SECTION 48

LAND UTILIZATION AND WATER RESOURCE INVENTORIES OVER EXTENDED TEST SITES*

by

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INTRODUCTION

During the past decade, many actual and potential applications for remote sensing technology have been determined. This past year has seen a tremendous amount of interest generated in the application of remote sensing to problems related to land-use. A key element in applying remote sensing to land-use studies involves accurate identification of basic and vegetative cover types. In work with automatic data processing (ADP) techniques it is found that as information requirements become more specific, the analysis task becomes more complex. In dealing with many problems involving automatic mapping of vegetative cover types conditions, one finds that an analysis sequence similar to that shown in Figure 1 must be pursued. As is indicated, there are many possible categories of basic cover types, and within the "vegetation" category there are many potential subgroups. Once a particular species has been identified, there are many interrelated factors affecting the potential yield of that crop. Of course, the crop yield is of considerable importance to a large number of "users", but since yield cannot be measured directly from remote distances, the factors related to yield and condition of the crop must be determined.

Much of the LARS research effort this past year was devoted to the Corn Blight Watch Experiment, discussed in the January 17th session of this review. As is indicated in Figure 1-C, Southern Corn Leaf Blight is only one of many different kinds of diseases or other stress factors which can affect vegetative conditions. This first figure

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*In this paper, results from a number of studies are summarized; researchers are identified in the Acknowledgement section.

indicates the degree of difficulty of some of the problems encountered in the corn blight analysis sequence, thereby giving some insight into the real significance of being able to reliably identify the corn at various stages of development as well as identifying blight levels within the corn.

In addition to the work on the corn blight this year, several other analysis tests were completed which resulted in significant findings. These aspects of our work will be discussed as follows:

1. Field spectral measurements of soil conditions.
2. Analysis of extended test site data. This discussion involves three different sets of data analysis sequences.
3. Urban land-use analysis, for studying water runoff potentials.
4. Thermal data quality study, as an expansion of our water resources studies involving temperature calibration techniques.

FIELD SPECTRAL MEASUREMENTS OF SOIL CONDITIONS

In order to accurately interpret remote sensor data, an adequate understanding of energy-matter interactions is mandatory. Use of a field spectroradiometer for detailed studies of selected situations in a natural environment offers one of the best ways for developing a better understanding of many of these complex energy-matter interactions. One study completed this past year involved work with several soil conditions using an Exotech Field Spectroradiometer. (The paper by Dr. LeRoy Silva describes this instrument.) Since the instrument is capable of measuring incoming irradiance as well as the radiance from the soil of interest, the resultant data could be reduced to percent reflectance measurements. Although the instrument is capable of obtaining data throughout the optical portion of the spectrum and data were actually collected throughout the 0.4-16 micrometer wavelengths, limitations in our software for handling the recorded data forced the restriction of reduction and analysis of the visible wavelengths.

Figure 2-A shows the spectral reflectance in the visible portion of the spectrum for three different soil types. One sees that there is a much wider variation in the reflectance characteristics for these different soil types than normally is found for different species of green vegetation. In this illustration, only spectra for dry soil conditions are shown. Figure 2-B indicates the dry versus wet reflectance for two soil types, and one sees some very marked differences, with the dry soil conditions having much higher reflectances than the wet soil conditions. However, it is not always easy to separate dry from wet soil moisture conditions when different soil types are involved.

Figure 2-C shows a very high reflectance for dry Fincastle soil but a reflectance for the wet Fincastle that is very similar to the reflectance for dry Dana soils. Nevertheless, much work has indicated that it ought to be possible to use the thermal and microwave portions of the spectrum to considerable advantage in separating wet and dry soil conditions, even among the many different soil types of concern.

Not only do variations in soil moisture cause distinctive differences in percent reflectance for the same soil type, but variations in the surface condition, such as crusting, will cause very distinct differences in percent reflectance. Figure 2-D shows the reflectance for a soil sample in which the action of the rain had crusted, or smoothed out the soil surface, causing a relatively high reflectance. After the crust was broken, the surface soil condition was still dry, but a much lower reflectance was measured at all wavelengths in the visible region.

From these few examples, one sees that several natural causes of large variations in spectral response can be encountered. A field instrument such as the Exotech spectroradiometer has many advantages such as a fast scan rate; use under natural illumination conditions; and the collection of data from approximately the same instantaneous field of view, as well as look angle, as the scanner in the aircraft. Future studies with this instrument should enable significant progress to be achieved in determining the optimum times during the growing season for flight missions to be scheduled, studying spectral characteristics of various vegetative and soil conditions throughout the optical wavelength region, species differentiation as a function of temporal changes, and other energy-matter interactions.

ANALYSIS OF EXTENDED TEST SITE DATA

In studying results from several of our computerized analyses of multispectral scanner data collected over fairly large geographical areas, it became apparent that several possible causes of spectral variability must always be considered. Some of the major causes of such variability which are particularly noticeable in analysis of vegetative ground cover and which are of primary concern to the user of this data are:

- .Percentage of Vegetative Cover
- .Spectral Response of Vegetation
- .Spectral Response of Soil Background
- .Illumination, Crop and/or Sensor Geometry, and Instrumentation Variables

Some of these variables are a function of the vegetation and soils while others are not. In our work in the Biogeophysical Research Program, we are particularly interested in the spectral characteristics of the vegetation and soils, but we find that illumination, geometry, and instrumentation factors affect the scanner data in ways that frequently make it difficult to separate and identify which factors are affecting the spectral characteristics of vegetative ground cover. Therefore, one must consider all possible factors which could affect spectral characteristics of scanner data, in order to properly and accurately interpret this type of data.

One of the major questions that frequently arises is: How well can one extrapolate from small sets of training sample data obtained in one geographic location to an automated classification of large geographic areas? Certainly, if we are ever going to utilize these techniques on an operational basis, we must know the limitations and capabilities for extrapolating small data sets to large areas. In looking to the future and preparing for ERTS and SKYLAB, considerable effort this year was devoted to further examination of natural and other causes of spectral variability, and how this influences our capability to extrapolate to large geographic areas.

CLASSIFICATION OF A 42,000-ACRE AREA

The first study over extended test sites to be reported upon involved data collection in a north-south flightline in Central Indiana. These data were collected in late April (spring-time) from an altitude of 3200 feet by the University of Michigan multispectral scanner system. We have previously reported on our capability to reliably identify basic cover types (Hoffer, 1968). In further analysis of this data, we utilized less than 1% of the total area as a training set. All of the training data came from one small area near the northern part of the flightline. After classification, 256 test areas were selected at random, accounting for several thousand data points in each cover type category, and the computer classifications were tabulated for all data points in these test areas. The results indicated accuracy of over 97% for the automated classification of the basic cover types. However, we did notice a slight decrease in accuracy as the area being classified became more distant from the area where the training samples had been obtained. Samples from the northern and from the southern portions of the flightline were then selected and compared. Figure 3 shows the results of this comparison for three different wavelength bands. The cross hatched areas indicate data from northern portions of the flightline and solid blocks indicate data from the southern portion

of the flightline. The length of the bar indicates the mean spectral response, plus or minus one standard deviation. Therefore, a longer bar will indicate more variability, whereas the bars of shorter length indicate relatively small amounts of spectral variability within that particular wavelength band and cover type. As can be observed, there is little difference in spectral response between the northern and the southern portions of the flightline for the bare soil areas. Water showed a distinctly higher response in the southern portion of the flightline than in the water in the northern portion of the flightline in the visible wavelengths but, as expected, there is little difference in radiance in the reflective infrared portion of the spectrum. The low response in the reflective IR for water is attributed to the high absorption characteristics of water in these wavelengths, while the differences in response between the northern and southern portions of the flightline in the visible wavelengths is ascribed to different sediment loads between the North and South Fork of the White River, where the data was obtained. We had anticipated that vegetation in the southern portion of the flightline would have a higher response than the vegetation in the northern portion of the flightline. This was the case in the blue portion of the visible wavelengths, but in the reflective infrared, just the opposite situation occurred. It is believed that this was because the data collected in the northern portion of the flightline largely consisted of dense winter wheat stands and forested areas that were mostly in the low-lying bottom-lands along the streams. These forested bottom-lands consisted of cottonwood and sycamore trees which had leafed out earlier than the upland forest cover that predominated in the southern portion of the flightline. Thus, just because data came from a more northerly area, it is not safe to assume that the vegetation as a whole will be leafed out more in more southerly areas on any particular date during the spring.

In summary, we believe that the variability observed in this set of data was caused primarily by the natural spectral differences in the materials involved.

EAST-WEST FLIGHTLINE EXTENDING OVER A 133-MILE AREA

Since the basic cover type mapping in the first analysis had indicated some slight changes in spectral response but since these changes did not seriously affect the classification results, the next logical step seemed to be to conduct a more complicated analysis involving identification of a particular crop species over a large geographic area. To limit some of the north-south geographic variation which had been observed in the first analysis, and which can be severe in large geographic areas, flightlines were laid out in an east-west direction to sample a 40-county area in Indiana and Illinois, as shown

in Figure 4-A. To limit the total amount of data collected, only segments from a 133-mile flightline were recorded. The length of each of these segments and the distance between the segments is indicated in Figure 4-B.

The multispectral scanner data for this experiment were obtained by the University of Michigan aircraft on July 1, 1970. However, the analysis of these data had not been completed in time for the 3rd Annual Earth Resources Program Review, so are reported this year. As an indication of the difficulties sometimes encountered in conducting this type of experiment, the following comments are included. Initially, it was planned that the following conditions were to have been met as nearly as possible:

(1) Wheat would be at a mature stage of development. It was assumed that approximately uniform conditions of maturity would exist along an east-west flightline and that therefore the wheat would have a similar spectral response throughout the data.

(2) All data would be obtained from a 5000-foot altitude during a single flight sequence to minimize differences in atmospheric attenuation and electronic drift in the data.

(3) Ground observations of cover types (species and crop condition) would be obtained for Flightline 25 in Indiana. Aerial photography taken at the same time as the scanner data would then be used to extrapolate cover type identification from FL 25 to the other flightlines to the west.

(4) The classifier would be trained with data from FL 25 and this training set would be used to classify data from the entire sequence of flightlines covering a geographic area of more than 130 miles from the eastern-most end of FL 25 to the western-most end of FL 43.

The actual conditions at the time of the flight failed to meet the desired ones in several ways. This caused a number of changes in the data analysis plans and affected some of the results and conclusions.

Since flight missions through NASA must be set up several months in advance because of aircraft scheduling requirements, we had requested the flight for the last week in June because past experience had indicated that in Indiana this would be the optimum time for mature wheat. Normally, harvesting does not start until the early part of July. However, in 1970 the crop conditions were on the early side of "normal," and the flight was conducted during the latter portion of the scheduled time period (July 1). This combination resulted in data in which some of the wheat in Indiana was being harvested or had been harvested at the time of flight. In Illinois, the growing conditions appeared to be about one week ahead of those in Indiana, and much of the wheat had been harvested. Some fields, believed to be wheat

stubble, already had an undergrowth of weeds, giving these fields a spectral response somewhat like that of hay fields. Since both standing wheat and wheat stubble were present, we were required to train the classifier portion of the computer programs on both mature wheat and wheat stubble of varying age and condition.

At the time data was being collected, scattered cumulus cloud cover developed over the eastern portions of the flightline area, thereby forcing the FL 25 data to be collected from 3,500 feet altitude and with variable cloud shadow effects on the ground, whereas the other four flightlines of data had been collected from 5000 feet altitude under mostly clear, sunny conditions. This change in data collection caused the use of FL 40 (on the Indiana-Illinois border) for a training area, with FL 25 being used only as a test area to check effects of altitude change and cloud shadows.

The use of aerial photos in lieu of ground observations on some of the flightlines did not prove to be as reliable for accurate identification of cover types as had been anticipated. This was due to variable illumination conditions in parts of the flightline at the time the photography was obtained, poor quality and resolution in the black and white photography, and completely unusable results for the color infrared photos. The variability of ground cover conditions added to the difficulty.

The procedures used in the experiment were therefore modified to optimize utilization of the actual data collected. This resulted in the following set of objectives being defined:

(1) Reaffirm previous work at LARS showing the capability for identifying wheat vs. everything else. Test and training samples to be obtained from FL 40.

(2) Determine capability for identifying wheat (or wheat stubble) over an extended test site area, using training samples from one geographic area to classify a completely different area. In this case, the training samples from FL 40 would be used to classify data from FL 41, 42, and 43. Test samples from all four flightlines would be obtained to quantitatively check classification results.

(3) Determine the capability for classifying FL 25 data using training samples from FL 40, recognizing the fact that FL 25 data were collected from 3500 feet altitude under somewhat cloudy conditions, as opposed to 5000 feet altitude and mostly clear conditions for the FL 40 data.

(4) Determine variability of incoming solar radiation at the aircraft location over the entire 130-mile flightline area, and utilize data handling techniques developed by LARS to calibrate the spectral reflectance data as a function of the sun sensor signal.

(5) Determine utility of sun sensor calibration techniques for increasing accuracy of automatic classification of cover type, if significant variability is found in sun sensor signal in Step 4 above.
(6) Determine major sources of variation in spectral response of cover types, the severity of such variations as it affects automatic classification techniques, and whether such variations can or cannot be corrected with various calibration and data analysis procedures.

Results

Initial analysis efforts showed that calibration of the data only for electronic drift was not adequate to allow accurate classification over the entire area. The ability to classify automatically wheat vs. everything else was demonstrated again (LARS, 1970) using training and test samples from FL 40. However, the classification of the other flightlines was only partially successful. There were many misclassifications present (primarily as wheat in areas that were not wheat), and a light threshold applied to the training data tended to cause most of the test area data to be thresholded.

The sun sensor signal for the entire flightline was examined and found to show significant changes in solar illumination (Figure 5). Generally, a moderate upward shift was found as the aircraft moved along the flightline. In some cases, distinct changes could be seen between the end of one flightline and the beginning of the next, and in FL 40 there were rapid, marked changes in illumination, even though the area was only six miles long and was flown in approximately three minutes.

The LARSYSAA multispectral scanner analysis program system contains a data calibration function in which the user may select the type of calibration to be applied, dependent upon his knowledge of any problems existing in the data (Phillips, 1969). The usual calibration is one which corrects for low frequency drift in the data collection or data processing system. If illumination changes are known to exist in the data run, an additional calibration may be made to change the data to a constant level in each data line. This will force data amplification to a fixed level in an attempt to correct for illumination changes as they are detected by the sun sensor.

Illumination usually will change as the aircraft moves through differing atmospheric conditions, and the sun sensor provides a measure of these changes as they are detected at the aircraft. Illumination at the aircraft may not change at the same time or at the same rate as

illumination at the ground target. An example is the situation in which the aircraft enters a cloud shadow and the sun sensor shows an abrupt change while the target may continue to be in full sunlight. The reverse will occur when the target is in shadow and the aircraft remains in full sunlight. These types of situations do not allow use of the sun sensor calibration, because such calibration under those circumstances would cause even larger differences in amplitude of the data. However, in the 40-county test site, the sun sensor pulse indicated a gradual increase in illumination. Thus, a two-point calibration for both drift and amplification could be effectively used, and was applied to this data.

In Figure 5, the abrupt change in Flightline 40 was due to an electronic gain change, or manual change in amplification of the signals. This gain change occurred in all the middle infrared channels (1.0-1.4, 1.5-1.8 and 2.0-2.6 μm), and caused distinctive changes in the gray scale printouts of the data at that point. The sun sensor calibration procedure adjusted effects of this gain change.

The results of the classifications with data calibrated for both drift and the sun sensor signal showed encouraging improvements in accuracy. On FL 40, the training data had an overall classification accuracy of 99% (98.5% correct classification for wheat, using 662 data points, and 99.9% correct classification for all other crops or cover types, using 3,104 data points). The test sample accuracy showed somewhat variable results from flightline to flightline, as shown in Table I. This is thought to be due to the natural variation in condition or degree of maturity of the cover types. Classification accuracy was very high in FL 43, approximately 80 miles distant from the area where training samples had been selected.

As a check on the effects of calibration on classification accuracy, two additional classifications were made. The first used the same channels that had been selected from the two-point calibration data but used data that had been calibrated only for electronic drift. The last classification used the best five channels, again using the data calibrated only for drift. In the latter case, the feature selection algorithm indicated a different set of 5 channels than had been used in the previous classification. The spectral bands were 0.55-0.58, 0.66-0.72, 0.80-1.00, 1.00-1.40, and 1.50-1.80 micrometers.

The test field percentages are given in Tables I, II, and III for the three classifications. For ease in comparison, Figure 6 shows the classification accuracy of the wheat test fields. The two-point calibration is consistently the best classification, with the two classifications having only drift calibration being about equal. The last classification, using the best five combinations of wavelength bands, was slightly more sensitive to accurate wheat classification

than the other classification using data calibrated only for drift, but was still much less accurate than the classification using data having two-point calibration. All three classifications had similar high test field accuracies in FL 40 where the training statistics had been obtained.

One additional test was made, using data from FL 25, the east-west line across Tippecanoe County, Indiana. These data were collected on the same flight as the data for FL 40-43, but FL 25 was flown at a lower altitude (3500 feet above terrain), and about 20 minutes later. Scattered cumulus clouds were present over this area. The line begins about 21 miles east of the FL 40 end point. The FL 25 data were classified using the training statistics obtained from FL 40 and the two-point calibration. A set of 17 wheat fields and 4 large areas of other cover were selected as test fields. Wheat fields were classified with 90.5% accuracy, but the other fields were only 30.6% correctly classified, indicating that many points were misclassified into the wheat category or thresholded. Vegetative conditions along this flightline were quite different than in the training area, as indicated by the fact that the wheat harvest was less than half finished on this flightline, in contrast to having been nearly completed in many areas in the Illinois flightlines. However, it is believed that the variable cloud conditions at the time these data were collected caused more error in these classification results than either the difference in altitude or the differences in vegetative cover conditions.

The conclusions from this experiment included the following:

(1) The capability for accurately identifying wheat using ADP techniques was shown to be high over relatively small areas (about 9 square miles).
(2) When training samples from one area were utilized to classify data from other geographic areas, classification accuracies tended to be rather poor unless a two-point calibration (which corrected for both electronic drift and variations in solar illumination) was utilized. The test field results indicated that without the two-point calibration, there was a general decrease in accuracy as classification was attempted for areas further and further from the training site.
(3) Proper calibration allowed recognition accuracies of 91% to be obtained for test areas 80 miles away from the training sample location.
(4) In general, the two-point calibration (drift and illumination) should be utilized in all data analysis involving large geographic areas.

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(5) The calibration procedures utilized appeared to satisfactorily adjust for manual changes in the gain setting, although further analysis along this line is recommended.
(6) Use of the sun sensor to calibrate the scanner data proved unsatisfactory under conditions of scattered cumulus clouds, since the shadow conditions on the ground were quite variable and differences in illumination at the airplane and on the ground below the airplane did not coincide.
(7) Even though conditions of the ground cover were striking and more pronounced along the east-west flightline area than had been anticipated, adequate training of the classifier (involving selection of representative samples of data from the various conditions and stages of maturity), allowed reasonably accurate automatic classification results to be obtained from an area extending more than 90 miles from east to west.

It is strongly recommended that additional studies of natural variability over large geographic test sites be conducted for many cover types and species. It is anticipated that ERTS and SKYLAB data will offer many excellent opportunities for this type of endeavor.

ACREAGE ESTIMATES FOR A 504-SQUARE-MILE AREA

The third study to be reported involving automatic classification results over extended test sites concerned an attempt to convert automatic classification results to acreage estimates of various cover types, and to compare these acreage estimates to existing figures published by the Crops and Livestock Reports of the Statistical Reporting Service, U.S. Department of Agriculture, and the Census of Agriculture, U.S. Department of Commerce (Johnson, 1971).

In this study, five flightlines in Tippecanoe County, Indiana were analyzed. Tippecanoe County is an area of 504 square miles, or 322,560 acres, and the scanner data were collected by aircraft from an altitude of 5000 feet; a scanner swath width of 1.11 miles was utilized, resulting in an area of 82,072 acres being overflown. Therefore, 25.75% of the total area in Tippecanoe County was included in the sample. Each resolution element digitized and analyzed represented an area equivalent to approximately 1600 square feet (the resolution element immediately below the airplane represents a much smaller area than one off to the side of the flightline because of the geometry of multispectral scanners.) The data for each of the five flightlines was classified into cover types designated as:

.corn
.soybeans
.forages
.trees
.bare soil
.water

The "forages" category represents hay, pasture, wheat stubble and oat stubble. Table IV indicates the number of RSU's in each of the cover types in the test areas, the number of RSU's correctly classified in each cover type (by flightline), and the percentage correct classification for each cover type in the test areas. The accuracy of the training categories was even better than the test classification, as anticipated. Training field accuracies are not given here as they do not really represent the overall accuracy of automatic classification for the flightline. Figure 7 shows the classification results for each of the flightlines involved. This bar graph represents the material in Table IV, but in more understandable form, and with the water, soil, and tree classes combined as "other," since they represent relatively small numbers of data points. In this case, the height of the bar indicates the total number of points considered in testing the classification results. The number of points correctly classified are then indicated by the lower portion of the bar, the number incorrectly classified by the upper portion of the bar, and the percentage correct classification is also shown at the top of the individual bars. In comparing the height of the bar with the number of data points involved, (shown on the ordinate), one sees that there may be as much acreage planted in soybeans as in corn for an individual flightline. In other flightlines, there will be twice as much corn as soybeans present. This indicates that our techniques for sampling need to be carefully developed, and that an accurate sample of cover types is mandatory in order to obtain accurate acreage estimates for large geographic areas. Figure 8 shows the combination for all five flightlines. Again the height of the bar shows the number of data points involved in testing the accuracy of the classification. An actual percentage correct classification for the test areas for each of the four major cover type groups considered is shown at the top of the bar. Figure 9 shows the overall results for the sample area in terms of the percent correct classification. In this figure, the number of data points involved in determining the percent classification for each of the cover types is indicated on the bar. The classification accuracy for the "water," "soil," and "trees" categories (previously grouped together as "other") is also shown.

Since it appeared that the accuracy of the classification was reasonably high, the next step was to convert each resolution element in the scanner data to an acreage figure. Table V shows the number of data points in each cover type class for the entire area overflown. For this data, an average of 27.2 resolution elements in the scanner

data was used to represent one acre of cover type. This figure was then expanded to the entire 322,560 acres for the county, and an acreage estimate for each of the cover types of interest for the entire county was obtained. Figure 10 shows the results obtained. The percentage of the total area in the county estimated to be in the different cover types is also indicated. As can be seen, the computer acreage calculations resulted in an estimate of 323,850 acres for the total area in the county, whereas the actual area is 322,560 acres. Considering the fact that geometric correction had not been made on the data and that an average figure was used to represent the resolution elements for all look angles of scanner data, it is felt that this difference is well within the accuracy of the techniques utilized, and is therefore negligible.

The estimated acreage for the different cover types obtained by computer classification were then compared with the Census of Agriculture reports and the Crops and Livestock reports. In some cases, the different cover types could not be directly compared because the officially published figures did not contain any data for certain cover types which were used in our computer classification. As shown in Figure 11, there is a fairly wide variation in even the published estimates of acreage for some of the cover types. For example, the published reports indicate a variation for corn of from 82,510 to 76,900 acres. Therefore, we feel that our remote sensing estimate of 84,210 acres of corn in the county is well within reason, and compares favorably with the accuracy of current techniques for estimating acreage.

These results are particularly significant, in that this may be the first time that acreage estimates have been obtained from multispectral scanner data and that these estimates have then been compared to published figures for different cover types over a reasonably large geographic area. At least two factors appear to be required in order to obtain acreage estimates with scanner data which are reasonably close to actual acreage estimates for the area. First, the sample covered by the scanner data must be large enough to be representative of the area. Minimal sample size and number of samples required for any particular area would, of course, be a function of the variability of the materials within the area. A great deal of additional work needs to be done in sampling techniques for remote sensing purposes. The second requirement for accurate acreage estimates of an area would be that sufficiently accurate classification results must be obtained. Again, additional work remains to be done in order to define what a "sufficiently" accurate classification really involves.

URBAN LAND-USE ANALYSIS

Land-use is changing every year in many parts of the world and our nation. Such land-use changes often involve large geographic areas. The greatest portion of these changes in the United States during recent years has occurred when agricultural and forest lands are converted to housing, industry, highways, public buildings and parks. The effects associated with these changes are numerous and far-reaching. We feel that remote multispectral sensing has a potential for obtaining valuable data to use in land-use analysis and planning future developments. The capability for satellites to obtain remote sensing data over large geographic areas and at regular time intervals should offer a great deal of potential information to adequately plan for the early development of the landscape of our nation.

In a pilot project this past year, a typical small subdivision located near Lafayette, Indiana over which scanner data has been obtained, was analyzed. Automatic data processing techniques were utilized to determine the amount of the area in this urban development which was under hard surface cover and that which was under permeable cover types. Figure 12-A shows a black and white version of a color infrared photo of the area analyzed. Figure 12-B depicts the automatic computer classification of the areas identified as either trees, shrubs, or grass. Comparison between Figures 12-A and 12-B indicates a high degree of accuracy for the computer classification results. Figure 12-C shows the areas identified by the computer as man-made and hard surface areas. These have been subdivided into either "roof" or "streets and driveways." In some cases, the classification for roof surfaces is somewhat inaccurate due to shadow effects. However, the total hard surface area classification appears to be fairly accurate.

The classification accuracy of this analysis was tested using two different photointerpretation techniques. The first involved the use of a very fine dot grid count of the area. The second procedure was to planimeter the hard surface areas. Figure 12-D shows the comparison between the percentage of the area shown in Figure 12-A as determined by dot grid techniques, and the computer classification results. Thus, the computer indicated that 8% of the area was covered by roof surfaces, the photointerpretation dot grid estimate indicated 8.2% coverage by roof surfaces, etc. In total, the computer estimate indicated that 24.4% of this area was covered by hard surface whereas the dot grid analysis indicated 21.5% of the area had a hard surface cover.

We believe that the results of these types of analyses could be a value in planning for culverts and other runoff design specifications

in urbanized watershed areas. For example, a one-inch rain in a one-hour time period for an area such as this, where about 20-25% of the area is under impermeable cover, would call for a different runoff design than an area where 50% of the watershed is under hard surface cover.

This was the laboratory's first attempt to quantify an urban land-use scene. The results show promise for the role of remote sensing in the rapid identification and mapping of present and changing patterns in land-use. The rapid changes taking place in this country and the increasing pressure on our land resources indicate that these techniques will prove most valuable for the management and development of our land resources in the years ahead.

WATER QUALITY STUDIES

The water quality studies to be reported upon are an extension of water resource studies involving temperature calibration techniques of multispectral scanner data. The University of Michigan multispectral scanner has hot and cold plates mounted within the field of view of the thermal infrared channels. These calibration plates can be used to obtain calibrated data, in order to remotely measure true radiometric temperatures, providing the emissivity of the objects being scanned is approximately $\varepsilon = 1.0$. The previous work at LARS has shown that these calibration techniques can be used with a high degree of accuracy for obtaining temperature maps of water bodies. Measurements made of the water temperature from boats on the river at the time the scanner was flown over confirm that the accuracy of temperature measurements obtained from scanner calibration is usually with .2-.4°C of the temperature obtained for the same area from the scanner data.

In studying the correlation between temperature measurements made on the river and the temperature obtained from calibrated scanner data, we noticed that the scanner data seemed to be quite variable as one viewed the entire water body. Further investigation appeared to indicate that the variation observed was not due to normal variations in temperature of the water surface, but rather was due to noise in the scanner data. In an attempt to reduce the amount of noise in the scanner data, a sequence of line averaging and weighted line averaging studies were carried out. One must remember that in utilizing data from line scanner systems from altitudes of 2000 feet, only every 8th scan line is required for contiguous scanner coverage. Thus in our digitization process, seven of the eight scan lines normally were not being utilized. By digitizing all eight scan lines and averaging all eight scan lines, or four out of the eight, or three out of the eight, etc., we found that the amount of noise in the data could be substantially reduced. Figure 13 shows a single column line of data taken along the line of flight; the top of

this graph shows results of a single scan line, the bottom graph shows the results where eight scan lines were averaged together and displayed as single scan lines of data. The reduction in the amount of variability in the scanner data, due to use of the line averaging technique is quite apparent in this figure. Figure 14 shows the results of such line averaging applied to an entire segment of the flightline, and displayed in a map format. On the left is the scanner printout of calibrated thermal data in the 8 to 13.5 μm portion of the spectrum. The Wabash River is flowing from north to south, and the Tippecanoe River enters the Wabash from the west (left). From the calibration levels indicated for the data, it can be easily observed that the Tippecanoe River is cooler than the Wabash River into which it flows. Just above the junction of these two rivers there appears to be quite a great deal of variability in the temperature of the river as indicated by the scattering of points representing different temperature levels. The results of averaging eight scan lines and displaying them as a single scan line are shown on the right. In this case one sees that there is a much smaller amount of temperature variation in the data displayed. The results of averaging four scan lines and then not using the intervening four scan lines of data obtained at this altitude showed very similar results to those displayed in this figure. Thus, it appears that a considerable increase in data quality can be obtained through some of these preprocessing techniques. In addition, corrections for scanner look angle, sun angle, etc. must frequently still be applied. Additional work remains to be done to determine the effect of such line averaging techniques on the quality of the data for agricultural vegetation and soil analysis problems.

SUMMARY AND GENERAL CONCLUSIONS

The work this past year has indicated more clearly than ever before that when dealing with natural vegetative soil and hydrologic features, the natural variability of these materials is significant. However, as indicated in Figure 15, there are several other factors besides the natural geographic variation of the materials which can cause distinct and significant variation in the signals being recorded. We are looking forward with great anticipation to working with data from ERTS and SKYLAB, since data collected in these experiments will be obtained over a large geographic area and in an extremely short time period (as compared to the time required to collect the flightline data using an aircraft system), and also the satellite data will involve a much smaller scan angle. The ERTS and SKYLAB data should therefore allow some of the causes of spectral variability such as illumination conditions, instrumentation drift and adjustments, and atmospheric conditions (which change over time), to be minimized. This will allow us to better

understand the regional variation and spectral response of the vegetation, water, and soils, with which the Biogeophysical Group at LARS is particularly concerned.

Conclusions of the projects this past year involve several additional aspects, which can be summarized as follows:

1.) Basic cover types can be automatically mapped with a high degree of accuracy in spite of the natural variability of the material.
2.) Calibration of scanner data allows significant improvement in the accuracy of classification of crop species when extrapolating from one geographic area to another many miles away.
3.) Calibration and preprocessing techniques significantly improve many aspects of data quality. However, these techniques must be applied to the multispectral scanner data with caution, for they could cause more harm than help in the automatic classification of any particular set of data. For example, under conditions of variable cloud cover, sun sensor calibration proved quite unsatisfactory. In general, however, it would appear that drift and illumination calibration will generally be required for aircraft data collected over large geographic areas.
4.) Variations in ground cover conditions often are much more pronounced than anticipated. However, adequate training of the classifier, involving selection of samples to represent the total range of crop conditions and stages of maturity, did allow satisfactory classification of the data. Studies involving adaptive classification techniques must be developed and tested.
5.) Preliminary work on aerial estimates of acreage of major crop species and various other cover types for areas in excess of 300,000 acres indicated a high degree of accuracy, and offers good promise for improving current techniques for such acreage estimates. It is significant that these results were obtained with scanner data that had not been geometrically corrected. This technique also appears to offer another method of evaluating the accuracy of classification results, provided the area sampled is large enough, and that the existing acreage figures from other sources are reasonably accurate.

It is believed that these results concerning a developing capability to accurately identify and map various agriculture cover types and obtain accurate acreage estimates (as were indicated in Figure 18) are among the major milestones that have been achieved in automatic data analysis research to date.

ACKNOWLEDGEMENT

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TABLE I. CLASSIFICATION ACCURACY FOR TEST FIELDS IN AN EAST-WEST 133-MILE FLIGHTLINE, USING DRIFT AND GAIN CALIBRATION

Spectral bands: Best 5 bands when using 2-point calibration--0.50-0.52, 0.55-0.58, 0.66-0.72, 1.00-1.40, and 1.50-1.80.

Calibration: 2-point (drift and gain)

	Percent Correct Recognition			No. Test Fields	No. Data Points Used to Calculate Percentage Accuracy
Flightline	Overall	Wheat	Other Cover Types	Wheat/Other	Wheat/Other
40	96	92	96	10/10	519/2749
41	77	78	77	13/21	874/1430
42	82	79	84	8/13	802/1202
43	96	96	96	3/12	301/6322

Overall accuracy for all four flightlines = 91.2%; average accuracy for four flightlines = 87.8%.

TABLE II. CLASSIFICATION ACCURACY FOR TEST FIELDS;
BEST 5 WAVELENGTH BANDS WHEN USING DRIFT CALIBRATION ONLY

Spectral bands: Best combination of 5--0.55-0.58, 0.66-0.72, 0.80-1.00, 1.00-1.40, 1.50-1.80.
Calibration: Drift only

	Percent Correct Recognition*		
Flightline	Overall	Wheat	Other Cover Types
40	94	89	95
41	74	68	76
42	65	74	59
43	81	66	82

*Number of test fields and data points used to calculate percentage accuracy of classification results are identical to those shown in Table I.

TABLE III. CLASSIFICATION ACCURACY FOR TEST FIELDS; DRIFT CALIBRATION ONLY

Spectral bands: Same bands utilized as for classification (shown in Table II) using 2-point calibration--0.50-0.52, 0.55-0.58, 0.66-0.72, 1.00-1.40, 1.50-1.80.
Calibration: Drift

	Percent Correct Recognition*		
Flightline	Overall	Wheat	Other Cover Types
40	93	92	93
41	50	71	41
42	49	77	30
43	70	71	71

*Number of test fields and data points used to calculate percentage accuracy of classification results are identical to those shown in Table II.

TABLE IV. CLASSIFICATION ACCURACY FOR TEST FIELDS IN FIVE FLIGHTLINES IN TIPPECANOE COUNTY, INDIANA

Flightline	Cover Type					
	Corn	Soybeans	Forages	Water	Soil	Trees
21	4388/4144*	4169/4115	6700/6420	212/212	1037/933	168/154
22	8376/8218	3770/3512	5627/5440	310/310	611/560	540/537
23	11494/10081	6201/5551	8245/7922	658/657	132/124	606/602
24	8643/8004	3800/3176	8178/7989	166/164	344/249	385/384
25	6521/6236	4266/4008	6814/6678	237/237	713/600	591/590
Totals	39422/36683	22206/20362	35564/34449	1583/1580	2837/2466	2290/2267
Percentage Classification Accuracy-93.1% (by cover type)		91.7%	96.9%	99.8%	86.9%	99.0%

*Number of R.S.U.'s Present in Test Fields for Each Cover Type/Number R.S.U.'s Correctly Classified Into Each Cover Type.

TABLE V. COMPUTER CLASSIFICATION RESULTS FOR THE ENTIRE AREA OVERFLOWN (83,072 ACRES)

Flightline	Total Data Points	Cover Type						
		Corn	Soybeans	Forages	Water	Soil	Trees	Cultural and Other
21	446,810	102,428	101,361	167,786	1292	4350	24,168	45,428
22	391,118	127,859	65,469	131,461	1371	3992	25,190	35,776
23	495,388	111,996	72,302	219,567	5087	4508	38,728	43,200
24	449,690	122,604	84,904	130,823	1390	4306	64,268	41,395
25	505,232	125,440	73,890	230,762	2019	6801	29,328	36,992
Totals	2,288,238	590,327	397,926	880,399	11,159	23,957	181,679	202,791
Percentage	100.0%	25.8%	17.4%	38.5%	0.5%	1.0%	7.9%	8.9%

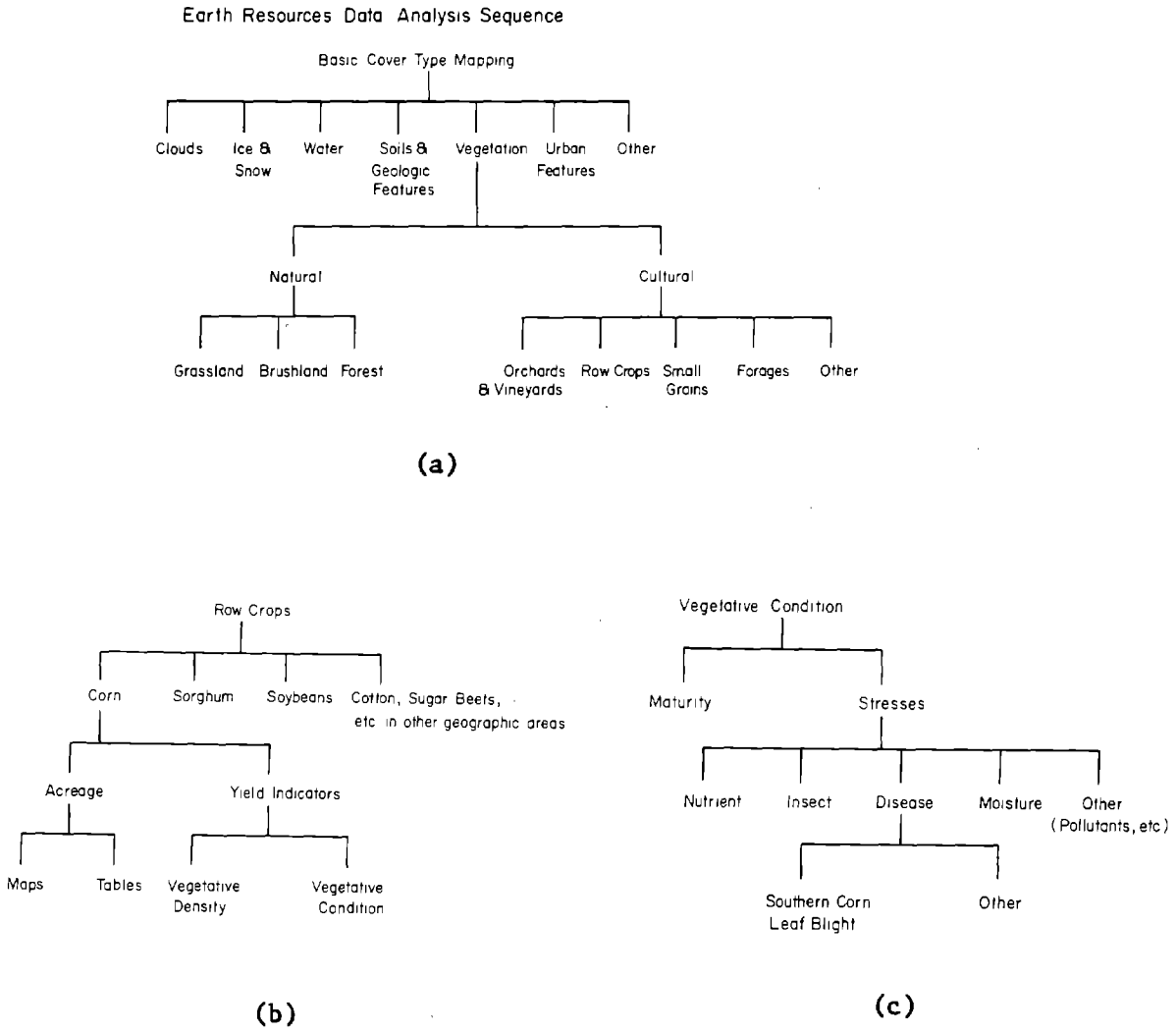


Figure 1. Data analysis sequence in automatic identification and mapping of various earth resources and their condition. Figure 1-a shows the basic cover types that could be mapped and one possible subdivision for the vegetative category. The acreage and yield factors are of primary concern for each species of concern, as pointed out in 1-b. The complex interactions of many stress factors, all of which may influence spectral response of the vegetation being sensed, are indicated in 1-c.

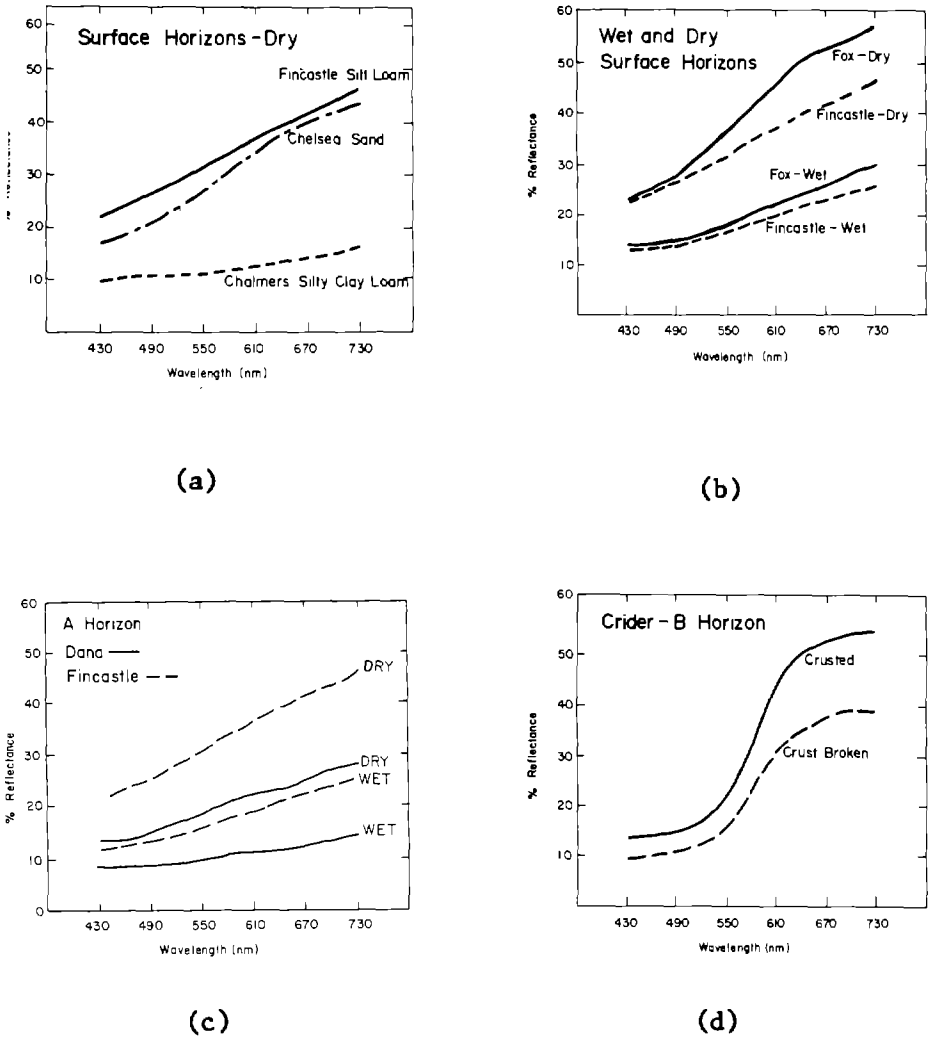


Figure 2. Spectral reflectance of various soil conditions. These data were obtained in situ under conditions of natural illumination. Figure 2-a shows reflectance of three soil types in a dry condition, while 2-b shows marked differences in reflectance between wet and dry soils for two soil types. Figure 2-c indicates that the reflectance for some soil types in a dry condition is very similar to the reflectance of other soils that are wet. The surface condition of a dry soil can cause significant differences in spectral reflectance, as shown in 2-d.

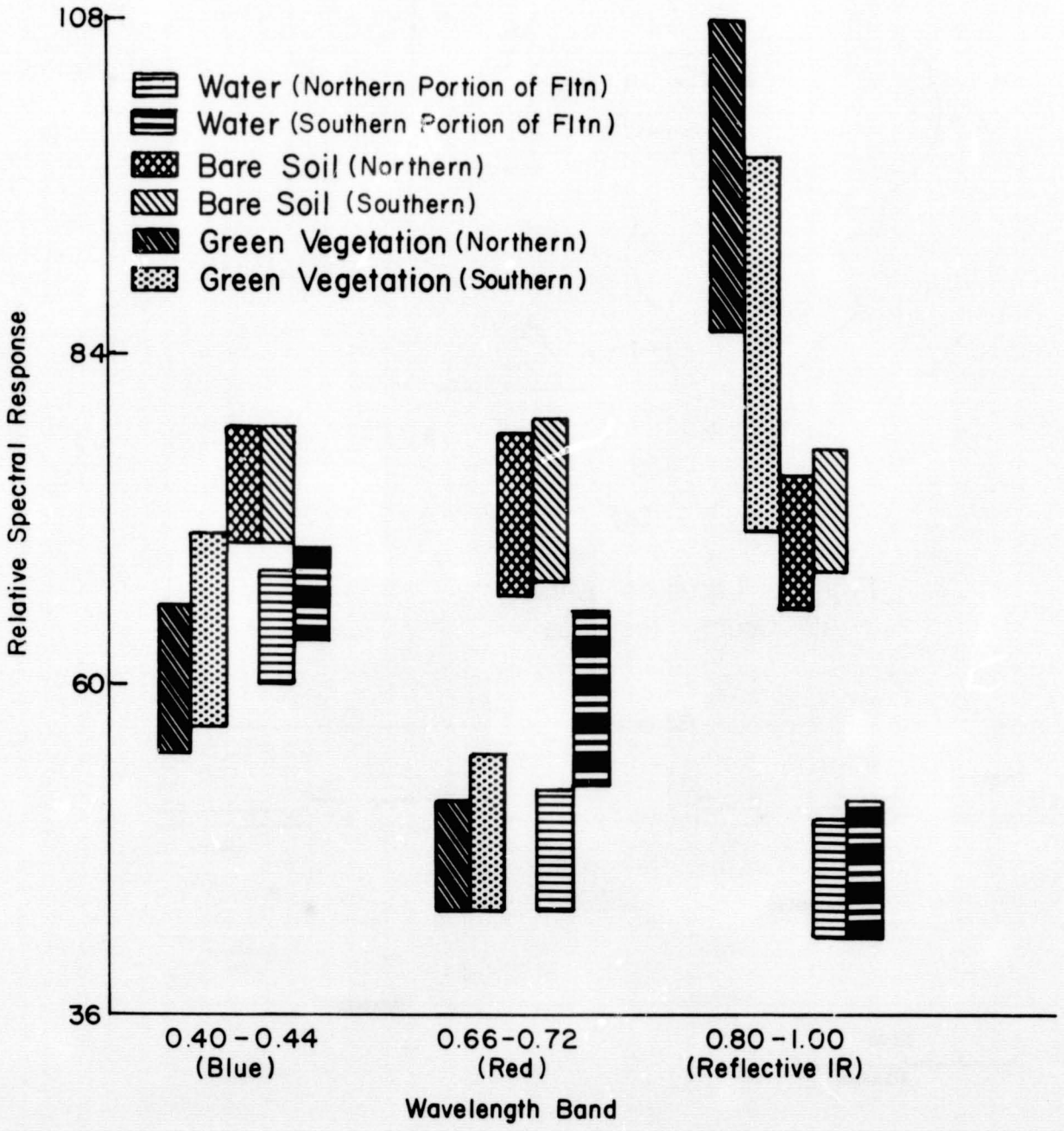
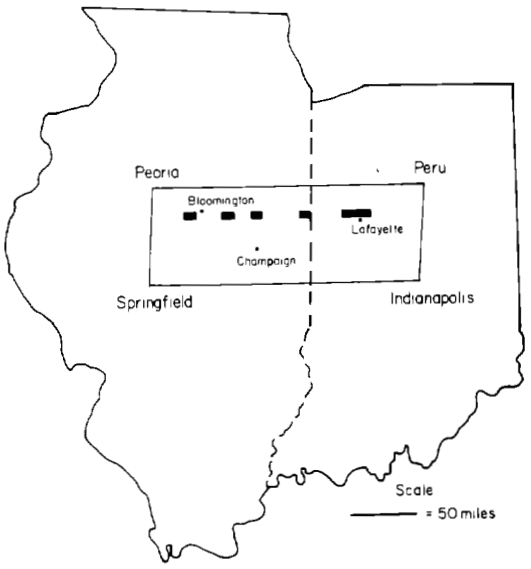
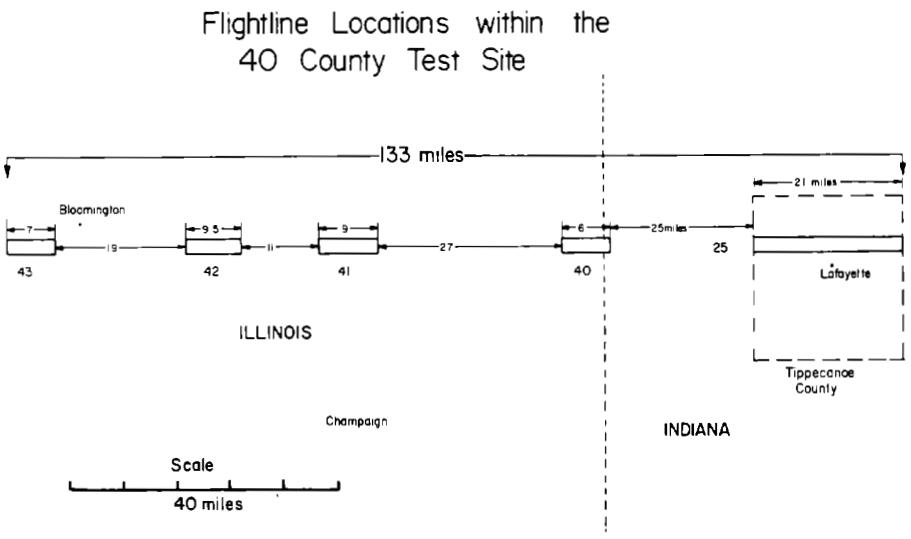


Figure 3. Spectral variabilitv of basic cover types along a North-South flightline. Data from areas about 60 miles apart are shown for three wavelength bands. The bars represent mean spectral response ±1σ. Distinct differences exist for the water and the vegetation response between the two locations sampled.



(a)



(b)

Figure 4. The 40-County test area showing the general location of the flightlines is shown in 4-a. The length of the flightline segments and distances between segments is shown in 4-b.

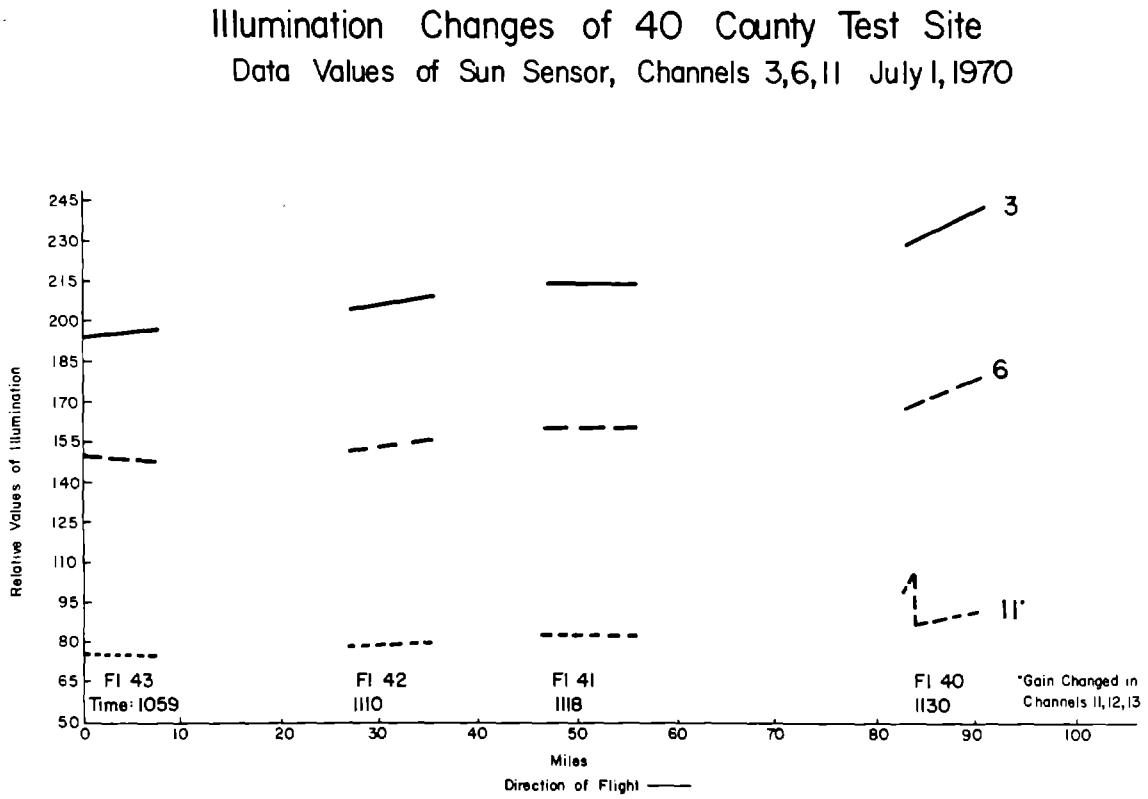


Figure 5. Sun sensor signals in three wavelength bands, along E-W flightline. Time of data collection is also shown, and indicates a general upward shift in illumination levels from west to east as the data were being collected. A distinct change in gain setting is indicated in the Channel 11 data in F.L. 40. These changes were corrected in the calibration procedures.

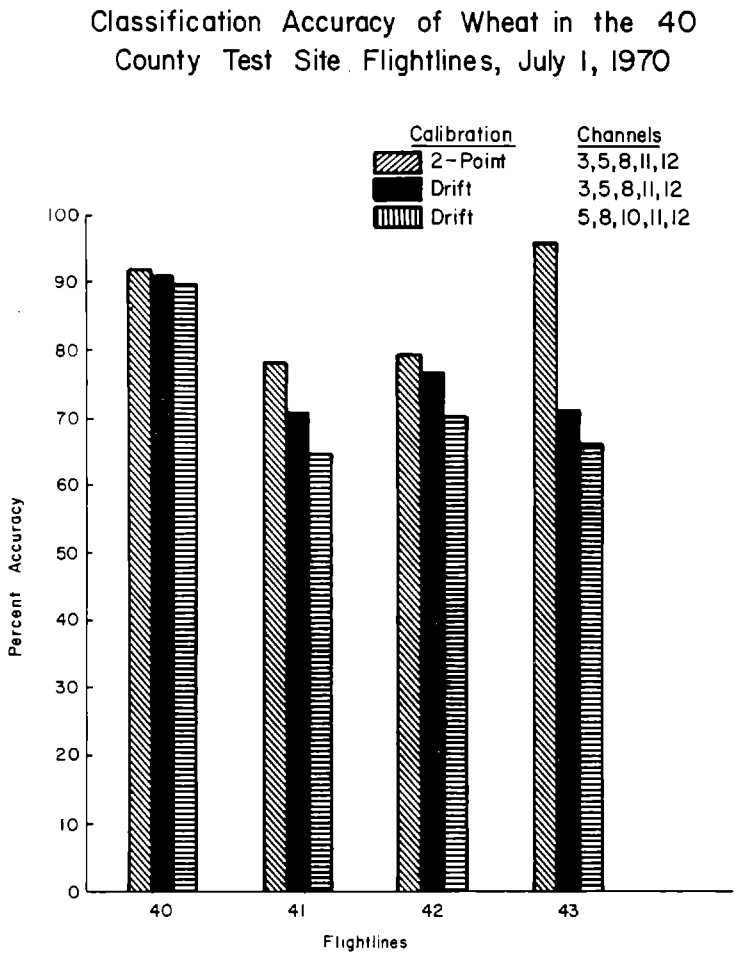


Figure 6. Classification accuracy for wheat test fields in each of the flightline areas. Only F.L. 40 was used for selection of training samples. The 2-point calibration (drift and sun sensor) appears to give much more accurate classification results than drift calibration only. Note that F.L. 40 (where the training samples were selected), is approximately 80 miles from F.L. 43.

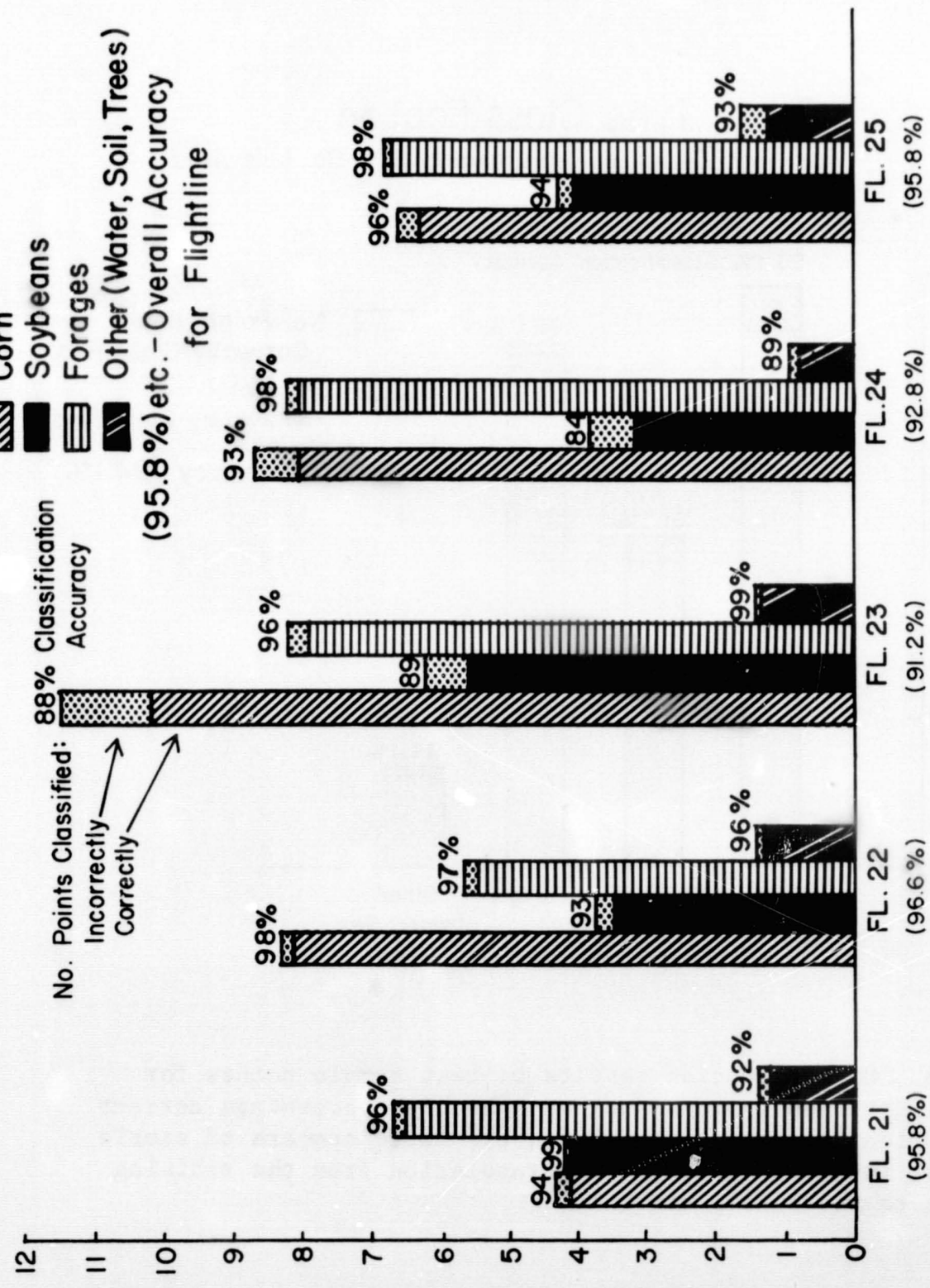


Figure 7. Classification results of test fields in each of the five flightlines. Note that a large number of individual sample points were utilized in determining percentage accuracy.

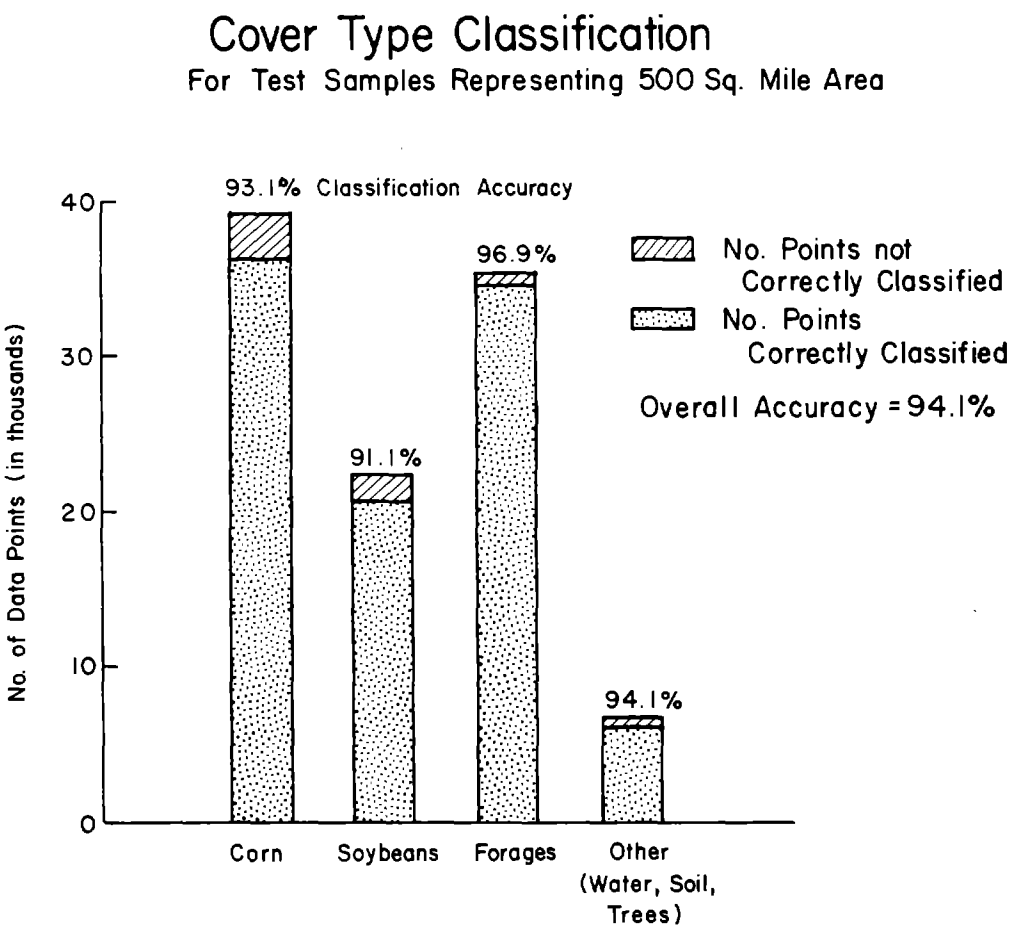


Figure 8. Classification results of test sample points for all flightlines in combination. The high percentage correct classification shown, along with the large numbers of sample points, indicates very good extrapolation from the training fields to the entire area.

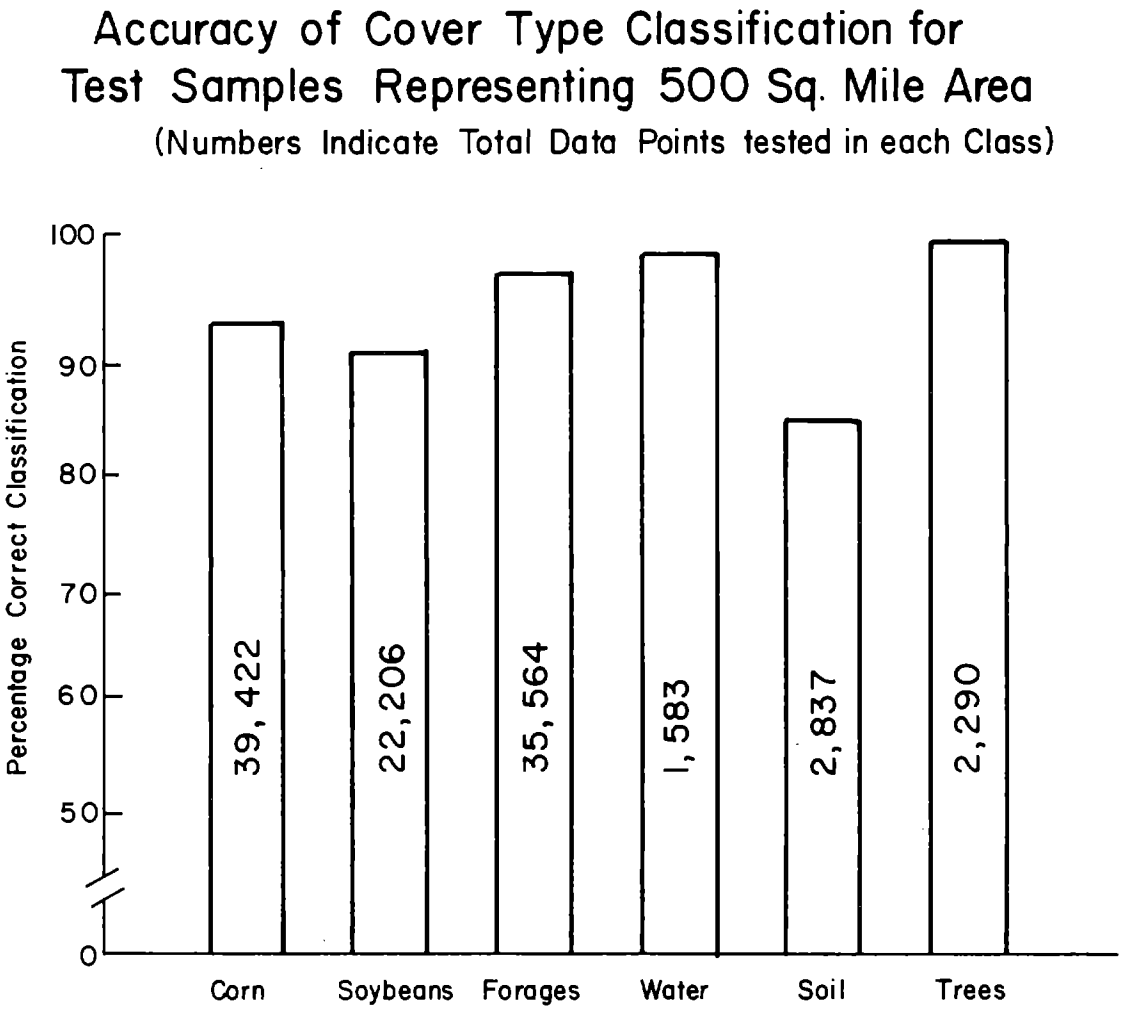


Figure 9. Accuracy of classification of test samples. The accuracy and number of data points involved are indicated. The individual classes of water, soil and trees (previously combined as "other") are also shown.

ADP Results of Acreage Estimates
(Actual Area = 322,560 Acres)

Cover Type	Computer Classification Acreage Estimate*	Percentage of Total Area
Corn	84,210	26.0
Soybeans	56,760	17.5
Forages (Hay, Pasture, Stubble)	123,020	38.0
Woods	25,940	8.0
Urban & Other (Roads, Water, Misc.)	33,920	10.5
Total =	323,850 Acres	100%

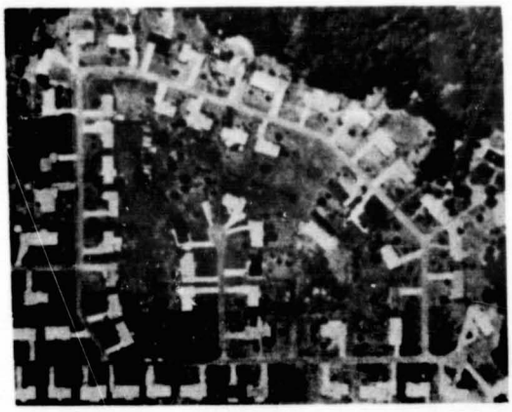
*An Estimated 83,072 Acres Were Scanned

Figure 10. Acreage estimates of major cover types in Tippecanoe County, based upon computer classification of the various cover types. The cover types have been combined to facilitate comparison with published figures of acreage estimates.

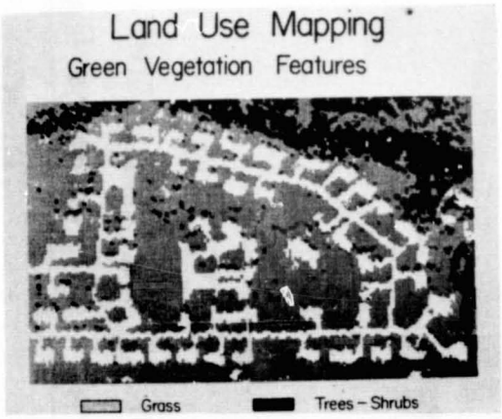
Comparison of Acreage Estimates for a 322,560 Acre Area

Cover Type	Computer Classification of MSS Data	Census of Agriculture	Crops and Livestock Report
Corn	84,210	82,510	76,900
Soybeans	56,760	60,470	56,900
Forages	123,020	109,860	———
Woods	25,940	21,210	———
Urban & Other	33,920	———	———
Total =	323,850 Acres		

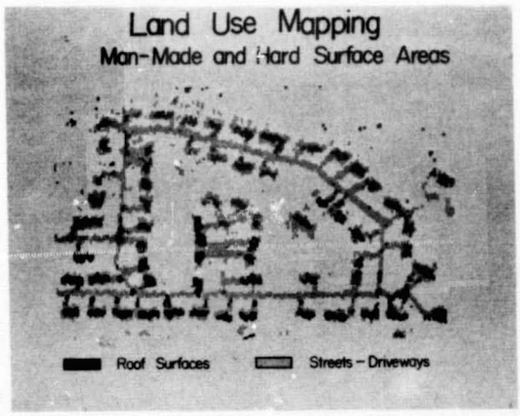
Figure 11. Comparison of acreage estimates based upon automatic classification of multispectral scanner data to published estimates of various cover types for Tippecanoe County. Note that estimates by different agencies have a moderate amount of variation, and that the estimates obtained by remote sensing techniques are relatively close to the other estimates.



(a)



(b)



(c)

COMPARISON OF RESULTS

Material	Computer Classification	Estimate
Roof	8.0	8.2
Asphalt	10.1	7.6
Concrete	6.3	5.7
Trees	15.2	18.6
Grass	60.1	59.9

(d)

Figure 12. (a) Black and white reproduction of a color infrared photo of subdivision study area. (b) Computer printout of classification results showing only areas classified as tree & shrubs or as grass. (c) Printout of areas classified as man-made and hard surface area. (d) Percentage of total area classified into the various cover types by computer compared to area percentages estimated by a very fine dot grid and using an aerial photo.

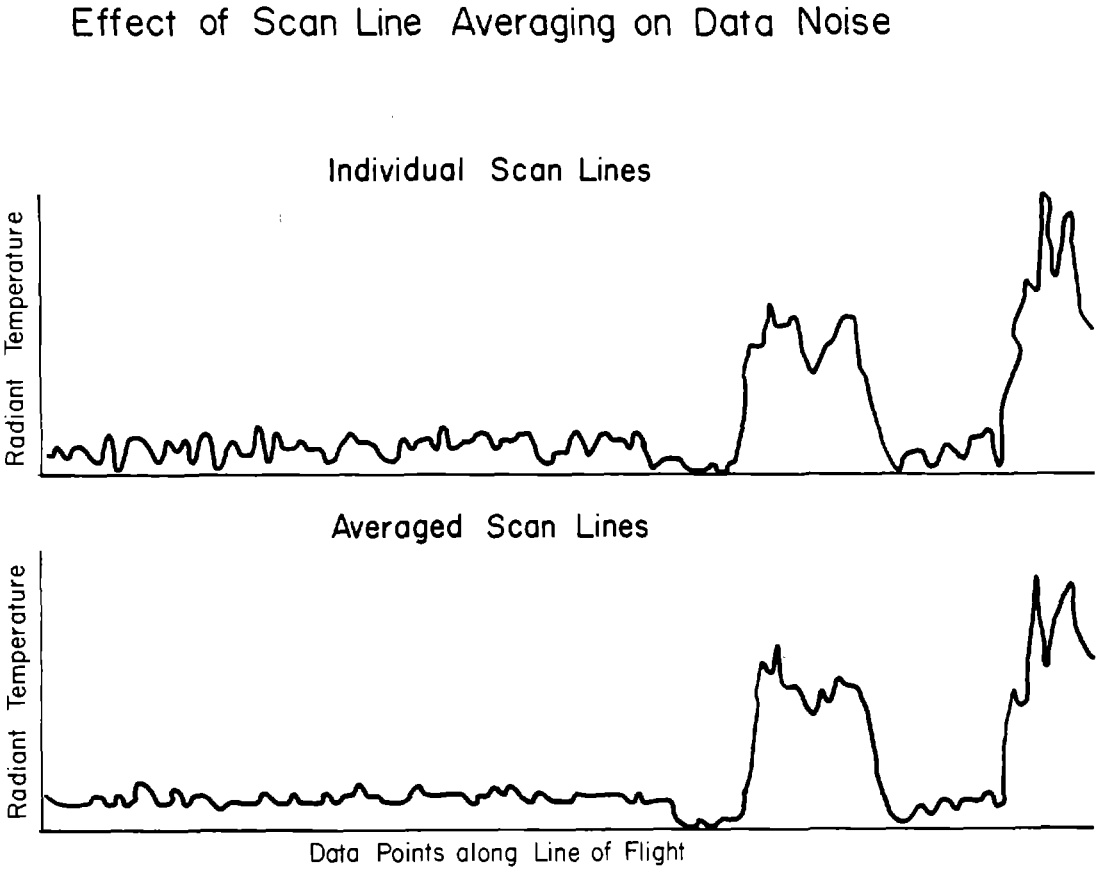


Figure 13. Effects of scan line averaging on data noise. Data on top shows data points along the line of flight for a single column of data, using non-averaged scan lines. Bottom data shows averaged scan lines. The reduction in the amount of noise in the data is evident.

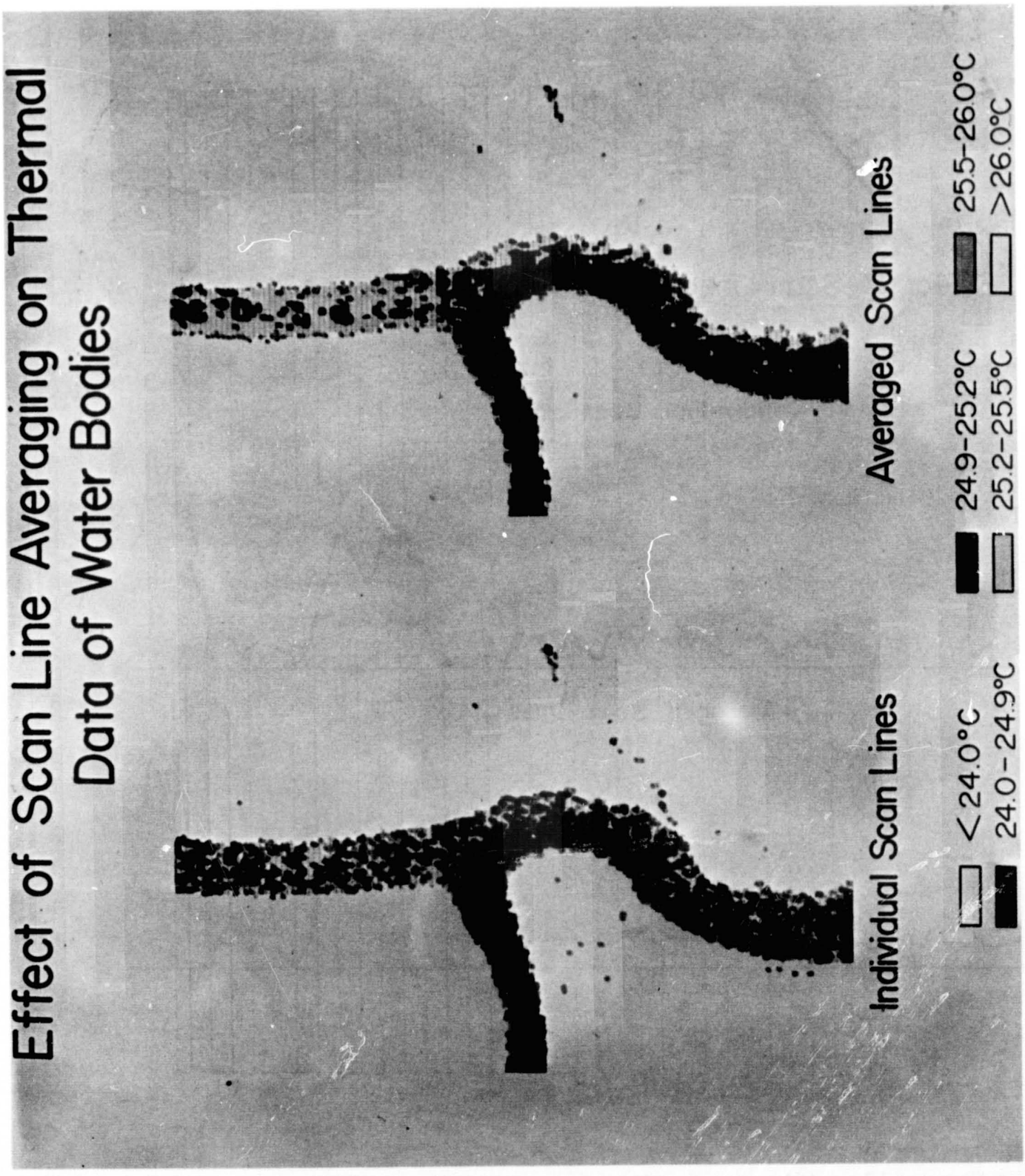


Figure 14. Computer printout of thermal data calibrated to indicate true radiometric temperature, and comparing individual scan lines and averaged scan lines of data. Note the more distinct "speckled" pattern in the individual scan line data, particularly in the portion of the Wabash River above the point where the Tippecanoe River comes in from the left (west).

Causes of Spectral Variability

- Natural, Geographic Variation of the Materials
- Illumination Conditions
- Atmospheric Conditions
- Instrumentation Drift and Adjustments
- Data System Imperfections

Figure 15. Major causes of spectral variability. Satellite data from ERTS and SKYLAB should allow some of these factors to be minimized (as compared to aircraft data collection techniques) thereby allowing a better understanding of the natural geographic variations of the vegetation, soils, water, and other earth resources materials of concern.