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VARIABLES IN AUTOMATIC CLASSIFICATION
OVER EXTENDED REMOTE SENSING TEST SITES[1]

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ABSTRACT

Four major causes of variation in response of multispectral scanner data were examined utilizing data from two large test sites. In one case, data throughout a 70-mile flightline was automatically classified with a high degree of accuracy (98%), utilizing training samples from a single small segment of the data. In the second case, spectral data for wheat and other cover types were calibrated and utilized to train the computer, resulting in data up to 90 miles away being classified with an acceptable degree of accuracy (91%), although significant changes in solar illumination and ground cover conditions existed.

1. INTRODUCTION

For many types of agricultural surveys, there is a need to collect data over large geographic areas and process such data into useful information in a timely manner. Remote sensing techniques offer obvious potentials for rapid data collection over vast areas; however, in processing large quantities of data, one encounters a number of difficulties, particularly when the resultant information is needed within a matter of days. Because there are rapid changes in crop conditions and weather throughout the growing season, and since many agricultural crops are annuals having only 90 to 120-day growth cycles from germination to harvest, the need for very rapid data processing techniques is apparent, if the data collected are to be useful for more than just historic information.

In response to this need for obtaining timely information from large agricultural areas, research has been conducted to develop techniques for automatic processing of remotely sensed data. Multispectral scanner data are particularly appropriate for automatic data processing since such data can be recorded initially as an electronic signal which is then conducive to computerized data processing techniques (3, 4, 5). The feasibility of using computers and automatic data processing techniques for processing large quantities of multispectral scanner data has been established, both by the Laboratory for Applications of Remote Sensing, Purdue University, and the Institute of Science and Technology, University of Michigan.

A difficult but extremely important phase of automatic classification of vegetative cover and other earth resources materials is the selection of adequate and correct data with which to train the computer. Much of the difficulty lies in the variability of the spectral data from the cover types or earth resources with which we are dealing (1, 2). Four possible reasons for such spectral variability or changes are:

(1) changes in atmospheric and/or illumination conditions along the flightline;
(2) changes due to natural, geographic variability of the vegetation, water, or soils (e.g. crop maturity, leafing out of trees);
(3) adjustments in instrumentation setting; and
(4) random variations in the instrumentation involved in the many phases of gathering, recording, or processing the data.

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Within each of these four broad categories of possible causes of variability in spectral response are many, many detailed causes of variation. For example, changes in spectral response due to natural variability of exposed soil could be caused by differences in soil moisture, organic matter content, texture, tillage practices, surface roughness, iron oxides, and other chemical characteristics such as salt accumulations. It is beyond the scope of this paper to discuss in detail all the factors that can cause variability in spectral response. Rather, we simply want to indicate that many possible causes for spectral variation in scanner data exist within each of the four major categories defined.

2. OBJECTIVES

Experience with multispectral scanner data and automatic data processing techniques has indicated that it is sometimes difficult to utilize training samples from one geographic area for classification of data from a distant location, or to utilize training sample data from one time of year for classification of data collected at a different time of year or in a completely different year. Therefore, to develop further the capability for an eventual, operational ADP system, it becomes critical that the following questions be examined:

(1) How much variation in spectral response exists in scanner data collected over a relatively large geographic area?
(2) Which of the four major reasons outlined above are most important in causing changes in spectral response in different geographic locations?
(3) How can corrections be made for changes in spectral response and how well do such corrections work?

In this analysis, we worked with two sets of data collected with the University of Michigan scanner system over test areas as large as then existed.

The first data studied were from a flightline extending 70 miles south of Indianapolis. The particular objective of this study was (a) to determine the accuracy in identification of all green vegetation, bare soil and water in the entire flightline, regardless of natural variability and (b) to study the variations in spectral response for these three basic cover conditions caused by variations in instrumentation, atmosphere and natural conditions.

The second set of data studied came from a large area involving 40 counties in central Indiana and Illinois. Five segments from an east-west flightline which extended over 133 miles were analyzed to determine (1) the variation in spectral response of wheat along an east-west flightline as a function of natural variability, instrumentation, or atmospheric variations, and (2) the ability to identify and map winter wheat over an area of this size, if training samples are selected from only one portion of the area. This second objective would, of course, involve calibration of the data in the event that major variations in spectral response were found which caused poor classification accuracies when using "raw" or uncalibrated data.

3. HIGHWAY 37 DATA ANALYSIS

Multispectral scanner data had been collected in 17 discrete wavelength bands from an altitude of 3,200 feet along the entire 70-mile flightline. At that altitude, the 80° F.O.V. of the scanner covers a swath width of just over one mile, thereby producing about a 70-square mile area to be classified (Figure 1). For this analysis, only the first 12 wavelength bands (in the 0.4-1.0 micrometer range) were considered because of the configuration of the scanner.

For the automatic classification, approximately ten areas from each class were selected for training samples. These included areas of light and dark soils, river and pond water, and a variety of green vegetation conditions including pasture, winter wheat and forest cover. Since the data were collected in late April, the trees were in various stages of leafing out, agricultural cover such as winter wheat and pasture was quite varied, and areas of bare soil varied considerably in moisture content. Figure 2 shows a photo mosaic of one segment of the flightline along with gray scale printouts of two of the wavelength bands used in the classification. The photo mosaic gives an indication of the variability of the cover types.

All of the training samples were selected from one relatively small area twenty miles from the north end of the 70-mile flightline. In this way, if there was variability in spectral response due to atmospheric conditions, instrumentation changes, or natural changes between the northern and southern portions of the flightline, our classification results would become less accurate as we progressed in the automatic analysis from the beginning to the end of the flightline.

The entire 70 miles of flightline data were automatically classified into green vegetation, bare soil and water categories. Figure 3 shows the classification results for the same area seen in Figure 2. It should be pointed out that the photo mosaics in Figures 2 and 3 were compiled from data flown for planning purposes about ten days before the scanner data were flown. There were several areas which were green vegetation when photographed, but had been plowed (bare soil) before the scanner data were flown. Therefore, these particular areas, which appear to be green vegetation on the photos but bare soil on the printout, were indeed correctly classified.

The image labeled "B" on Figure 3 is the computer printout showing the automatic classification results for this area. The light tones indicate the areas classified as bare soil. The medium tones indicate the areas classified as green vegetation, and the dark tones indicate water. All other ground cover conditions (such as dry, dead vegetation, roads, rooftops, etc.) have been thresholded and are shown as "blank" areas on the computer printout.

The printouts labeled "C", "D", and "E" in Figure 3 show only the areas classified into green vegetation, bare soil, and water, respectively. These are displayed in this manner to emphasize particular cover types which have been classified and to evaluate the accuracy of the automatic classification.

The single set of training samples from a relatively small area did allow for an accurate classification to be obtained over the entire 70-mile flightline. Figure 4, the classification results for an area south of Bedford, near the extreme southern end of the flightline shows the high degree of accuracy in this classification involving training samples from an area over 50 miles to the north.

To obtain a quantitative check on the classification results, 89 test areas were randomly selected from the computer data throughout the 70-square mile area. The classification results for these test areas were automatically summarized and showed that the average classification accuracy was 99.2 percent for green vegetation, 97.0 percent for soil and 99.7 percent for water. Table I contains the classification results for all of the individual RSU's contained in the test areas.

3.1. DISCUSSION

These classification results were particularly significant because this was the first time such a large geographic area had been automatically mapped, and the capability for extrapolating from training samples taken in one small segment of the flightline to the entire area had been demonstrated.

Although the classification results of the Indiana data were highly accurate for the entire flightline, there was a slight change in spectral response as the distance between the area classified and the training area increased. This was indicated by a slightly larger number of RSU's being thresholded near the southern end of the flightline. Because the materials being classified were spectrally very different in some wavelength bands the results were not greatly affected by the relatively small differences in response. However, the observed spectral variability indicate a need for further study to determine the probable cause, so that proper instrument calibration could be designed if necessary.

When these data were collected, the U of M aircraft did not have their current capability for recording incoming solar radiation at the aircraft altitude, using the "sun sensor". Ground measurements of insolation were not obtained, so consequently there was no accurate method of determining if there had been a change in atmospheric conditions between the north and south ends of the flightline. Since adjustments in gain-settings of the scanner during the flight will normally produce dramatic, sudden changes in spectral response of all cover types, it was thought that this was not the reason for the observed variations. Possible electronic variations in the data collection system had been corrected by a drift calibration procedure that is applied to all data in the digitization process. Since it was known that the trees near the south end of the flightline were leafed out more than those near the north end, it seemed reasonable that such natural variation could be the major cause of spectral differences along the flightline.

To check this hypothesis, test data were selected from the south end of the flightline and compared to the training sample data in the northern area. We found that the spectral response for soil did not change much, but that the spectral response for vegetation was quite different, as was that for the water. The differences in the spectral response for the water were not observed in the reflective infrared wavelengths since water absorbs strongly in these wavelengths, but were apparent throughout the visible, apparently due to the fact that one set of data came from the North Fork of the White River, the other from the South Fork of the White River. (Perhaps different levels or types of pollution are causing these differences, since it is known that both branches are seriously polluted!) At any rate, we concluded that natural variability were the most probable cause of the spectral shifts present in this set of data.

4. 40 COUNTY ANALYSIS

Since we had observed slight changes in spectral response in the Highway 37 data but the results for such basic cover type mapping had not been seriously affected, 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. For this task, data were collected over a series of flightlines in a large 40-county test area in central Indiana and Illinois (Figures 5 and 6). The flightlines were oriented in an east-west direction covering a total distance of over 130 miles.

In carrying out this experiment, the following conditions were to have been met as nearly as possible:

(1) Wheat would be at a mature stage of development. We 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. 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 appearing, 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 us to use FL 40 (on the Indiana-Illinois border) for our training area, with FL 25 being used only as a test area to check effects of altitude changes 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 modified to utilize the actual data collected in the best way. 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 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.

4.1. RESULTS

Our initial analysis efforts showed that calibration of the data only for electronic drift was not adequate to allow accurate classification over the entire area. We did demonstrate again (6) the ability to classify automatically wheat vs. everything else, 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.

We then examined the sun sensor signal for the entire flightline and found that there were significant changes in solar illumination (Figure 7). 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 (7).

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 2 point calibration for both drift and amplification could be effectively used, and was applied to this data.

In Figure 7, 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 drift and amplification 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 II. 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, nearly 90 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 2-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 II, III, and IV for the three classifications. For ease in comparison, Figure 8 shows the classification accuracy of the wheat test fields. The 2-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 2-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 2-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.

5. CONCLUSIONS AND RECOMMENDATIONS

Basic cover types could be identified and mapped with a high degree of accuracy over large geographic areas using automatic data processing techniques, in spite of natural variations in spectral response of the vegetation and water. Training samples from one small area proved satisfactory for classifying over 70 square miles of data with an accuracy of about 98 percent.

The capability for accurately identifying wheat using ADP techniques was shown to be high over relatively small areas (about 9 square miles). When training samples from one area were utilized to classify data up to 90 miles away, it was found that accuracies were rather poor unless a 2-point calibration was utilized, thereby correcting for both electronic drift and variations in solar illumination. Proper calibration allowed recognition accuracies of 91% to be obtained for test areas up to 90 miles away from the training sample location. The test field results also indicated that without the 2-point calibration, there was a general decrease in accuracy as classification was attempted for areas further and further from the training site. This would indicate that the 2-point calibration (drift and illumination) is generally required in all data analysis involving large geographic areas. Such calibration appeared to satisfactorily adjust for manual changes in the gain setting, although further analysis is recommended. 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.

Variations in condition of ground cover were striking and more pronounced along the east-west flightline area than had been anticipated. However, 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.

REFERENCES

1. Hoffer, R. M. 1967. Interpretation of remote multispectral imagery of agricultural crops. Laboratory for Agricultural Remote Sensing, Volume No. 1, Research Bulletin No. 831, Purdue University Agricultural Experiment Station, Lafayette, Indiana. 36 p.

2. Hoffer, R. M. and F. E. Goodrick. 1970. Geographic considerations in automatic cover type identification. Proceeding of Indiana Academy of Science. (In print)

3. Laboratory for Agricultural Remote Sensing. 1967. Remote multispectral sensing in agriculture; Volume No. 2, (Annual Report). Research Bulletin No. 832, Agricultural Experiment Station, Purdue University, Lafayette, Indiana. 75 p.

4. Laboratory for Agricultural Remote Sensing. 1968. Remote multispectral sensing in agriculture; Volume No. 3, (Annual Report). Research Bulletin No. 844, Agricultural Experiment Station, Purdue University, Lafayette, Indiana. 176 p.

5. Laboratory for Agricultural Remote Sensing. 1970. Remote multispectral sensing in agriculture; Volume No. 4, (Annual Report). Research Bulletin No. 844, Agricultural Experiment Station, Purdue University, Lafayette, Indiana. 112 p.

6. Landgrebe, David A. 1967. Automatic identification and classification of wheat by remote sensing. Research Progress Report 279, Agricultural Experiment Station, Purdue University, Lafayette, Indiana. 7 p.

7. Phillips, Terry L. 1969. Calibration of scanner data for operation processing programs at LARS. Information Note 071069, Laboratory for Applications of Remote Sensing, Purdue University, Lafayette, Indiana. 7 p.

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A special thanks to the LARS staff for their work in the various phases of digitizing and analyzing these data.

TABLE I. HIGHWAY 37 DATA CLASSIFICATION SUMMARY, BY TEST CLASSES*

Class	Total No. of Samples	Pct. Correct**	No. of Samples Classified Into: Grn. Veg.	Soil	Water	Thresholded
Grn. Veg.	1095	99.2	1086	1	5	3
Soil	3105	97.0	2	3012	0	91
Water	887	99.7	1	1	844	1
Total	5087					

Overall Accuracy = 97.9; Average Accuracy by Class = 98.6 (Overall accuracy is based on the number of data points correctly classified in each class, thereby reflecting the influence of different cover types having different areas represented.)

* Serial No. 302005213, Entire 70-mile flightling, using segments). Spectral bands used: 0.40-0.44, 0.58-0.62, 0.66-0.72, 0.80-1.00 μm.

** Total number of samples tested divided into number of samples correctly classified. Thresholded samples are counted as errors. (For example, for soil:

$\frac{3012}{3105} \times 100 = 97.0\%$ Correct Recognition.)

TABLE II. CLASSIFICATION ACCURACY FOR TEST FIELDS IN 40-COUNTY FLIGHTLINES, 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)

Flightline	Percent Correct Recognition: Overall	Wheat	Other Cover Types	No. Test Fields Wheat/Other	No. Data Points Used to Calculate Percentage Accuracy 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 III. CLASSIFICATION ACCURACY FOR TEST FIELDS; BEST 5 WAVELENGTH BANDS WHEN USING DRIFT CALIBRATION

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

Flightline	Percent Correct Recognition*: 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 II.

TABLE IV. 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

Flightline	Percent Correct Recognition*: 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.

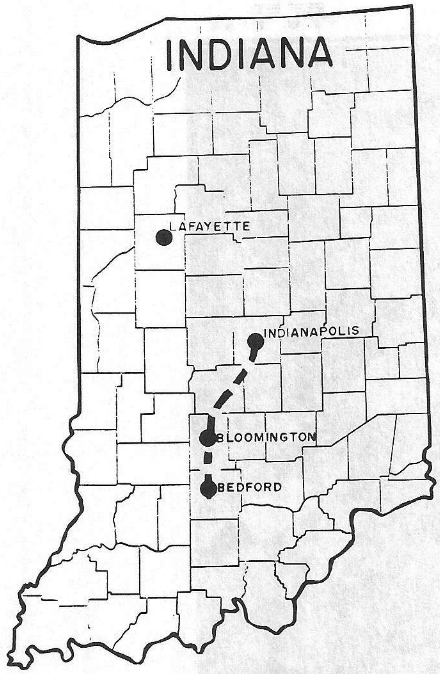

FIGURE 1. LOCATION OF THE 70-MILE FLIGHTLINE ALONG INDIANA STATE HIGHWAY 37.

FIGURE 2. SEGMENT OF THE HIGHWAY 37 STUDY AREA. Left, aerial photo mosaic. Center, gray scale of the same area, in the 0.66-0.72μ_m wavelength band (visible red). Right, gray scale of area in 0.80-1.00μ_m band (reflective infrared). Note reversals in tone between visible and infrared, especially for green vegetation which is highly reflective in infrared.

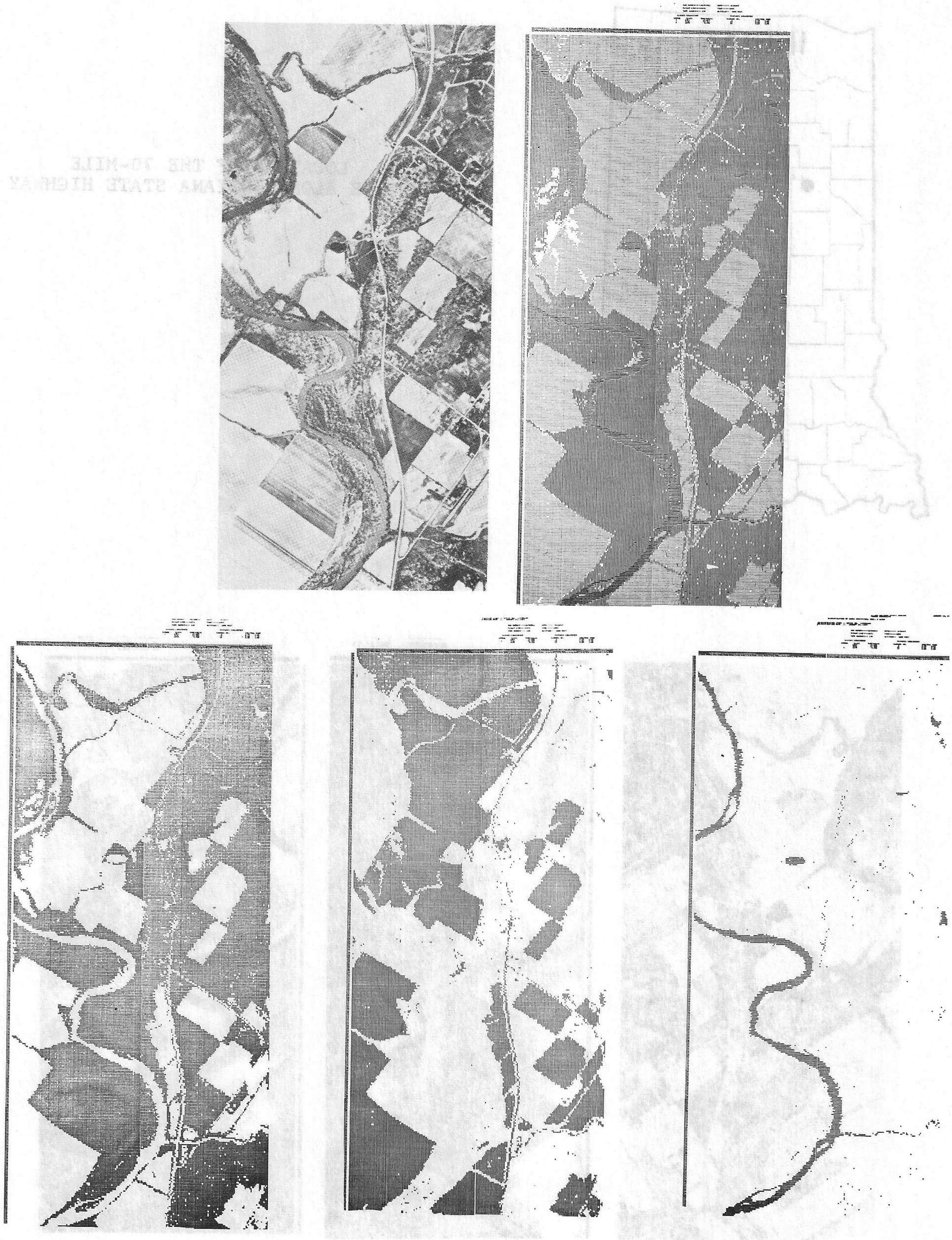

FIGURE 3. COMPUTER CLASSIFICATION RESULTS FOR SAME AREA SHOWN IN FIG. 2. Top left: Aerial photo mosaic. Top right: Classification of area into 3 cover types (light tone is soil, medium tone is green vegetation, and dark tone is water). Bottom left: Printout of green vegetation only. Center: Printout of bare soil only. Bottom right: Printout of water only.

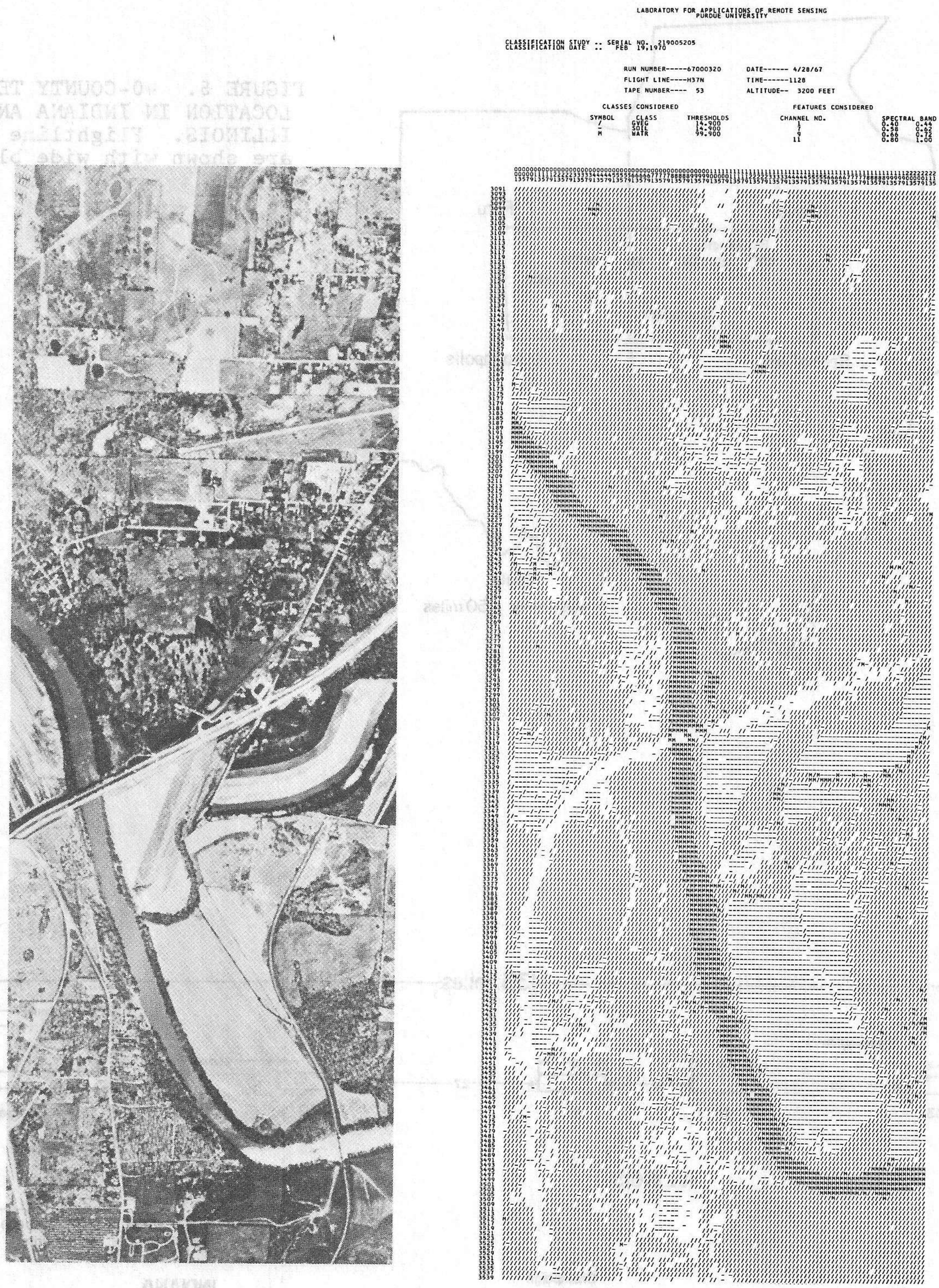

FIGURE 4. AREA NEAR BEDFORD, SHOWING CONTINUED ACCURACY OF CLASSIFICATION AT EXTREME END OF FLIGHTLINE.

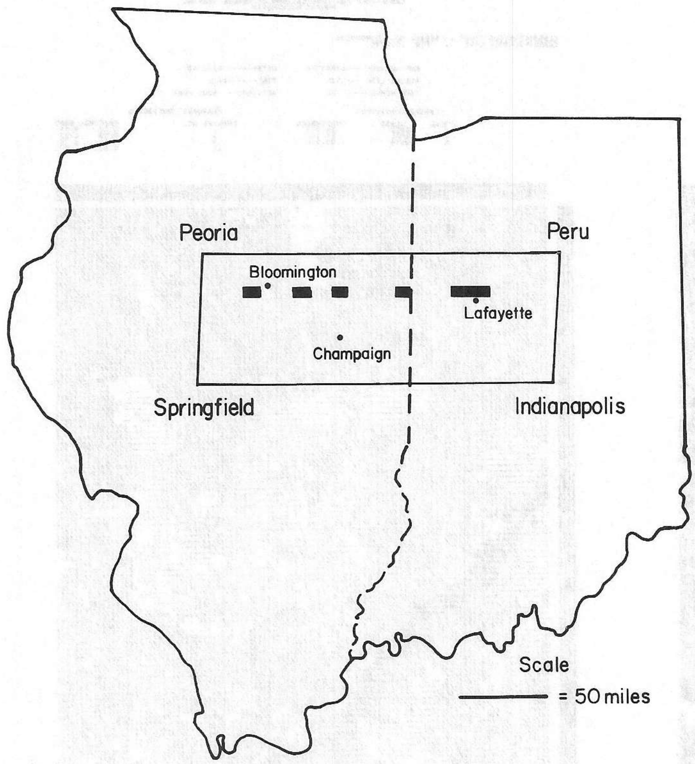

FIGURE 5. 40-COUNTY TEST SITE LOCATION IN INDIANA AND ILLINOIS. Flightline areas are shown with wide black lines.

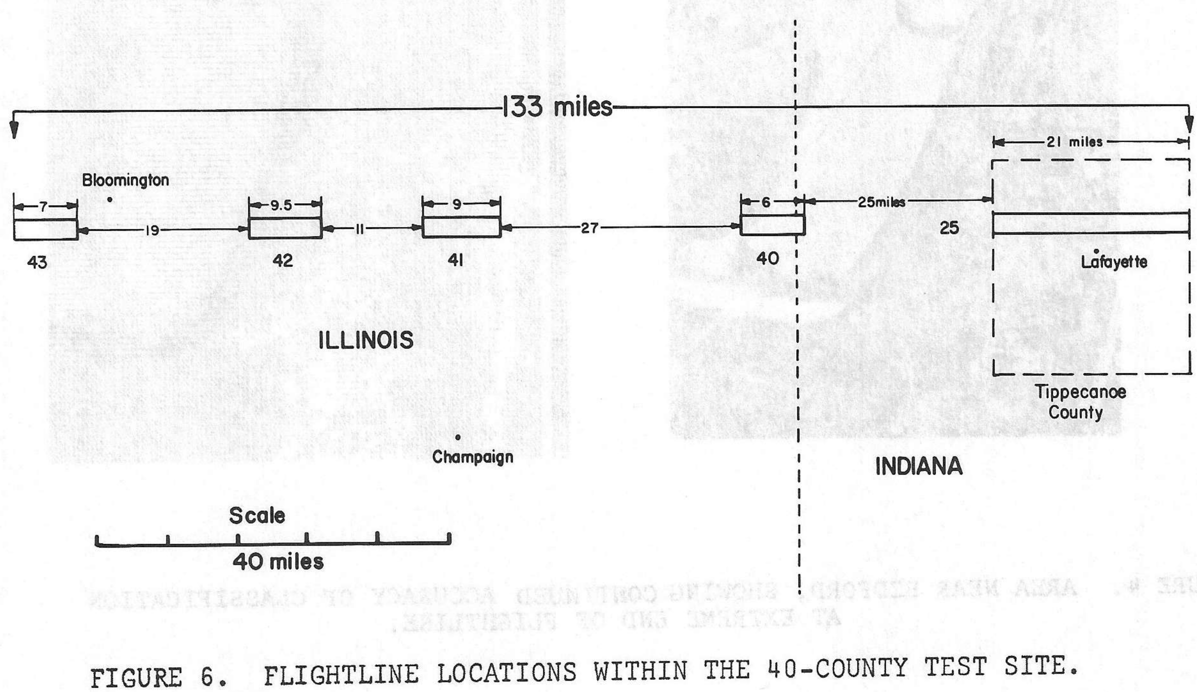

FIGURE 6. FLIGHTLINE LOCATIONS WITHIN THE 40-COUNTY TEST SITE.

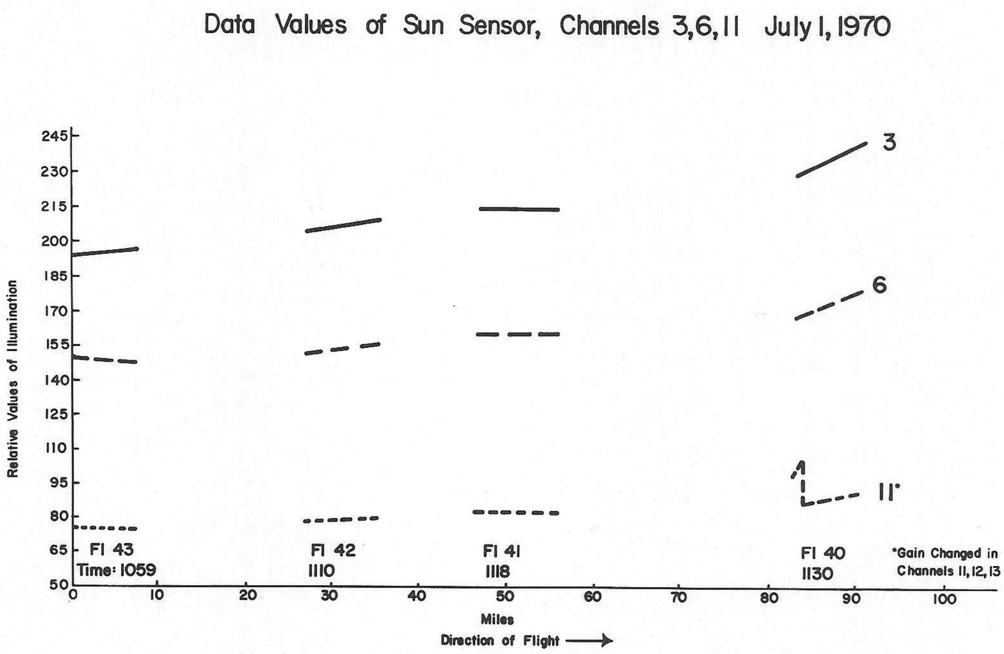

FIGURE 7. ILLUMINATION CHANGES IN 40-COUNTY TEST SITE. Relative values of illumination as detected by the sun sensor for 3 representative channels are shown in position over the 4 flightlines. Time given is the starting time of each flightline. Note gain change shown in FL 40.

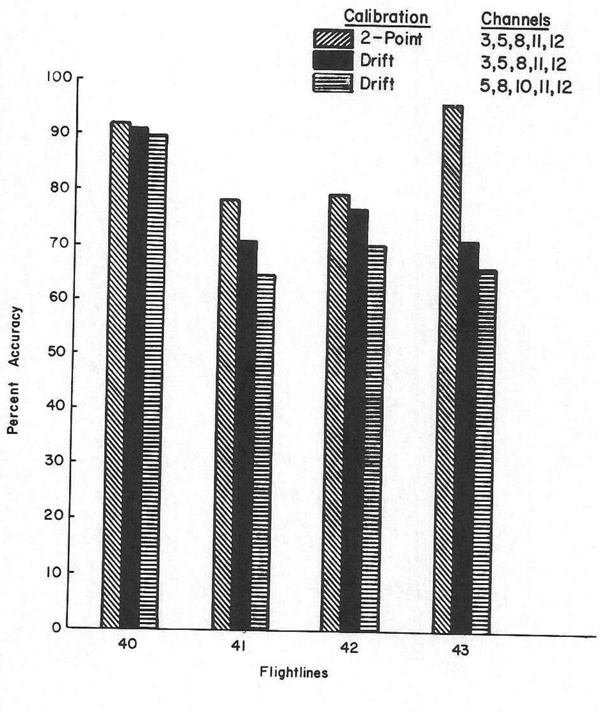

FIGURE 8. CLASSIFICATION ACCURACIES FOR WHEAT IN ALL FOUR FLIGHTLINES. Training samples from FL 40 were used to classify all flightlines. Different calibration techniques and wavelength band combinations were utilized.