tanguay, 1969c).

initial 35 classes to 18 or less. Because $NSCLAS has the tendency to "find" the desired number of data clusters (classes) in the data which are most easily separated, it was deemed desirable to allow the program to first find the maximum number of classes in the data then reduce these classes to 18 or less manually by using a fixed separability.

Procedure for Recombining Clustered Classes

Using the ordered list of class separability information from $NSCLAS, two classes were combined if their separability value was less than 1.0. The separability value of 1.0 was used because it related a ratio of unity for the distance between a pair of cluster (class) centers and the sum of their cluster spread or variance. In theory, when the ratio of the distance between the class centers, D (Figure 9), to the sum of the class variances, r + r', is equal to 1.0, the outer limits of the two cluster classes are touching. For separability values between a pair of classes of less than 1.0 the classes were termed spectrally inseparable and grouped; for those pairs of classes with separability values greater than 1.0 the classes were termed spectrally separable and not grouped.

The regrouping procedure for the $NSCLAS derived classes started with the pair of classes with the lowest separability value from the ordered separability list and stopped with that pair of classes with a separability value of 1.0. A pair of classes were not grouped together until all member (linked) classes were linked to each other. Figure 10 shows a simplified regrouping procedure for only six classes reduced to three. Classes A, B, C and E, F were grouped because each member class was linked with each other. Group E, F was not grouped with group A, B, C

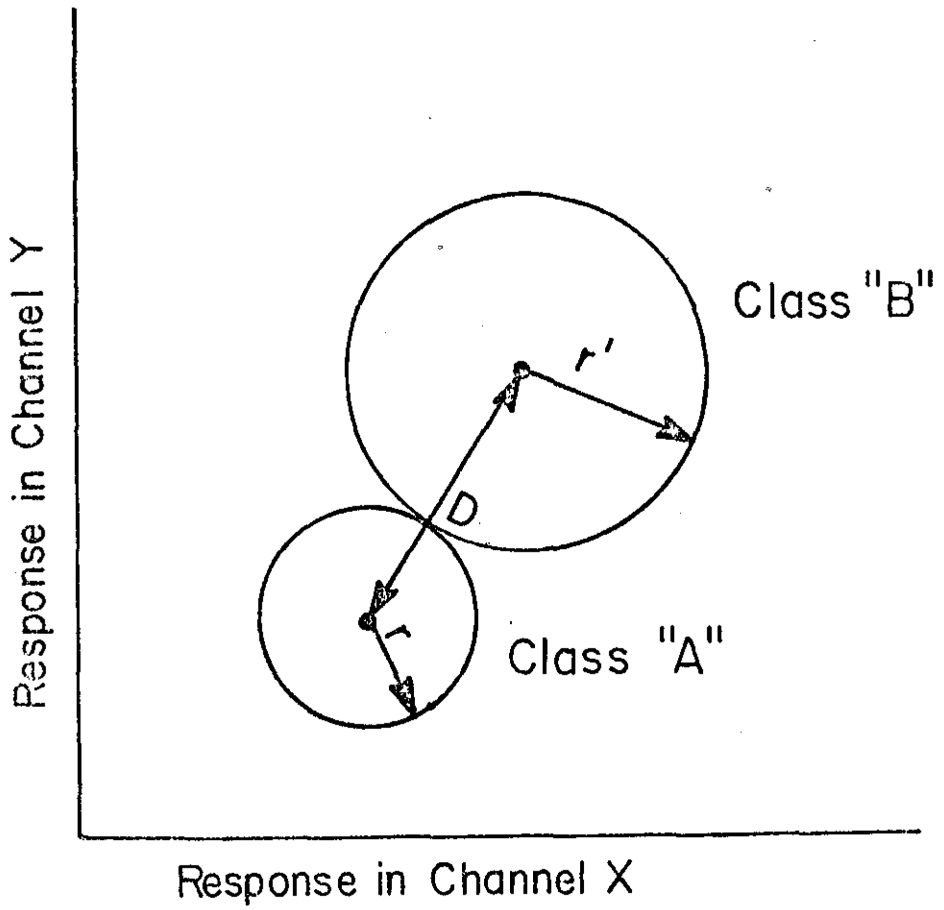


Figure 9. Plot of two classes in two channels representing a separability value of 1.0.

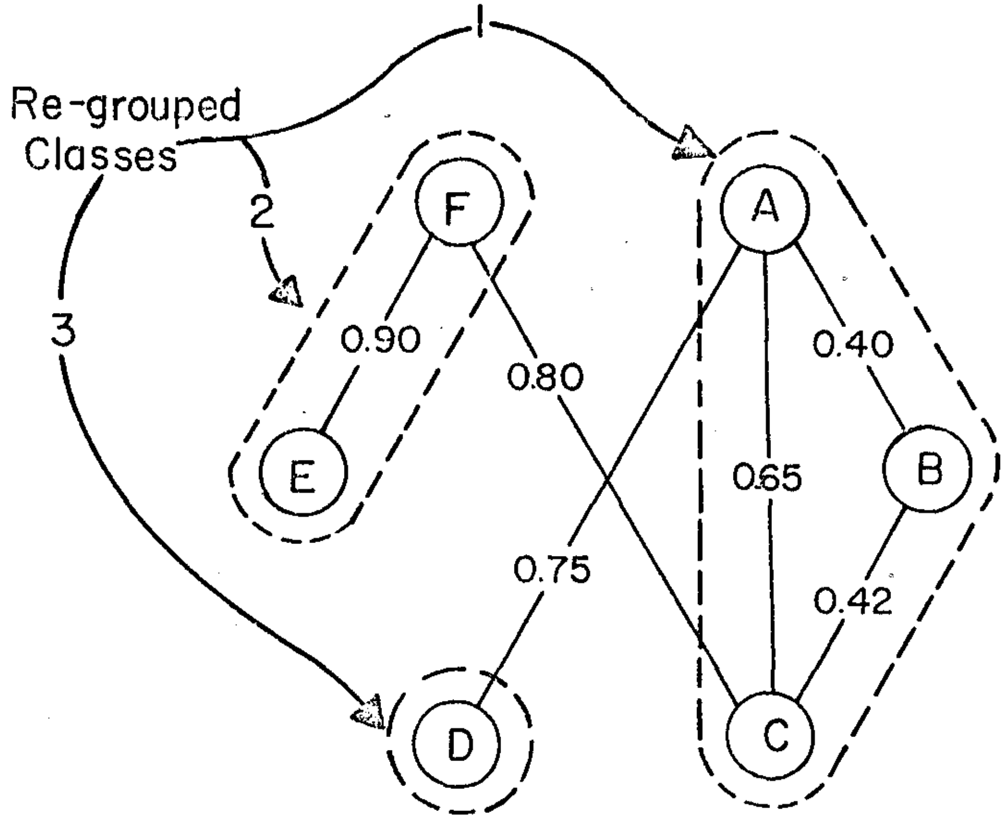


Figure 10. Re-grouping procedure for reducing six classes to three. (numbers represent separability values between classes)

because not all member classes were linked; for the same reason class D cannot be grouped with A, B, C.

This procedure was applied to each of the three dates of data. The 35 $NSCLAS generated classes for the May, July and September data dates were reduced by the above outlined procedure to 12, 16, and 12 classes, respectively. The mere fact that the May and September data reduced to a fewer number of classes than did the May indicated that the May and September data contained fewer spectrally separable classes than did the July data. This was expected because the May data were characterized by mostly bare soil, some green vegetation and water, and the September by mostly mature or harvested crops and water; however, the July data reflected many complicated green vegetation differences, bare soils, and water.

The third option used, MIN. POINTS, equal to 2, provided a means by which the coordinates (line and column number) of two or more data points that belonged to the same $NSCLAS class were saved on computer punch cards for input into the next computer program in the analysis, $STAT. The MIN. POINTS option of 2 or more data points was used for selection of every data point because of the high variances usually associated with classes composed of single data points. Errors in data overlay (registration) and lack of purity of single data points explained most of the high variances.

Results and Discussion

Interpretation of classification results is accomplished by randomly selecting representative test areas of different land uses from the multispectral data obtained for each flightline date. From these test areas the total number of land use sample points in each different spectrally separable computer class were tabulated. This tabulation for each flightline date yielded the percent correct recognition of a land use category by different spectrally separable computer classes (Appendix, Tables B1, B2, and B3).

The assignment of a land use category to a spectrally separable computer class is made by selecting the computer class or classes with the highest percentage of samples identified with that land use category. In some cases, a land use category was not associated with any specific computer class and therefore, could not be differentiated for that flight date. Conversely, several spectrally separable computer classes often mapped the same land use category. In this instance the computer classes were grouped and their results summarized for the specific land use category. A summary of the grouped spectrally separable classes for the assigned land use categroies for their flight dates is found in Table 7.

Only one land use category was assigned to a spectrally separable computer class because only one alphanumeric display symbol can be used to display each computer class. This symbol was assigned to each computer class to graphically represent its distribution on a computer printout display for each classified flightline date (Figures 11a, b, and c). For grouped computer classes (i.e., computer classes that are assigned to the same land use category) the same symbol is assigned to each computer class within the group.

Table 7. Summary of land use category assignments to $NSCLAS derived spectrally separable computer classes.

Land Use	Land Use Code	Spectral classes[1] May	July	Sept.
I. Resource Production				
A. Agricultural				
1. crop production				
a. row crop	A	1,2,3,4	6,11	3,7
b. small grain	B	7	2, 3	1,4
2. forage production				
a. hay	C	9	7	5,6
b. pasture	D	10	12	---
B. Forest				
1. continuous	E	11	9,13	10,11
2. discontinuous	F	---	14	---
C. Extraction	G	---	4, T*	T
II. Water Resource				
A. Ponded and Lake				
1. fresh water	H	8	16	---
2. waste treatment . . .	I	12	15	12
B. Marshland	J	---	8,10	8, 9
III. Urban				
A. Urban Core	K	5,6,T	1	2
B. Suburban	L.	---	5	---

1 Numbers represent the unique spectrally separable classes for each flight date.

* The letter "T" represents data points that were "thresholded" (page 25).

Figure 11. Computer land use classification displays and actual land use categories present in a representative segment of Flightline 219.

LEGEND

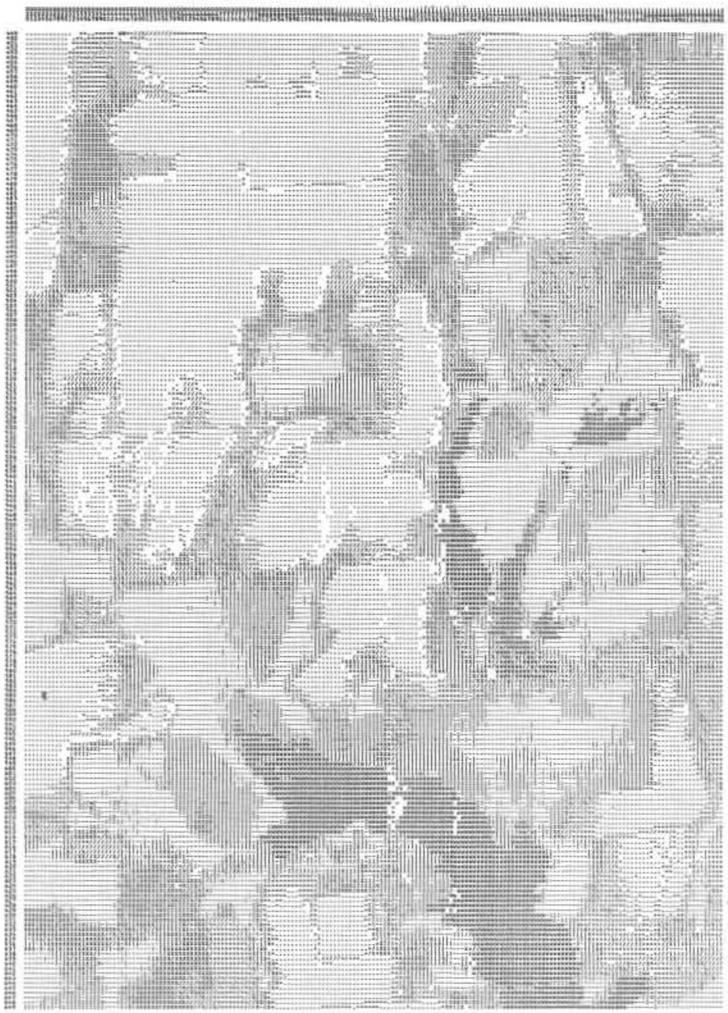
Land use category	Land use code	Computer display symbol
Row crop	A	.
Small grain	B	/
Hay	C	X
Pasture	D	I
Forest, con.	E	-
Forest, discon.	F	-
Extraction	G	(blank)
Fresh water	H	W
Waste water	I	W
Marshland	J	O
Urban	K	=
Suburban	L	L

LARSYSAA, VERSION 3 — LABORATORY FOR APPLICATIONS OF REMOTE SENSING, PURDUE UNIVERSITY

SERIAL NUMBER————	32821500	CLASSIFIED—	MAR 28,1972
RUN NUMBER————	71017100	DATE————	MAY 25,1971
FLIGHT LINE——	C6N BLT LO FL219	TIME————	1224 HOURS
DATA STORAGE TAPE/FILE—	582/ 3	ALTITUDE————	3000 FEET
REFORMATTING DATE—	JUNE 4,1971	GROUND HEADING————	180

CHANNELS USED

CHANNEL 3	SPECTRAL BAND 0.50 TO 0.54 MICROMETERS	CALIBRATION CODE = 1	C0 = 10.95
CHANNEL 6	SPECTRAL BAND 0.58 TO 0.65 MICROMETERS	CALIBRATION CODE = 1	C0 = 16.40
CHANNEL 11	SPECTRAL BAND 1.00 TO 1.40 MICROMETERS	CALIBRATION CODE = 1	C0 = 13.10
CHANNEL 12	SPECTRAL BAND 1.50 TO 1.80 MICROMETERS	CALIBRATION CODE = 1	C0 = 5.500



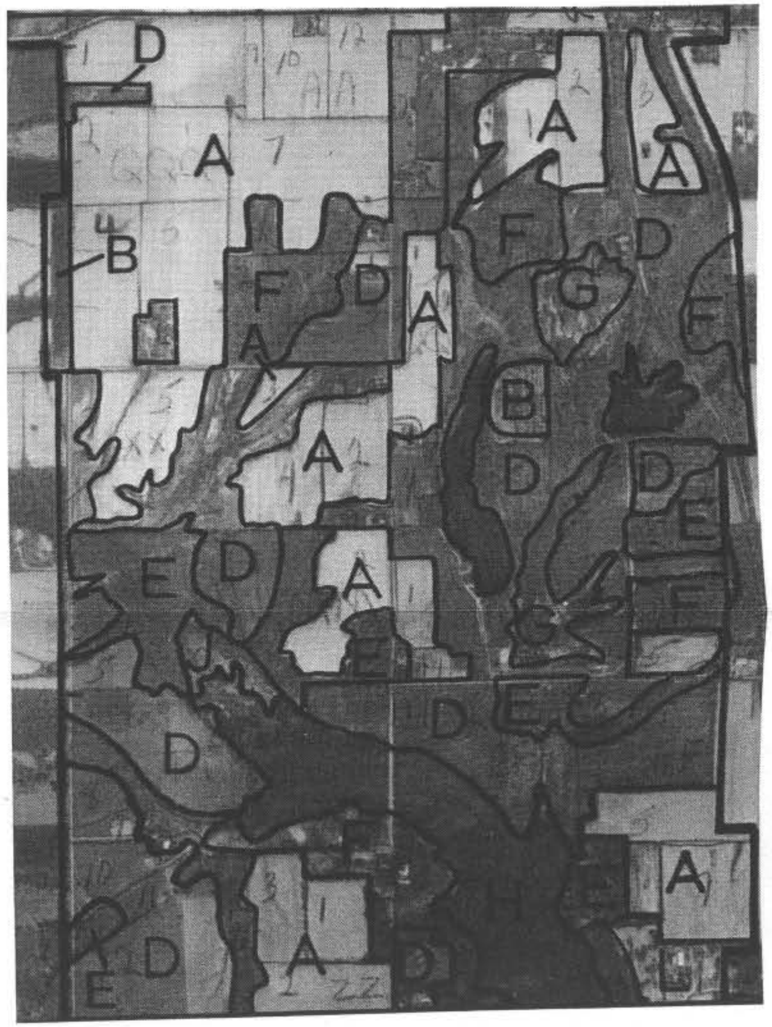
LARSYSAA, VERSION 3 — LABORATORY FOR APPLICATIONS OF REMOTE SENSING, PURDUE UNIVERSITY

SERIAL NUMBER————	48421500	CLASSIFIED—	APR 4,1972
RUN NUMBER————	71039800	DATE————	JULY 21,1971
FLIGHT LINE——	C6N BLT LO FL219	TIME————	1050 HOURS
DATA STORAGE TAPE/FILE—	411/ 2	ALTITUDE————	5000 FEET
REFORMATTING DATE—	JULY 22,1971	GROUND HEADING————	180

CHANNELS USED

CHANNEL 6	SPECTRAL BAND 0.52 TO 0.57 MICROMETERS	CALIBRATION CODE = 1	C0 = 24.65
CHANNEL 7	SPECTRAL BAND 0.61 TO 0.70 MICROMETERS	CALIBRATION CODE = 1	C0 = 38.15
CHANNEL 8	SPECTRAL BAND 0.72 TO 0.80 MICROMETERS	CALIBRATION CODE = 1	C0 = 16.96
CHANNEL 10	SPECTRAL BAND 1.20 TO 1.80 MICROMETERS	CALIBRATION CODE = 1	C0 = 24.80

(c) September



(d) Actual land use categories

By computing the percentage of each land use category that is associated with each computer class or grouped computer classes, an indication of the recognition of each land use class is obtained (Tables 8a, 8b, and 8c). Land use categories that are not recognized by any computer class appear as columns of dashes. Ideally a well-mapped land use category is characterized by none to very few low percentages of "other" land use categories appearing in the same column. An example of a well-mapped land use category is land use "I" (waste treatment) in the May and July data flights (Tables 8a, and 8b, respectively). Although the accuracy of land use category "I" for the July flight is much better than that of the May (97% *vs.* 59%), both dates show that no other land use categories are confused with the recognition of land use "I".

The accuracy of the spectrally separable computer classes in recognizing a land use category is calculated by totaling the percentages of each assigned land use category in each computer class for each flight date. This information plus the average recognition accuracy by land use category and by flight date is summarized in Table 9; a summary of the "best" computer recognition results by land use category considering all three flight dates is shown in Table 10.

Classification Results by Land Use Category

Agriculture: crop production: "row crop" (Code A). The crops corn and soybeans represent the land use category "row crop." It is mapped best in the May flight (Figure 11a) at an accuracy of 99 percent. This accuracy can be attributed to the fact that all the land representing this category is predominantly bare soil for this date. Kristof and

Table 8. Percent recognition of land use categories with multispectral techniques.[1]

(a) May

Computer Mapped Land Use Categories

Actual Land Use Categories	A'	B'	C'	D'	E'	F'	G'	H'	I'	J'	K'	L'
A	99	--	--	--	--	--	--	--	--	--	1	--
B	26	23	16	13	15	--	--	--	--	--	7	--
C	--	9	38	--	53	--	--	--	--	--	--	--
D	--	9	30	39	13	--	--	--	--	--	9	--
E	--	--	1	4	95	--	--	--	--	--	--	--
F	--	3	1	20	56	--	--	--	--	--	10	--
G	10	19	1	26	23	--	--	4	--	--	18	--
H	--	--	--	--	--	--	--	40	59	--	1	--
I	--	--	--	--	--	--	--	5	95	--	--	--
J	--	--	--	27	73	--	--	--	--	--	--	--
K	14	14	1	--	--	--	--	4	--	--	68	--
L	2	--	24	29	6	--	--	2	--	--	21	--

(b) July

Computer Mapped Land Use Categories

Actual Land Use Categories	A'	B'	C'	D'	E'	F'	G'	H'	I'	J'	K'	L'
A	25	15	10	2	32	--	1	--	--	12	3	1
B	5	60	32	--	--	--	1	--	--	2	--	--
C	--	--	99	--	--	--	--	--	--	--	--	1
D	6	15	15	11	7	4	15	--	--	23	--	4
E	2	--	--	--	56	41	--	--	--	--	--	--
F	--	--	--	--	10	90	--	--	--	--	--	--
G	--	8	--	--	--	--	77	6	--	--	8	--
H	--	--	--	--	--	--	9	24	47	--	26	--
I	--	--	--	--	--	2	--	1	97	--	--	--
J	--	--	4	--	--	--	27	8	--	60	--	--
K	--	24	--	--	--	--	36	--	--	--	40	--
L	5	22	21	4	4	3	4	--	--	12	15	9

[1] See Table 7 for definition of land use categories.

Table 8, cont.

(c) September

Computer Mapped Land Use Categories

Actual Land Use Categories	A'	B'	C'	D'	E'	F'	G'	H'	I'	J'	K'	L'
A	49	3	13	--	--	--	--	--	--	27	8	--
B	17	62	7	--	3	--	--	--	--	3	7	--
C	--	--	73	--	--	--	--	--	--	26	--	--
D	21	4	48	--	4	--	--	--	--	12	14	--
E	--	--	--	--	94	--	--	--	--	6	--	--
F	1	--	--	--	87	--	--	--	--	11	--	--
G	--	--	3	--	--	--	94	--	--	--	3	--
H	--	--	--	--	1	--	--	--	99	--	--	--
I	--	--	--	--	--	--	--	--	100	--	--	--
J	7	--	--	--	18	--	--	--	--	75	--	--
K	10	49	5	--	2	--	12	--	--	2	25	--
L	20	8	28	--	14	--	4	--	--	12	14	--

Table 9. Summary of percent recognition of computer classification results.

Land Use Category	Land Use Code	May	July	Sept.
Row crop	A	99	25	49
Small grain	B	23	60	62
Hay	C	38	99	73
Pasture	D	39	11	--
Forest, continuous	E	95	56	94
Forest, discontinuous	F	--	90	--
Extraction	G	--	77	94
Fresh water	H	40	24	--
Waste water	I	95	97	100
Marshland	J	--	60	75
Urban core	K	68	40	25
Suburban	L	--	9	--
Average for Mapped Categories		62%	54%	71%
Overall Average		41%	54%	47%

Table 10. Best overall computer classification results using all dates.

Land Use Category	Land Use Code	Date	Percent Accuracy
Row crop	A	May	99%
Small grain	B	Sept.	62%
Hay	C	July	99%
Pasture	D	May	39%
Forest, continuous	E	May	95%
Forest, discontinuous	F	July	90%
Extraction	G	Sept.	94%
Fresh water	H	May	40%
Waste water	I	Sept.	100%
Marshland	J	Sept.	75%
Urban core	K	May	68%
Suburban	L	July	9%
		Overall Average	72%

Zachary (1971) have shown that computer analysis techniques using multispectral data have mapped bare soil from other surface covers. Row crops are the only land use which are found as bare soil at this time of year in Indiana.

For the other two dates row crops were not classified very well. The prime reason appears to be that this land use category is not characterized by crop types which are clearly distinct from other categories (Tables 8b and 8c). The literature reported that remote sensing techniques can distinguish well between these crop types (Chapter 1, page 5). These results were arrived at through thorough computer training on specific crops. The techniques utilized in this study did not allow such precise computer training. As this procedure is refined, higher recognition accuracies between crop types would be expected.

Agriculture: crop production: "small grain" (Code B). This land use category is represented by ten fields of the cover type, winter wheat. The best results (60 and 62 percent for July and September, respectively) are obtained when the crop is harvested and the fields are in stubble. The July photography (Figure 8b) shows indications that some of the winter wheat fields have been replanted with a cover crop which is still green in September (Figure 8c). Apparently the mixture of stubble and light cover crop for the July data and the abundance of a green cover crop in the September data improve the mappable characteristics of this class for these dates. This information helps to explain that wheat is confused with one other category for each date: "hay" in July and "row crop" in September (Tables 8b and 8c, 32 and 17 percent, respectively).

The poorest identification accuracy for this class (23 percent) was obtained from the May data. The greatest confusion associated with the class was "row crop" (26 percent). This confusion is probably explained by several areas of low ground cover in many of the wheat fields for this date, and these areas are mapped "bare soil" as is the category "row crop" for this date. These is also some confusion with other categories which are associated with other lush, green cover materials, in particular, the categories "hay" and "pasture." Another possible explanation to this confusion is that the ten small wheat fields did not contribute enough training samples to adequately train the computer. For most of the other categories much larger fields were available for training.

<u>Agriculture: forage production: "hay" (Code C)</u>. Land use category "hay" is mapped best (99 percent, Table 8b) in July and next best (73 percent, Table 8c) in September. The July classification is mapped well and not confused with any other land use category, but the September data are confused (26 percent) with the category "marshland." In reviewing the photography (Figure 8c) much of the short, green marshland vegetation appears to resemble many hay fields. The May data yields the poorest accuracy (38 percent) because of much confusion (53 percent) with the dense forest class: "forest, continuous." Two possible explanations for this confusion are that both categories are quite green at this date and the possibility that the tree cover is not dense enough such that the grass around the trees is seen.

Agriculture: forage production: "pasture" (Code D). Land use category "pasture" is not mapped very well for any date. It is mapped only for the two dates May and July with accuracies of 39 and 11 percent, respectively. In the May data "pasture" is confused with the classes "hay" and "forest, continuous," 30 and 13 percent, respectively. The July data show that the same confusion exists but to a much greater degree; the category "pasture" is related to eight other categories (Table 8b).

Although this land use category is not assigned to any spectral classes in the September data, it is still possible to observe the other categories in which it is misclassified. The largest amount of this misclassification occurs in the categories "hay" and "row crop." From the photography for this date (Figure 8c) it is seen that ground conditions for pasture are very similar to some fields of corn and soybeans (class "row crop") and hay.

Forest: "continuous" and "discontinuous" (Codes E and F). The land use category "forest, continuous," which is composed of heavily forested land, is mapped best in May and September at 95 and 94 percent accuracy, respectively (Tables 8b and 8c). The classification on both dates is not confused greatly with any other categories. The July data map this category with considerably less accuracy (56 percent) because 41 percent of this category is mapped in the less densely forested class, "forest, discontinuous."

The category "forest, discontinuous" is mapped in July with an accuracy of 90 percent with only 10 percent assigned to the category "forest, continuous." For the dates May and September (Tables 8a and 8c) when this class is not mapped, the majority of its points are mapped into the category "forest, continuous."

"Extraction"(Code G). The category "extraction" is composed of two small areas, totaling about 0.3 km.^{2}, located in the center portion of the flightline. The class is characterized by spoil, swampwater areas, and low shrub and forested areas. It is mapped best in September at 94 percent accuracy. Little confusion from other categories is associated with this category for this date; it is displayed as "blanks" in the computer printout (Figure 11c). A small percentage of other materials are also displayed as blanks on the computer display. These data points represented materials from several categories such as "urban core" and "extraction" that were not recognized by the computer during classification. These data points are referred to as "thresholded" points and are represented by the letter "T" in Table 7.

The July data show the second best results of 77 percent for this category, and errors showed confusion with the categories "fresh water," "small grain" and "urban core" (Table 8b). Considering the overlapping of materials included in these categories, it is reasonable to expect confusion from these categories.

For the May data this land use category is not mapped well enough to be assigned to a computer class. It is confused with several categories such as water, bare soils, green vegetation and hard surfaced materials. Spring rains have raised the water level in the areas of "extraction," and and computer has mapped them accurately as "water" (Figure 11a).

Water Resource: ponded and lake: "fresh water" and "waste treatment (Codes H and I). The category "fresh water" is consistently shown to be poorly mapped or not mapped at all, whereas the class "waste treatment" is consistently mapped well. Studying Tables 8a, 8b, and 8c, it is seen that there is a close relationship between these two categories. For each of the three dates where the major percentage of "waste treatment" is mapped there is an associated high percentage of "fresh water" also mapped: May, 100 and 99 percent; July, 98 and 71 percent, and September, 100 and 99 percent. From these results it is suggested that the two categories should be grouped together for these sets of data. In the selected computer classification displays (Figures 11a, b and c), these categories are grouped.

Water Resource: "marshland" (Code J). Marshland is characterized by short and tall grasses, some trees and some water covered areas. This category is only mapped in two dates (July and September) with 60 and 75 percent accuracies, respectively. The July data are most associated with the category "extraction" (27 percent) and the September are most associated with the category"forest, continuous" (18 percent) and to a lesser extent with the category "pasture" (7 percent). One would expect this confusion due to the overlapping of materials with other categories similar to the land use category "extraction."

Urban: "urban core" (Code K). "Urban core" is characterized by man-made hard surface materials and an almost complete lack of green, natural materials. This class is mapped for all three dates. This category for the May data, mapped with an accuracy of 68 percent, is confused most with "row crop" and "small grain", those categories identified largely because of the reflectance of bare soil. For July this category is mapped with an accuracy of 40 percent and is confused with two categories that have some areas of bare soil or highly reflective surfaces such as "extraction" and "small grain." "Urban core" for September is mapped with only 25 percent accuracy. Most of the confusion (49 percent) comes from the category "small grain" with "row crop," "hay" and "extraction" categories accounting for the remainder

Urban: "non core" (Code L). The land use category (urban) "non core" is mapped only in the July data and there with a poor accuracy of 9 percent. For this date this category is confused with nine other classes that relate to every land use category except "fresh water" and "waste water." Similar confusion is also found in the other two dates. The reason for this is that an urban scene is a very complex area to characterize; its range in materials may include all types of natural and man-made materials. This explains why this category is associated with so many different categories.

Transportation: "motoring" and "railroad" (Codes M and N). The table of results (Table 9) show that no test results are displayed for these two categories. The physical area of materials representing these categories is too small to be purely characterized in either computer training or test samples. The actual area covered by materials associated with these categories is one reason why these categories could not be mapped; the other is a problem in the registration of data channels. The overlay of data points in each data channel (data registration) is usually within ± 2 data points. In other words, the location of a data point in a particular channel of data would be aligned within ± 2 data points in another channel of data. Because of the small sized areas of these categories and the errors associated with data registration, it is very difficult to obtain pure samples for computer training and testing. As is suggested in the preliminary study conclusions (Chapter 2, page 27), collection of data from a lower altitude or an improvement in scanner resolution would have to come about before good results could be obtained for these land use categories.

Results of Best Classification for Combined Dates

Using the best classification results for each land use category, an accuracy of 72 percent for all land use categories was obtained (Table 10). No combining or grouping of categories were used to arrive at these results. Had computer classes been grouped to map combined land use categories, the accuracy would have been higher.

An alternative to using only the best single classification result for each land use category would be to use a temporal data overlay procedure. This procedure would produce data such that each data point is overlayed by the corresponding data point from each successive date of collected data. The concept behind such a procedure is that the information contributed by each successive data point over time is additive. Analysis of the "layered" data could then possibly yield better results than using any single set of data.

Evaluation of the Selected Classification Scheme

A minimum level of accuracy in the interpretation of the data of about 85 or 90 percent or better is suggested by Anderson (1971b). This was suggested because results such as these would be nearly comparable with the level of accuracy attained by the Bureau of the Census of Agriculture. Although, for any date analyzed, the overall accuracy did not reach 85 or 90 percent; the 54 percent accuracy for July (Table 9) is impressive considering the fact that these results were arrived at by automatic methods.

It is felt that the lack of spectrally separable computer classes contributed in two ways to the loss in accuracy of the land use classification scheme. First, it left four land use categories unassigned for both May and September data. The classification accuracy of the mapped categories for these dates (Table 9), are 62 and 71 percent, respectively, but when the overall accuracies are calculated for these dates, the accuracies dropped to 41 and 47 percent, respectively (Table 9). Had more spectrally separable classes been found in the data for these dates, the four unmapped land use categories for each date probably would have been mapped. Secondly, it crowded some land use categories together and caused confusion and decreased classification accuracies. Increasing the number of computer classes would essentially increase the possibility of land use categories falling into single computer classes.

Evaluation of the Spectrally Separable Training Class Approach To a Land Use Classification System

The overall design of this land use classification approach is centered around the concept that spectrally separable computer classes are determined for a set of data. These classes are then interpreted and used to identify and map those land use categories which they represent in the multispectral data. Two problems seemed to prevent this system from operating more effectively. The first problem was the physical overlapping of componets within land use categories. The second, which may be in part a function of the first problem, was the apparent inability for $NSCLAS program to identify spectrally separable computer classes that could uniquely characterize single land use categories.

Physical overlapping of land use categories seemed to be from the fact that components within some land use categories <u>did</u> overlap within a land use scene. For example, the categories "forest land" (trees) and "pasture land" (grass) are both found within the category "urban". Little can be done to correct misclassification within these categories. One possible solution is to revise the classification scheme to eliminate the category overlapping, but this would tend to decrease the detail of the present classification scheme. Another possible improvement in differentiating between categories would be to introduce spatial data with the spectral data. The techniques that are presently used for this type of analysis are relatively new and for the most part, are still in developmental stages.

The second problem involved land use categories such as "row crop" and "small grain" or "forest" and "hay", that (during the growing season) should be spectrally separable from each other. Ideally, each spectrally separable computer class ($NSCLAS selected classes) should characterize only one land use category; in very few cases is it found that a land use category is identified "purely." In other words, no other category should be found in a column or row for a particular land use category (Tables 8a, 8b, and 8c). Each of these three tables should have a diagonal of highly correct identification percentages for each "identified" land use category; it would be said then, that each land use category was mapped "purely." In the July and September data (Tables 8b and 8c), this is not the case. The overlapping or confusion between these categories seems to relate to the problem of the program $NSCLAS not being able to determine spectrally separable computer classes that adequately characterize individual land use categories in the data. A closer look at the July data provides an insight into some possible improvements in the procedure for analyzing the data.

The July data indicate an advantage for determining a larger number of spectrally separable classes in the data. In July (Table 7) all land use categories are assigned to at least one or more spectrally separable computer class. For each of the other dates, May and September (Table 7) four land use categories are unassigned. The increase of four computer classes in the July data does indicate an increase in the amount of spectrally separable information for that date. The question is raised, however, as to whether the increase in the number of mapable land use categories is attributable to the greater number of computer classes or to the increase in spectral information or both. To answer this question with the data collected from this study would be difficult, but one can speculate as to the effect of increasing the number of computer classes. Increasing the number of computer classes would spread the related land use categories among more computer classes.

Another possible means for increasing the separability between land use categories (and thereby increasing classification accuracy) would be to increase the sampling rate of the flightline. The sampling rate used for this study (2.5 percent of the data present in the flightline) was determined by $NSCLAS program limitations, (page 46). It is quite possible that this rate did not allow adequate sampling of small and heterogenous land use areas. This, in fact, partly explains the reason why the land use categories within "Transportation" could not be mapped (pages 64 and 65).

In summary, effects of some of the problems associated with the spectrally separable computer class approach to land use mapping can be possibly minimized in the following ways:

1. increase the number of spectrally separable classes from $NSCLAS.
2. increase the sampling rate of the flightline.
3. revise the classification scheme.
4. include spatial data with the spectral data in land use analysis procedure.

A Proposed Land Use Classification System

As already mentioned, the results seem to indicate confusion in the classification system from two areas: one, the program $NSCLAS and, two, the classification scheme itself. Two changes have already been proposed: to increase the number of spectrally separable classes from $NSCLAS and increasing the sampling rate of the flightline data. A second change will involve the rearrangeing of the analysis procedure and of the classification scheme. The change in the analysis procedure is discussed first.

The confusion between categories within the selected classification scheme has been shown to be caused by the overlapping of materials or even complete land use categories. It is suggested that the step in the analysis procedure where land use categories are assigned to spectrally separable computer classes (Table 6) be altered to assign "basic land characteristic materials" to the spectrally separable computer classes. The idea behind this change is that one or more "basic materials," such as grass, trees, bare soil, water, hard surface materials, and etc., are present in varying percentages in the make-up of any land use scene. The object is to spectrally characterize these classes of materials by assigning them to the $NSCLAS determined classes. Once this step is accomplished a new classification scheme must be derived.

The results seem to point toward a "ratio" approach for automatic land use classification. Many of the land use categories are not "purely" mapped by their assigned spectrally separable computer class, but are often mapped by percentages of many land use categories.

By assuming that each land use category can be characterized by a particular ratio of "basic material" classes (grass, trees, bare soil, etc.), a program could be written to classify a set of data, grid cell by grid cell,[1] into appropriate land use categories of similar ratios of "basic materials." To classify, the program would tabulate the percen- and ratios of the "basic materials" present in each grid cell and match that cell with the land use category that would have the closest ratio

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[1] A grid cell would simply be a single unit within a set of gridded data that would be a given number of data columns wide and a number lines long. The cell size could vary as the detail of the classification varied.

of "basic material." For instance, the land use category "urban" may be characterized by ranges in ratios of materials of 40 to 90 percent "hard surface" materials, 0 to 30 percent "trees" and 0 to 30 percent "grass." Should the calculated ratios of these materials for a particular grid cell fall within the designated range of the above given land use category "urban," then that grid cell would be classified in the land use category, "urban." The designated ranges of materials for a given land use category would vary with the time of year. For example, land use category "agriculture" could vary from ratios of "bare soil" "grass" and "trees" in the spring to no "bare soil" materials and ratios of specific "crops," "grass" and "trees" for the summer.

The flexibility of such a system as this is a unique attribute. Although the analysis procedure of the proposed system is patterned after a land use classification study, it is applicable to a wide selection of users. The interpretation of the $NSCLAS spectrally separable classes by the user (Stage 3, Table 11) for the basic information in which he is interested is what determines the use of the data.

This system would allow preanalyzed data (Stage 1, Table 11) to be available and usable to a large cross-section of users. The user would complete stages 3 and 5 (Table 11) for his own specific use. This system could save valuable computer processing and analysis time presently needed for multispectral data analysis.

Table 11. Analysis steps in the proposed new land classification system.

STAGE	DESCRIPTION
1.	Collection of Multispectral Scanner Data
2.	$NSCLAS Processing - to determine spectrally separable classes within data.
3.	$NSCLAS Interpretation - assignment of computer classes to represent "basic" scene materials.
4.	Classification of Data - based on spectrally separable classes as computer training fields.
5.	Specific User Program - (Land Use Analysis Program) it will ratio the identified "basic" scene materials in a data cell and assign it to the closest land use category of the same ratio.

Conclusions

Although much work is yet to be completed before a completely automated land use classification system can hope to be operational, the performance of this first attempted land use classification system utilizing only multispectral scanner data to characterize land use categories has produced these conclusions:

(1) The results indicated some limited ability for automatic computer analysis of remotely sensed scanner data to characterize broad land uses within an agricultural scene.

(2) The results indicated a need for a change in the data analysis procedure and land use classification scheme.

Further study is suggested in the following areas of multispectral scanner data analysis:

(1) Proceed with the development of a "ratio technique" for land use classification.

(2) Further the development of the "unsupervised, spectrally separable class approach" to computer training utilizing the program $NSCLAS.

BIBLIOGRAPHY

BIBLIOGRAPHY

1. Al-Abbas, A. H., P. H. Swain, and M. F. Baumgardner. 1972. "Relating organic matter and clay content to the multispectral radiance of soils." Soil Sci. (In press).

2. Anderson, J. A. 1971a. Land use classification schemes and the need for standardization. Papers from Conference on Land Use Information and Classification. U.S. Geological Survey and NASA: Co-sponsors. Washington, D.C. June 28 - 30. pp. 4-26.

3. Anderson, J. A. 1971b. Land use classification schemes. Photogrammetric Engineering. 37:379-388.

4. Ansari, A. Q., and W. E. Loomis. 1959. Leaf temperatures. Amer. J. Bot. 46:713-717.

5. Anuta, P. E. 1970. Spatial registration of multispectral and multitemporal digital imagery using fast fourier transform techniques. IEEE Trans. Geosci. Electron. GE-8, 4:353-368.

6. Barlowe, R. 1958. *In* Land Resource Economics. Prentice-Hall, Inc. Englewood Cliffs, N.J. pp. 7-10.

7. Bauer, M. E. 1972. The corn blight problem -- 1970 and 1971. LARS Information Note 012172. Laboratory for Applications of Remote Sensing. Purdue Univeristy. 19 pp.

8. Baumgardner, M. F., S. J. Kristof, C. J. Johannsen, and A. L. Zachary. 1970. Effects of organic matter on multispectral properties of soils. Proc. of the Indiana Acad. of Sci. 79:413-422.

9. Baumgardner, M. F., and C. J. Johannsen. 1972. *In* Manual of Remote Sensing. Vol. II, Chap. 8. (In press).

10. Bieberman, D. F. 1949. Stratigraphy of three wells in Sullivan and Vigo Counties, Indiana. Division of Geology, Indiana Dept. of Cons. Bloomington, Ind. pp. 3-7.

11. Bowers, S. A. and R. J. Hanks. 1965. Reflection of radiant energy from soils. Soil Sci. 2:130-138.

12. Clawson, M., and C. L. Stewart. 1965. Land use information: a critical survey of U.S. statistics including possibilities for greater uniformity, *In* Resources for the Future. Baltimore: Johns Hopkins Press. pp. 29.

13. Conference on Land Use Information and Classification. 1971. Co-sponsored by Dept. of Int., U.S. Geological Survey, and NASA. Washington, D.C. pp. 20-25.

14. Gates, D. M. 1962. *In* Energy Exchange in the Biophere. New York: Harper and Row, Inc. pp. 63.

15. Gates, D. M. 1963. The energy environment in which we live. Amer. Sci. 51:327-348.

16. Gates, D. M. 1965. Characteristics of soil and vegetated surfaces to reflected and emitted radiation. Proc. 3rd Symp. Remote Sensing of Environment. Univ. of Michigan, Ann Arbor, MI. pp. 573-600.

17. Gates, D. M. 1970. Physical and physiological properties of plants. *In* Remote Sensing with Special Reference to Agriculture and Forestry. National Academy of Sciences, J. R. Shay (ed.), Washington, D. C. pp. 224-252.

18. Gausman, H. W., W. A. Allen, V. I. Myers, and R. Cardenas. 1969. Reflectance and internal structure of cotton leaves, Gossypium Hirsutum L. Agronomy Journal. 61:374-376.

19. (A) Guide to the classification of land use. 1970. The Canada Land Inventory. Report No. 1. Department of Regional Economic Expansion. Ottawa, Canada. 61 pp.

20. Halliday, D., and R. Resnick. 1962. *In* Physics for Students of Science and Engineering. New York: John Wiley and Sons, Inc. pp. 901-920.

21. Hoffer, R. M. 1967a. Interpretation of remote multispectral imagery of agricultural crops. Report of the Laboratory for Agricultural Remote Sensing, Purdue University Agr. Exp. Sta. Res. Bull. 831., pp. 3-4.

22. ibid. 1967b. pp. 28-31.

23. Hoffer, R. M. and C. J. Johannsen. 1969. Ecological potentials in spectral signature analysis. *In* Remote Sensing in Ecology. Univ. of Georgia Press. P. Johnson (ed.), Athens, GA. pp. 1-16.

24. Holter, M. R. 1967. Infrared and multispectral sensing. BioScience 6:376-383.

25. Holter, M. R. 1970. Imaging with non-photographic sensors. *In* Remote Sensing with Special Reference to Agriculture and Forestry. National Academy of Sciences. J. R. Shay (ed.), Washington, D.C. pp. 73-161.

26. Johannsen, G. J. 1969. The detection of available soil moisture by remote sensing techniques. Ph.D. Thesis. Purdue Univ. (Library Call No. 22744). Univ. Microfilms. Ann Arbor, MI. (Order No. 70-8909). 287pp.

27. Johannsen, C. J., and M. F. Baumgardner. 1969. Remote sensing for planning resource conservation. Proceed. 1968 Annual Meeting, Soil Cons. Soc. of Amer. pp. 149-155.

28. Johannsen, C. J. and M. E. Bauer. 1972. Corn blight watch experiment results. LARS Information Note 012372. Laboratory for Applications of Remote Sensing, Purdue University. 23pp.

29. Kristof, S. J., and A. L. Zachary. 1971. Mapping soil types from multispectral scanner data. Proc. 7th Symp. Remote Sensing of Environment. Univ. of Michigan, Ann Arbor, MI. pp. 2095-2108.

30. Kryuchkov, V. V. 1961. Leaf temperature of some plants in the Khiban. Soviet P. Physiol. 8:502-504.

31. Kumar, R. 1972. Radiation from plants - reflection and emission: a review. Publication No. 72-2-2 of the School of Aeronautics, Astronautics, and Engineering Sciences, Purdue University. 105pp.

32. Laboratory for Agricultural Remote Sensing (LARS). 1968. Remote Multispectral Sensing in Agriculture. Vol. III. (Annual Report). Purdue Univ. Agr. Exp. Sta. Res. Bull. 844. 175pp.

33. Laboratory for Agricultural Remote Sensing (LARS). 1970. Remote Multispectral Sensing in Agriculture. Vol. IV. (Annual Report). Purdue Univ. Agr. Exp. Sta. Res. Bull. 873. pp. 94-108

34. Landgrebe, D. A., P. J. Min, P. H. Swain, and K. S. Fu. 1968. The application of pattern recognition techniques to a remote sensing problem. LARS Information Note 080568. Laboratory for Agricultural Remote Sensing, Purdue University, 16pp.

35. Lyon, R. J. P., A. Kilinc, J. Patterson, and R. M. Dickerson. 1969. Airborne geological mapping using infrared emission spectra. Proc. 6th Symp. Remote Sensing of Environment. Univ. of Michigan, Ann Arbor, MI. pp. 49-50.

36. Mallon, H. J. 1971. Experimental applications of multispectral sensor data to resource inventory and survey. Proc. 7th Symp. Remote Sensing of Environment. Univ. of Michigan, Ann Arbor, MI. pp. 77-78.

37. Mathews, H. L,, R. L. Cummingham, J. E. Cipra, and T. R. West. 1971. Applications of multispectral remote sensing to soil survey research in southeastern Pennsylvania. Soil Sci. (In press).

38. McClure, W. F. 1969. Spectral characteristics of tobacco in the near infrared region from 0.6 to 2.6 microns. Lab. Sci. 12:232-235.

39. Myers, V. I. 1970. Soil, water and plant relations. *In* Remote Sensing with Special Reference to Agriculture and Forestry. National Academy of Science, J. R. Shay (ed.), Washington, D.C. pp. 253-298.

40. Myers, V. I., and W. A. Allen. 1968. Electrooptical remote sensing methods as nondestructive testing and measuring techniques in agriculture. Applied Optics. 2:1819-1838,

41. Phillips, T. L. 1972. 1971 Corn blight watch experiment data processing, analysis, and interpretation. LARS Information Note 012272. Laboratory for Applications of Remote Sensing, Purdue University, 20pp.

42. (A) Review of the New York State Land Use and Natural Resources Inventory. 1970. Center for Aerial Photographic Studies, Cornell University, Ithaca, N w York. 28pp.

43. Shelton, R. L. 1967. Potential benefits to be derived from applications of remote sensing of agriculture, forestry and range resources. The Center for Aerial Photographic Studies, Cornell University, Ithaca, New York.

44. Smedes, H. W., K. L. Pierce, M. G. Tanguay, and R. M. Hoffer. 1969. Digital computer terrain mapping from multispectral data, and evaluation of proposed earth resources technology satellite (ERTS) data channels. Yellowstone National Park: Preliminary Report. Presented at NASA Manned Spacecraft Center, Houston, Texas. September 16 to 18, 1969. pp. 31-37.

45. (A) Standard System for Identifying and Coding Land Use Activities. 1965. Standard Land Use Coding Manual. Urban Renewal Administration and Bureau of Public Roads. Washington, D.C. 111pp.

46. Stoner, E. R., and E. H. Horvath. 1971. The effect of cultural practices on multispectral responses from surface soil. Proc. 7th Symp. Remote Sensing of Environment. Univ. of Michigan, Ann Arbor, MI. pp. 2109-2113.

47. Sullivan County, Indiana Soil Survey, (*In*). 1971. U.S. Dept. of Agriculture, Soil Conservation Service. Washington, D.C. pp. 64-66.

48. Tanguay, M. G. 1969a. Aerial photography and multispectral remote sensing for engineering soils mapping. Master's Thesis, Purdue University. pp. 51-52.

49. ibid. 1969b. pp. 232-262.

50. ibid. 1969c. pp. 83-87.

51. Wacker, A. G. 1969. Non-supervised classifier. LARS Program Abstract No. 0600. Laboratory for Applications of Remote Sensing, Purdue University, 8pp.

52. Wacker, A. G., and D. A. Landgrebe. 1971. The minimum distance approach to classification. LARS Information Note No. 100771. pp. 129-130.

53. Waggoner, P. E., and R. H. Shaw. 1951. Temperature of potato and tomato leaves. Plant Physiol. 27:710-724.

54. West, T. R. 1972. Engineering soils mapping from multispectral imaging using automatic classification techniques. Proc. 51st. annual meeting of Highway Research Board (In press).

APPENDICES

APPENDIX A

Table A . A COMPARISON OF SELECTED LAND USE CLASSIFICATION SCHEMES (after the Conference on Land Use Information and Classification, 1971).

Scheme from Study by Association of American Geographers

I. Resource Production and Extraction

   A. Agricultural
      1. Crop production (cropland)
      2. Fruit (orchards, groves, and vineyards)

   B. Grazing
      1. Rangeland grazing (rangeland)
      2. Livestock pasturing (pasture)

   C. Forestry
      1. Commercial
      2. Non-commercial

   D. Mining

   E. Quarrying

II. Transportation, Communication, and Utilities

   A. Transportation
      1. Motoring (highways, parking, terminals, etc.)
      2. Railroading (rights-of-way, yards, terminals, etc.)
      3. Flying (airports)
      4. Shipping (inland waterways and marine docks and related facilities)

   B. Communications
      1. Telephone lines and facilities
      2. Telegraph lines and facilities
      3. Radio stations and facilities
      4. Television stations and facilities

Canada Land Inventory

I. Urban

   1. Built-up area
   2. Mines, quarries, sand and gravel pits
   3. Outdoor recreation

II. Agricultural Lands

   1. Horticultural, poultry, and fur operations
   2. Orchards and vineyards
   3. Cropland
   4. Improved pasture and forage crops
   5. Rough grazing and rangeland

      a. Areas of natural grasslands, sedges, herbaceous plants, and abandoned farmland whether used for grazing or not
      b. Woodland grazing

III. Woodland

   1. Productive woodland
   2. Non-productive woodland

IV. Wetland (swamp, marsh or bog)

V. Unproductive Land (land which does not, and will not, support vegetation)

   1. Sand
   2. Rock and other unvegetated surfaces

VI. Water

Table A (cont.)

C. Utilities
   1. Electric
   2. Gas
   3. Water (including irrigation)
   4. Sewage disposal
   5. Solid waste disposal

III. Urban Activities

A. Urbanized livelihood areas (urbanized areas defined by the Bureau of the Census)
   1. Industrial
   2. Commercial
   3. Services
   4. Residential
   5. Recreational

B. Other urban livelihood (places of more than 2,500 population but not including urbanized areas
   1. Industrial
   2. Commercial
   3. Services
   4. Residential
   5. Recreational

IV. Towns and Other Built-Up Livelihood Areas

A. Industrial

B. Commercial

C. Services

D. Residential

E. Recreational

V. Recreational Activities (other than those in urban areas and towns)

A. Mountain oriented

B. Water oriented

C. Desert oriented

D. Forest oriented

Table A (cont.)

E. Other (including combinations of above)

VI. Low-Activity Areas

A. Marshland oriented

B. Tundra oriented

C. Barren land oriented (including lava flows, dunes, salt flats, mountain peaks above timber line, etc.)

VII. Water-Using Activities

A. Lakes

B. Reservoirs

C. Streams

D. Ponds

Table A (cont.)

Standard Land Use Coding Manual
(One- and Two-Digit Levels Only)

1. Residential

    11. Household units
    12. Group quarters
    13. Residential hotels
    14. Mobile home parks or courts
    15. Transient lodgings
    19. Other residential, NEC[1]

2. Manufacturing

    21. Food and kindred products - manufacturing
    22. Textile mill products - manufacturing
    23. Apparel and other finished products made from fabrics, leather, and similar materials - manufacturing
    24. Lumber and wood products (except furniture) - manufacturing
    25. Furniture and fixtures - manufacturing
    26. Paper and allied products - manufacturing
    27. Printing, publishing, and allied industries
    28. Chemicals and allied products - manufacturing
    29. Petroleum refining and related industries

3.

    31. Rubber and miscellaneous plastic products - manufacturing
    32. Stone, clay and glass products - manufacturing
    33. Primary metal industries
    34. Fabricated metal products - manufacturing
    35. Professional, scientific, and controlling instruments; photographic and optical goods; watches and clocks - manufacturing
    39. Miscellaneous manufacturing - NEC

New York State Inventory

A. Agriculture

Areas:
- Ao Orchards
- Av Vineyards
- Ah Horticulture, floriculture
- Ay Specialty farms
- At High-intensity cropland
- Ac Cropland and cropland pasture
- Ap Permanent pasture
- Ai Inactive agricultural land
- Ui Other inactive lands
- Uc Lands under construction

Point data:
- Ay Specialty farms
    - y-1 Mink
    - y-2 Pheasant and game
    - y-5 Aquatic agriculture
    - y-6 Horse farms
    - d Dairy farms: number
    - e Poultry operation: number
    - f Active farmsteads: number

F. Forest Land

Areas:
- Fc Forest brushland
- Fn Forest land
- Fp Plantations

W. Water Resources

Areas:
- Wn Natural ponds and lakes (1 acre +)
- Wc Artificial ponds and reservoirs (1 acre +)
- Ws Streams and rivers (100' $\pm$)
- Wh Hudson River
- Wm Marine lakes, rivers and seas

Table A (cont.)

4. Transportation, communication, and utilities

   41. Railroad, rapid rail transit, and street railway transportation
   42. Motor vehicle transportation
   43. Aircraft transportation
   44. Marine craft transportation
   45. Highway and street right-of-way
   46. Automobile parking
   47. Communication
   48. Utilities
   49. Other transportation, communication, and utilities, NEC

5. Trade

   51. Wholesale trade
   52. Retail trade - building materials, hardware, and farm equipment
   53. Retail trade - general merchandise
   54. Retail trade - food
   55. Retail trade - automotive, marine craft, aircraft, and accessories
   56. Retail trade - apparel and accessories
   57. Retail trade - furniture, home furnishings, and equipment
   58. Retail trade - eating and drinking
   59. Other retail trade, NEC

6. Services

   61. Finance, insurance, and real estate
   62. Personal services
   63. Business services
   64. Repair services
   65. Professional services
   66. Contract construction services
   67. Governmental services
   68. Educational services
   69. Miscellaneous

Wb Shrub wetlands, bogs, marshes
Ww Wooded wetlands

<u>Point Data:</u>
n Natural ponds and lakes: number
c Artificial ponds and reservoirs: number
p Ponds less than 1 acre in size: number
l Lake shoreline: miles
s Streams and rivers: miles

N. Nonproductive land

Ns Sand (unstabilized)
Nr Rock (exposed)

R. Residential Land Use

<u>Areas:</u>
Rh High density (50' frontage)
Rm Medium density (50-100' frontage)
Rl Low density (100' + frontage)
Re Residential estates (5 acres +)
Rs Strip development
Rr Rural hamlet
Rc Farm labor camp
Rk Shoreline cottage development

<u>Point data:</u>
k Shoreline developed in cottages: miles
z High-rise apartment buildings: number
v Trailer parks: number
x Rural non-farm residences never a farm residence: number
o Rural non-farm residences once a farm residence: number

Table A (cont.)

7. Cultural, Entertainment, and Recreational

   71. Cultural activities
   72. Public assembly
   73. Amusements
   74. Recreational activities
   75. Resorts and group camps
   76. Parks
   79. Other cultural, entertainment, recreation, and NEC

8. Resource Production and Extraction

   81. Agriculture
   82. Agricultural related activities
   83. Forestry activities and related services
   84. Fishing activities and related services
   85. Mining activities and related services
   89. Other resource production and extraction, NEC

9. Undeveloped Land and Water Areas

   91. Undeveloped and unused land area (excluding non-commercial forest development)
   92. Noncommercial forest development
   93. Water areas
   94. Vacant floor area
   95. Under construction
   99. Other undeveloped land and water areas, NEC

1/ NEC - Not elsewhere classified

C. Commercial Areas

<u>Areas</u>:
- Cu Central business district
- Cc Shopping center
- Cs Strip development
- Cr Resorts

I. Industrial Areas

<u>Areas</u>:
- Ii Light manufacturing
- Ih Heavy manufacturing

E. Extractive Industry

<u>Areas</u>:
- Es Stone quarries
- Eg Sand and gravel pits
- Em Metalic mineral extraction
- Eu Underground mining

<u>Point data</u>:
- Eu Underground mining: types present
- u-1 Oil and gas
- u-2 Salt
- u-3 Other
- u-4 Abandoned

OR. Outdoor Recreation

<u>Areas</u>:
- OR All outdoor recreation activities

<u>Point data</u>:
- OR Outdoor recreation facilities: types present
- OR-1 Golf courses
- OR-2 Ski areas, other winter sports
- OR-3 Beaches and pools
- OR-4 Marinas, boat launching sites
- OR-5 Campgrounds
- OR-6 Drive-in theaters, race tracks, amusement parks

Table A (cont.)

OR-8 Fairgrounds
OR-9 Public parks
OR-13 Shooting, archery
OR-16 Private company facilities, community areas

P. Public and Semi-Public Land Uses

<u>Areas</u>:
P All public & semi-public areas

<u>Point data</u>:
P Public & Semi-public areas - types present
P-1 Educational institutions
P-2 Religious institutions
P-3 Health institutions
P-4 Military bases and armories
P-5 Solid waste disposal
P-6 Cemeteries
P-7 Water Supply treatment
P-8 Sewage treatment plants
P-9 Flood control structures
P-11 Correctional institutions
P-1 Road equipment centers
P-16 Welfare centers, county farms

T. Transportation

<u>Areas</u>:
Th Highway interchanges, limited access right-of-way, etc.
Tr Railway facilities
Ta Airport facilities
Tp Marine port and dock facilities
Ts Shipyards
Tl Marine locks
Tt Communication and utility facilities

Table A (concluded)

Point data:

h Highway category: highest present

- h-o None
- h-3 Unimproved, gravel, town roads
- h-4 Two-three land highway
- h-5 Four-line highway
- h-6 Divided highway
- h-7 Limited access highway
- h-8 Limited access interchange

Tr Railway facilities: type present

- r-1 Abandoned right-of-way
- r-2 Active track
- r-3 Switching yards
- r-4 Stations and structures
- r-5 Spur

Ta Airport facilities: type present

- a-1 Personal
- a-2 Non-commercial
- a-3 Commercial
- a-4 Airline
- a-5 Military
- a-6 Heliport
- a-7 Seaplane base

Tb Barge canal facilities: types present

- b-1 Channel
- b-2 Lock
- b-3 Abandoned channel

Tt Communications & utilities: types present

- t-1 TV-radio tower
- t-2 Microwave station
- t-3 Gas & oil-long distance transmission
- t-4 Electric power-long distance transmission
- t-5 Water - long-distance transmission
- t-6 Telephone - long-distance transmission

APPENDIX B

Table B1. Summary of the May test field results showing the number of data points and percent of total data points in each computer class.

Spectrally separable computer classes

Land use categories	1		2		3		4		5		6		7	
	#	%	#	%	#	%	#	%	#	%	#	%	#	%
A	72	8	243	27	399	44	178	20	10	1				
B	14	2	123	15	63	8	6	1			54	7	185	23
C													14	9
D									6	1	102	8	112	9
E														
F					1		2	0	3	1	42	8	18	3
G	4	1	35	7	1		5	1	12	2	83	16	99	19
H														
I														
J														
K			1	1			9	12	8	10	32	42	11	14
L			2	0			19	2	3	0	104	13	143	18
Total data points for computer classes	90		404		464		219		42		417		582	

Table B1, cont.

Spectrally separable computer classes

Land use categories	8 #	8 %	9 #	9 %	10 #	10 %	11 #	11 %	12 #	12 %	T #	T %	Total data points for land use categories
A													902
B			130	16	101	13	120	15			1	0	797
C			58	38			80	53					152
D			359	30	475	39	156	13					1210
E			2	1	15	4	336	95					353
F			61	1	111	20	310	56			4	1	552
G	20	4	5	1	131	26	115	23			1	0	511
H	448	40			4	0	1	0	652	59	10	1	1112
I	3	5							61	95			64
J					12	27	32	73					44
K	3	4	1	1							12	16	77
L	19	2	192	24	237	29	49	6	2	0	61	8	811
Total data points for computer classes	490		808		1086		1199		715		89		

Table B2. Summary of the July test field results showing the number of data points and percent of total data points in each computer class.

Land use categories	Spectrally separable computer classes: 1		2		3		4		5		6		7		8		9	
	#	%	#	%	#	%	#	%	#	%	#	%	#	%	#	%	#	%
A	258		802	9	547	6	52	1	95	1	433	5	858	10	544	6	1167	14
B	2		194	21	366	39	7	1	3	0			305	32	15	2		
C									2	1			148	99				
D	4		59	2	403	13	444	15	121	4			458	15	634	21	15	0
E							2								2	0	196	23
F																		
G	5	8	2	3	3	5	38	60										
H	228	20	1															
I																		
J							8	17					2	4	26	54		
K	33	40	10	12	10	12	25	30										
L	380	15	185	7	377	15	80	3	237	9	3	0	534	21	267	10	25	1
Total data points for computer classes	910		1253		1706		656		458		436		2306		1488		1403	

Table B2, cont.

Spectrally separable computer classes

Land use categories	10 #	10 %	11 #	11 %	12 #	12 %	13 #	13 %	14 #	14 %	15 #	15 %	16 #	16 %	T #	T %	Total data points for land use categories
A	493	6	1709	20			1526	18	9	0					10		8638
B			44	5													940
C																	150
D	63	2	177	6			221	7	107	4	2	0					3043
E			18	2			287	33	358	41					1	0	869
F							6	10	54	90							60
G													4	6	11	17	63
H							1	0			536	47	276	24	101	9	1143
I									2	2	92	97	1	1			95
J	3	6											4	8	5	10	48
K															5	6	83
L	48	2	126	5	110	4	92	4							14	1	2551
Total data points for computer classes	607		2074		582		2133		603		630		285		147		

Table B3. Summary of the September test field results showing the number of data points and percent of total data points in each computer class.

Spectrally separable computer classes

Land use categories	1		2		3		4		5		6		7	
	#	%	#	%	#	%	#	%	#	%	#	%	#	%
A	116	1	683	8	2264	28	150	2	1083	13	11		1708	21
B	731	59	86	7	87	7	39	3	7	0	80	7	128	10
C									45		81	47	2	
D	25	1	463	14	461	14	97	3	444	13	1204	35	181	5
E									2	0			1	0
F									2	0			3	1
G			1	3					1	3				
H														
I														
J													3	8
K	59	49	30	25	12	10			2	2	3	3		
L	236	7	483	14	532	16	47	1	367	11	583	17	126	4
Total data points for computer classes	1167		1746		3356		313		1953		1962		2152	

Table B3, cont.

Spectrally separable computer classes

Land use categories	8 #	8 %	9 #	9 %	10 #	10 %	11 #	11 %	12 #	12 %	T #	T %	Total data points for land use categories
A	1397	17	793	10	10		1	0					8196
B													1230
C	24	14	21	12									173
D	341	10	51	2	114	3	19	1					3400
E	21	2	41	4	348	33	652	61					1065
F	24	5	27	6	143	32	249	55					452
G											34	94	36
H	2	0							2430	99	3	0	2461
I									105	100			105
J	12	30	18	45	7	18							40
K	2	2			2	2					10	12	120
L	157	5	235	7	317	10	132	4			120	4	3335
Total data points for computer classes	1190		1215		996		1051		2525		167		

APPENDIX C

Figure C1. Identification of agricultural cropland and an overlay of the land use categories present in Flightline 219.

Cropland*	
Soybeans	s
Pasture	p
Idle cropland	i
Rye	r
Wheat	w
Hay	h
Corn	c

Land use categories**	
Row crop	A
Small grain	B
Hay	C
Pasture	D
Forest, continuous	E
Forest, discontinuous	F
Extraction	G
Fresh water	H
Waste water	I
Marshland	J
Urban core	K
Suburban	L

* Annotated on aerial photograph (Note: penciled numbers and letters pertain to field and tract information)

** Annotated on overlay

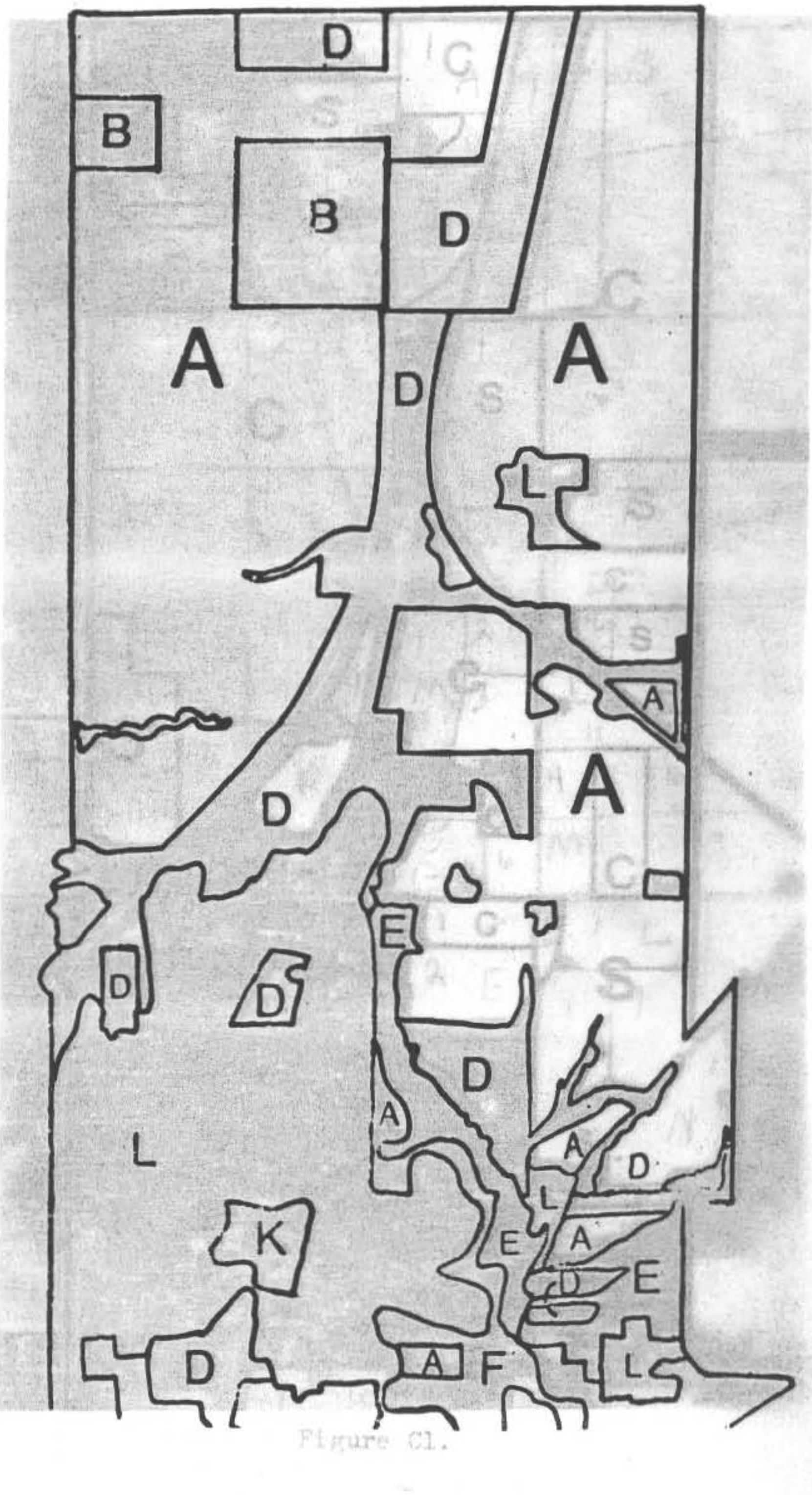
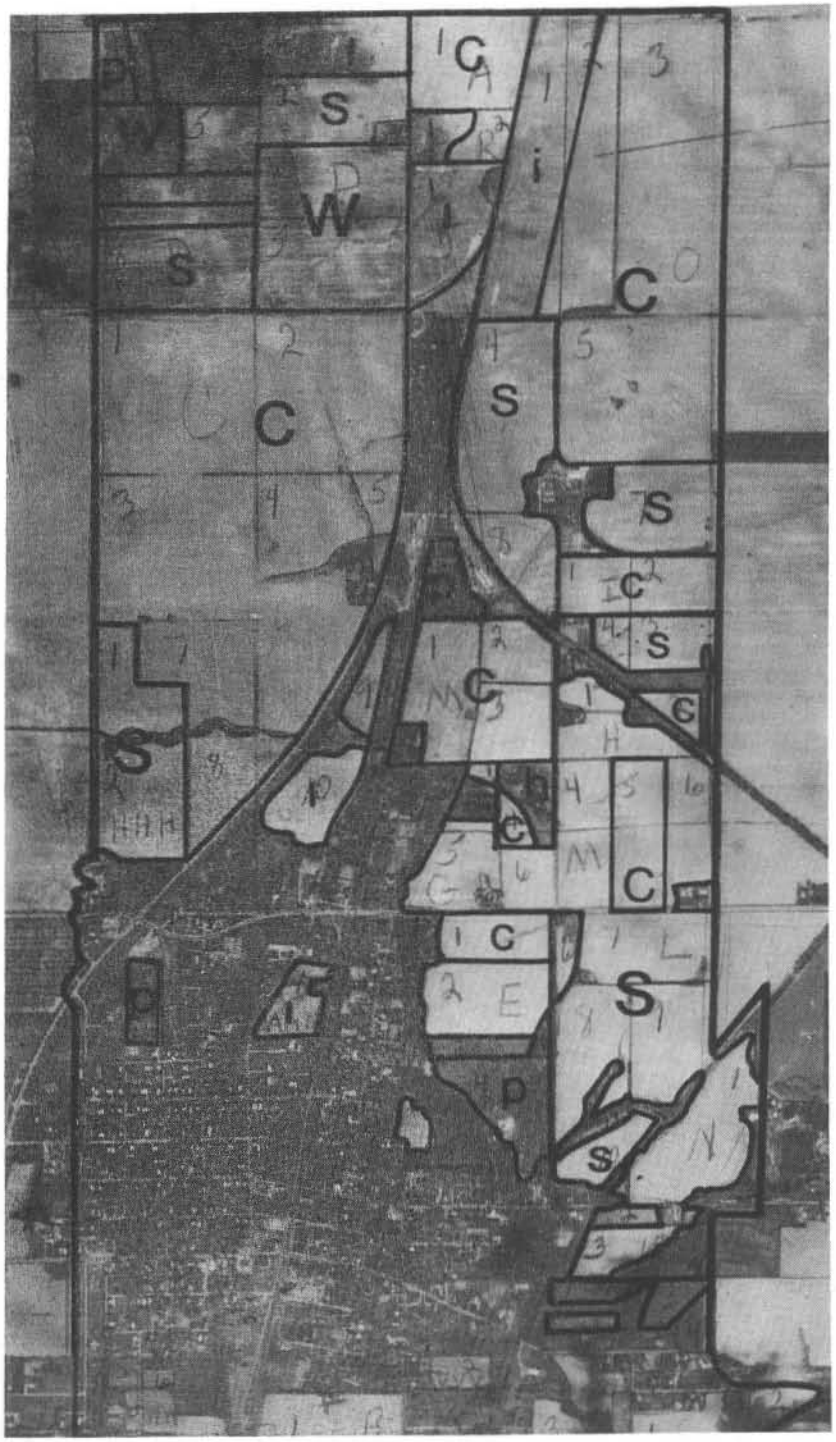


Figure C1.



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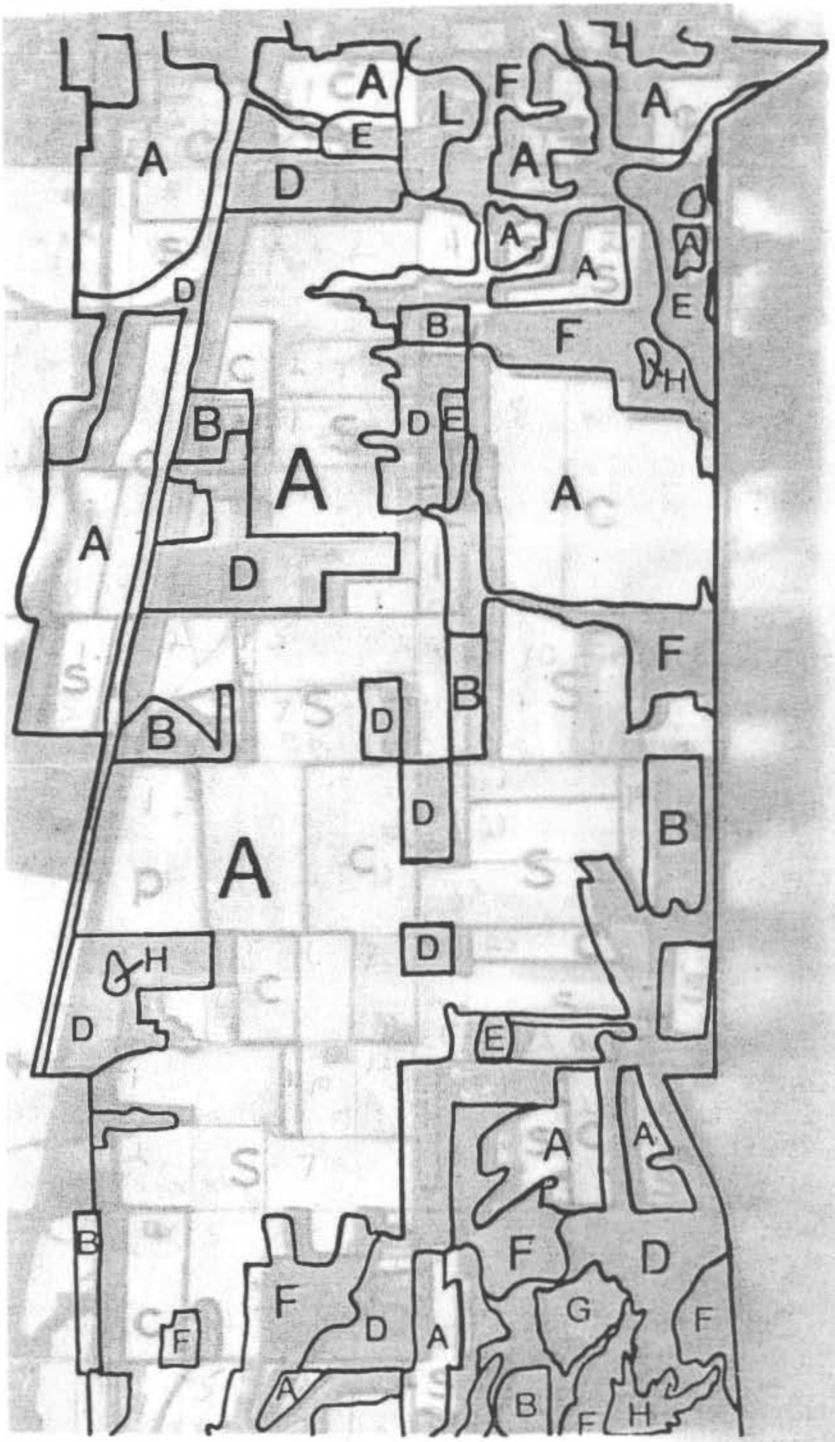

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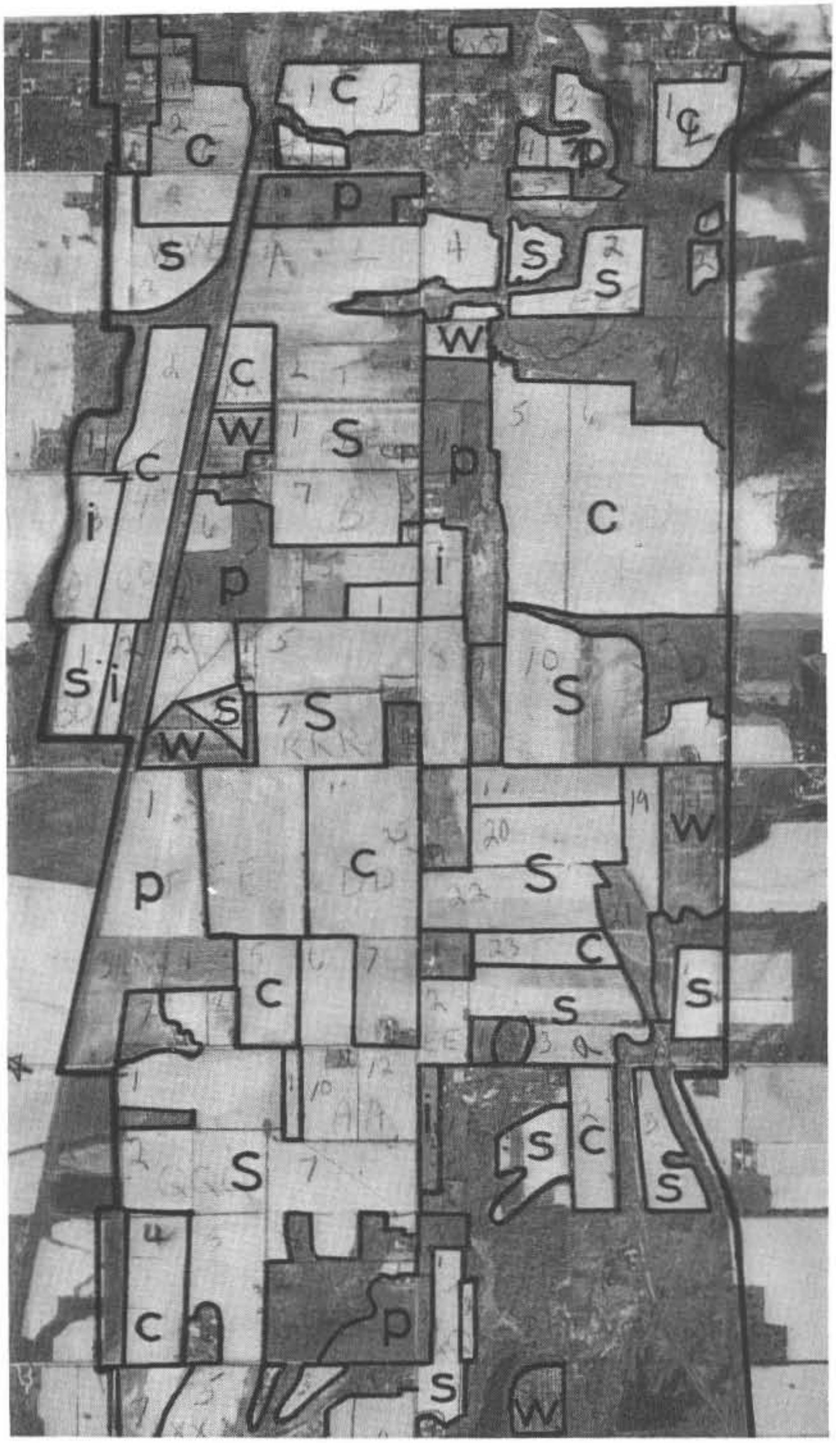

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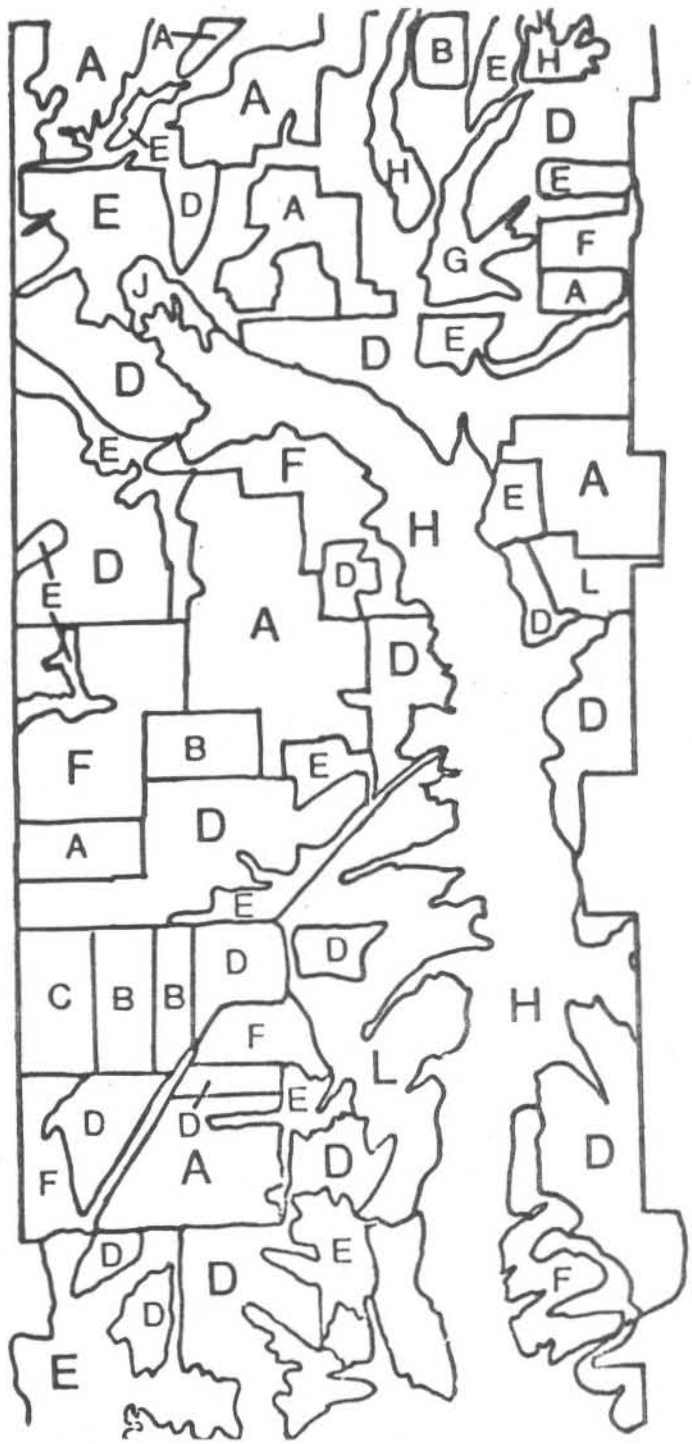

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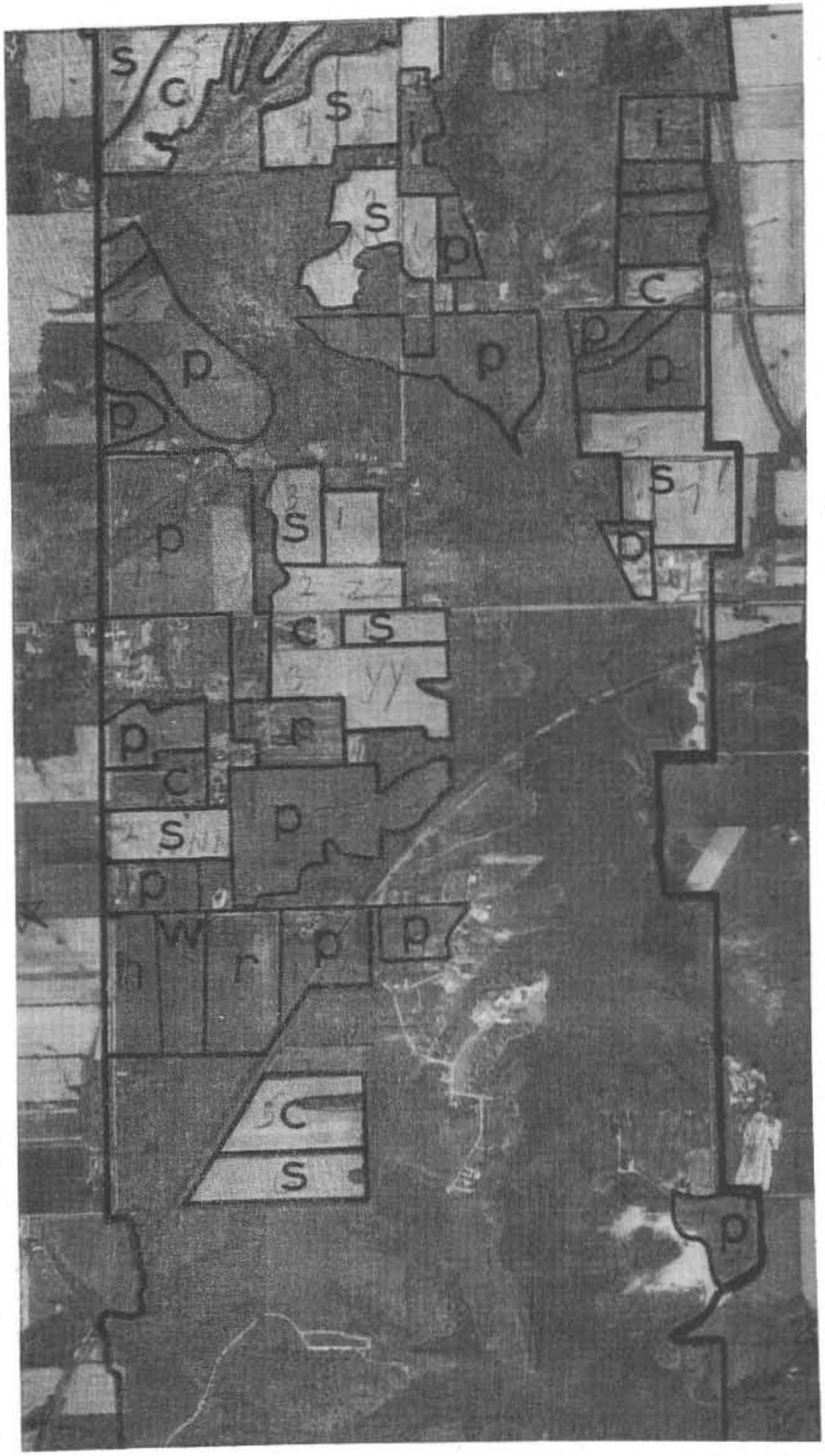

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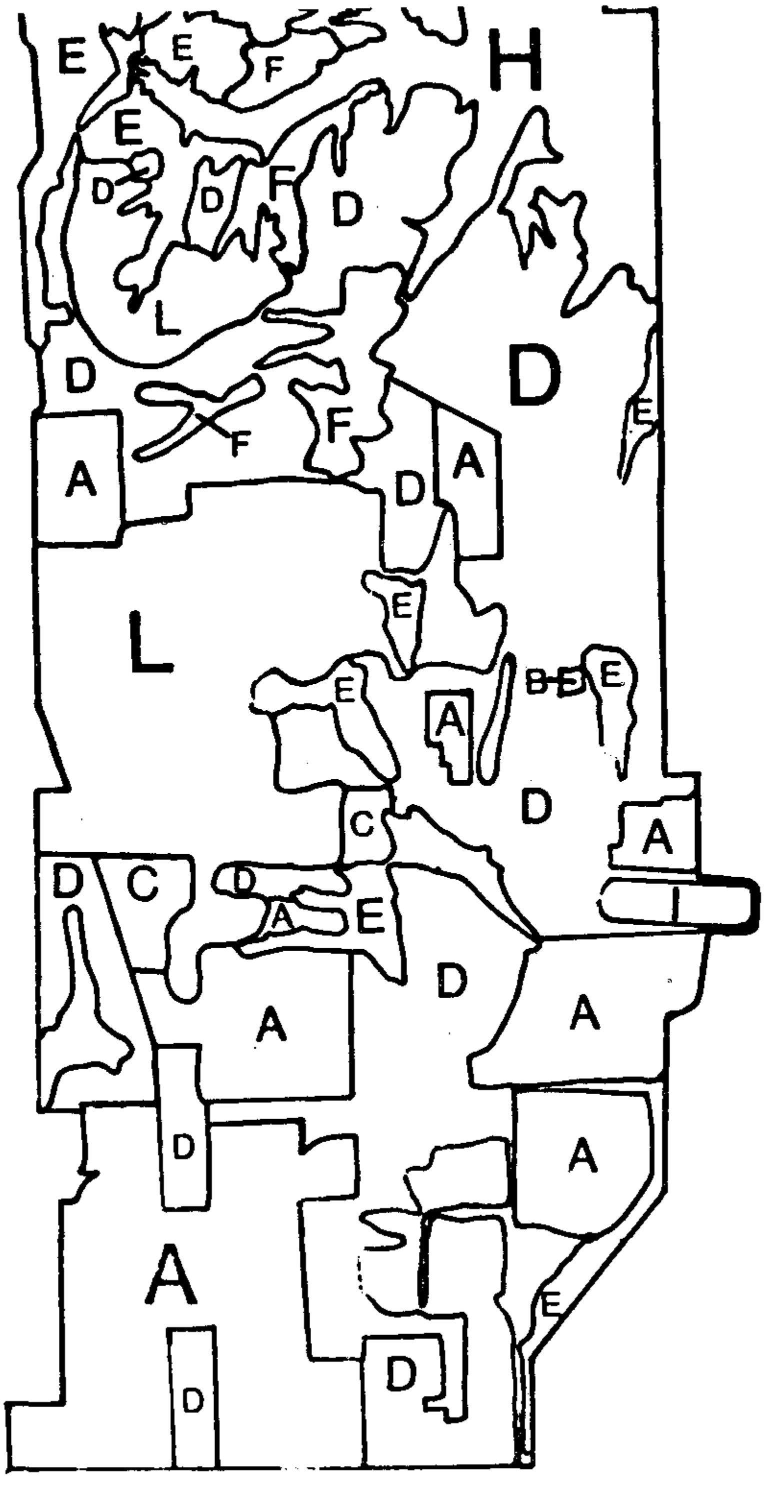
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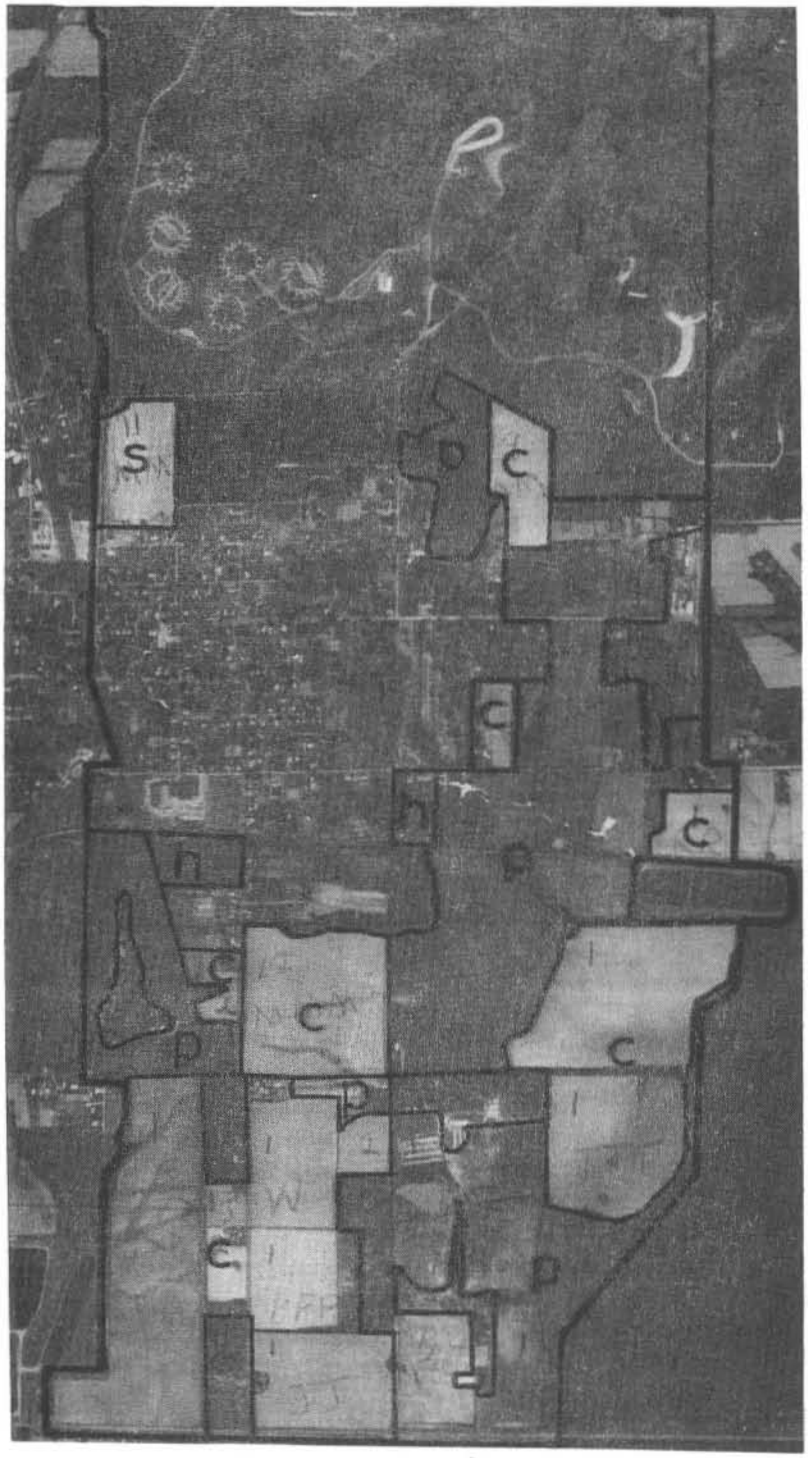

Figure C1. Concluded.

unclassified
Security Classification

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(Security classification of title, body of abstract and indexing annotation must be entered when the overall report is classified)

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3. REPORT TITLE

Land Use Classification Utilizing Remote Multispectral Scanner Data and Computer Analysis Techniques

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11. SUPPLEMENTARY NOTES	12. SPONSORING MILITARY ACTIVITY
	National Aeronautics and Space Administration

13. ABSTRACT

This research was designed to study the ability of present automatic computer analysis techniques with the use of multispectral scanner data to differentiate land use categories represented in a complex urban scene and in a selected flightline. An airborne multispectral scanner was used to collect the visible and reflective infrared data.

A small subdivision near Lafayette, Indiana was selected as the test site for the urban land use study. Multispectral scanner data were collected over the subdivision on May 1, 1970 from an altitude of 915 meters. The data were collected in twelve wavelength bands from 0.40 to 1.00 micrometers by the scanner.

The results indicated that computer analysis of multispectral data can be very accurate in classifying and estimating the natural and man-made materials that characterize land uses in an urban scene.

A 1.6 km. wide and 16 km. long flightline located in Sullivan County, Indiana, which represented most major land use categories, was selected for analysis. Multispectral scanner data were collected on three flights from an altitude of 1,500 meters. Energy in twelve wavelength bands from 0.46 to 11.70 micrometers was recored by the scanner.

A new, more objective approach to computer training was developed for analysis of the three dates of data. Emphasis was placed on the standardization of a procedure for analysis of data. The procedure offered faster and consistantly good duplication of attained results.

(Continued on other side)

unclassified
Security Classification

14. KEY WORDS	LINK A		LINK B		LINK C	
	ROLE	WT	ROLE	WT	ROLE	WT
(Abstract concluded) The results indicated an ability for automatic computer analysis of remotely sensed multispectral scanner data to characterize and map land use categories within the test area. Additionally, results indicated an alteration of the data analysis procedure and land use classification scheme.						

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