LARS Contract Report 112778

Final Report

Vol. III Processing Techniques Development

by **P. E. Anuta**
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Principal Investigator
D. A. Landgrebe

November 1978

Prepared for
National Aeronautics and Space Administration
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Earth Observation Division
Houston, Texas 77058
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Submitted by
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Purdue University
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CR160094

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(E79-10163) PROCESSING TECHNIQUES DEVELOPMENT, VOLUME 3 Final Report, 1 Dec. 1977 - 30 Nov. 1978 (Purdue Univ.) 177 p HC A09/MF A01 CSCL 05B
N79-21518
Unclas
G3/43 00163

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STAR INFORMATION FORM

1. Report No.	2. Government Accession No.	3. Recipient's Catalog No.
112778		

4. Title and Subtitle
Processing Techniques Development

5. Report Date
November 1978

6. Performing Organization Code

7. Author(s)
P. E. Anuta, M. M. Hixson, P. H. Swain

8. Performing Organization Report No.
112778

9. Performing Organization Name and Address
Laboratory for Applications of Remote Sensing
Purdue University
West Lafayette, Indiana 47906

10. Work Unit No.

11. Contract or Grant No.
NAS9-15466

12. Sponsoring Agency Name and Address
J. D. Erickson/SF3
NASA/Johnson Space Center
Houston, Texas 77058

13. Type of Report and Period Covered

14. Sponsoring Agency Code
Final Report 12/1/77 - 11/30/78

15. Supplementary Notes
D. A. Landgrebe was LARS principal investigator.

16. Abstract

Three investigations of data processing techniques for remote sensing are discussed in this volume. Part A deals with observation data labeling of training samples based on interpretation of Landsat data plus associated meteorological data and historical agronomic data--but without ground observations. The LIST (Label Identification by Statistical Tabulation) Method was found to provide a workable approach for discriminating small grains from other ground covers. Ways of making the method more objective and reliable were pursued.

Part B describes an investigation of crop inventory procedures based on Landsat data. An experiment design was formulated and pursued involving data collection and evaluation of classification procedures. An investigation was conducted of possible improvements in the LACIE (Procedure 1) classification techniques as applied to discrimination of corn, soybeans, and "other."

An investigation of the problem of merging multiple data types is described in Part C. Landsat and synthetic aperture radar (SAR) data were considered in this study. Registration accuracy achievable using first to fifth degree polynomial distortion functions was found to be highly data dependent. Crop separability was observed in histograms of the registered data. Digitization of ancillary data was also pursued.

17. Key Words (Suggested by Author(s))
Landsat, crop inventory, sampling, classification, image registration, radar, data merging, multi-type data, image interpretation, Procedure 1.

18. Distribution Statement
Original photography may be purchased from:
EROS Data Center
Sioux Falls, SD 57198

19. Security Classif. (of this report)	20. Security Classif. (of this page)	21. No. of Pages	22. Price*
Unclassified	Unclassified		

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

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1. INTRODUCTION

1.1 Background

Analysis of remotely sensed agricultural crop survey data by pattern recognition algorithms requires the availability of training samples (data of known classification). In large-scale Landsat crop surveys, training samples cannot be acquired solely by ground observations, due either to cost considerations or to inaccessibility of the survey site. For both of these reasons, the labeling of training samples based on interpretation of the Landsat data and associated ancillary data has been utilized in LACIE, in which the manual image interpretation process has been supported by meteorological data and historical agronomic data. Although the performance of the analyst-interpreters (AIs) in LACIE has apparently been adequate to support the project goals, it is widely recognized that the labeling process, implemented in this manner; involves a great deal of subjective judgement, and hence the accuracy and precision of the results can vary greatly from one AI to the next. The overall objective of this task has been to investigate ways to upgrade the objectivity and reliability of the image labeling process. The basic approach proposed involved introduction of quantitative methods, often related to pattern recognition, in place of subjective judgement wherever possible. At the outset, it was hoped that it might be possible to develop a completely machine-implemented labeling method.

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* This report covers work under Task 2.2a Application of Statistical Pattern Recognition to Image Interpretation. The report was compiled by Philip H. Swain.

1.2 Overview of Previous Work

Training sample labeling by manual interpretation of the Landsat imagery was a fundamental assumption of the LACIE approach. Initially individuals were required to select fields for classifier training by visually locating and outlining agricultural fields which appeared to be representative of all spectrally distinguishable ground covers. The selection process included identifying the ground cover as wheat or non-wheat. As loosely defined as this, the process was not effective, because the interpreter could not discern all significant variations in the image products provided and, furthermore, tended to be biased toward the selection of homogeneous and clearly delineated fields. As a result, significant spectral categories often were overlooked and classifier performance suffered accordingly.

The appropriate goal in classifier training is to sample the measurement space (spectral or spectro-temporal space) adequately to obtain a representative sample of the data to be classified. In order to be representative, the sample must include, at minimum, observations from every class of interest and every class which might be confused with a class of interest. Given no information about the distribution of data in the measurement space, the optimal strategy for obtaining representative training data would be to select a random sample. After selection, of course, there remains the task of labeling the selected observations to identify their ground cover classes.

To reduce interpreter bias and improve the probability of getting a representative sample for classifier training, the AIs were later required to label pixels which had been randomly selected from the segment. An assumption implicit in this approach is that a selection based on random location in the image will induce a random selection from the measurement space, an assumption that appears to be sound. Since the sample size was quite small (less than 100 pixels per segment out of more than 20,000 to be classified), the probability of missing spectral classes was still significant. Nonetheless, this sample selection method, incorporated into a generally more robust analysis procedure, resulted in improved classification results in later phases of LACIE.

With the analyst-subjective factor removed from sample selection, there remained considerable subjectivity in the labeling (ground cover identification) process, the problem specifically addressed by this investigation. To proceduralize the labeling process, a questionnaire containing segment-related and pixel-related questions was formulated at JSC to lead the AI systematically through the available image data and supporting data [1]. To the extent possible, based on exploratory work to date, the supporting data included quantitative aids, including spectrally "normalized" imagery [2] and temporal greenness/brightness trajectories for each pixel to be labeled [3]. This labeling method was called Label Identification from Statistical Tabulations (LIST).

Despite the availability of spectral aids, however, it remained for the AI to make a subjective integration of the evidence to produce the necessary set of cover type labels. This process remained tedious and subject to a great deal of analyst-to-analyst variability. An effort to improve this situation was mounted, in which some of the key questions were made more quantitative and an attempt was made to automate them [4]. The results were promising, although the reported experiments were carried out over too limited an area (two LACIE segments in North Dakota) to permit general conclusions. Nonetheless, this represented another positive step in the direction of making the derivation of training data more objective.

1.3 Objectives and General Approach

As noted previously, the overall objective of this investigation has been to improve the objectivity and reliability of the image labeling process in order to provide classifier training samples in the absence of ground truth. Our approach may be described in terms of three subobjectives, outlined below.

Analysis of the Current LIST Process. This required selection and acquisition of appropriate data, implementation of the process, and assessment of the labeling results produced by applying the process to the data.

Investigation of Possible Methods for Machine Implementation of the Labeling Process. The starting point was preliminary work reported in [4], to be implemented and applied to in-house data for comparison with results achieved by AIs.

Extension to more General Applications. It was originally planned to develop and test an extension of the LIST process to crop inventory involving corn, soybeans and other major crops. It was subsequently decided by LARS and JSC to concentrate all resources on the wheat inventory applications. A few comments on multicrop extensions, based on our experience with wheat, will be included near the conclusion of this report.

1.4 Overview of Accomplishments

The LIST process was implemented and applied to a total of 13 LACIE segments in Kansas, North Dakota and South Dakota. This permitted LARS personnel to gain insightful familiarity with the process and provided a data base for accomplishing the project objectives.

A number of weaknesses in the current LIST process were pinpointed. The length and tedium of the process adversely affect the attainable results. The analysts were able to suggest specific ways to make the use of LIST more efficient and even formulated an alternative questionnaire as a step in this direction. But they also recommended that analysts should have knowledge of and exposure to the wheat growing process if they are to be able to perform the AI role in an optimal fashion.

That role is still a very subjective one, however, the AI being expected to integrate diverse forms of information into the labeling process in ways that are not very quantitative. There are real possibilities for improvement, because we have shown that the process depends most critically on a few key features in the data which apparently can be quantified. Experimental results involving data from seven Kansas segments showed that a simple but completely computerized labeling method based on these features could perform at least as well as the AIs using the full LIST process.

These results may be used to advantage either by (1) replacing the AI and LIST by a faster and possibly less expensive machine-implemented labeling process of equal capability, or (2) providing the AI with the quantitative results to be used as an aid in obtaining still better results through integration of other forms of information.

Further research is required to establish the viability of the latter strategy. However, it seems clear that in the near term, in which multicrop extensions of the present technology are sought, the increased difficulty of the labeling task will require continued use of the AI as an active agent to bring together diverse sources of information which can contribute to accurate labeling.

Finally, it is important to recognize a fundamental limitation of the investigation reported here. The LIST process calls for data from four strategically timed acquisitions of the primary multispectral data, and the data base used in this study was selected to meet this requirement. Although the impact of poorly timed or missing acquisitions was not specifically considered, that impact clearly can be substantial. Further research will be required to minimize the sensitivity of the LIST process to less-than-ideal data acquisition.

2. DESCRIPTION OF THE RESEARCH

This investigation consisted of two distinct, though related, components. The first component, analysis of the LIST process, required implementation and use of the labeling process in order to gain insightful familiarity with it and to accumulate data with respect to both the results it could produce and how it produced them. We intended to assess both the strengths and weaknesses of the implemented LIST method, and determine, if possible, how improvements in the objectivity and reliability of the labeling process might be achieved.

2.1 Analysis of the LIST Process

Data Set Assembly.

In support of this task, a comprehensive data set was assembled based on multitemporal Landsat data for 13 LACIE segments (Table A-1). This data base consisted of a wide variety of types of information that were necessary for the AI to use in answering the LIST questions and ultimately labeling training samples. The primary data were in the form of five-inch positive transparencies of the Landsat data for each of four or more acquisition dates in each of the 13 segments. These transparencies were Production Film Convertor (PFC) products supplied by JSC in roll form. The available segments were visually screened by an AI and the segments and acquisition dates were selected based on the following criteria:

1. 1976 segments should be from the prime wheat producing states, Kansas and North Dakota;
2. 1977 segments should be from Central Plains states where winter/spring wheat is a major crop;
3. Landsat data must be available for four acquisitions, each during a time period corresponding to a significant biostage or growth development stage of the wheat crop;
4. The data must be largely free of clouds and haze.

The locations of the 13 LACIE segments selected based on these criteria are shown in Figure A-1.

Figure A-1. Location of the LACIE Segments Analyzed.

Table A-1. LACIE Segments Analyzed at LARS by the LIST Method

State	LACIE Segment Number	County	Growing Year
Kansas	1163 1165 1852 1855 1857 1860 1865	Coffey Linn Lane Trego Grant Hodgeman Stevens	1976
N. Dakota	1633 1637 1661 1652 1897	Foster Stutsman McIntosh Stark McHenry	1976 1977
S. Dakota	1681	Roberts	1977

Once the film products for the 13 segments were assembled, they were photographically enlarged at LARS to an 8" x 10" paper print. The enlargements made it much easier for the analyst to locate and evaluate the individual pixels of interest.

An additional film product, supplied by JSC as part of the supporting data, was a supplemental color product (Kraus product) [2]. This photographic product, also enlarged and printed at LARS, was similar to the false color product discussed above, but its colors were "normalized" to produce an image in which a similar hue of redness was expected to always indicate a similar amount of green biomass and possible degree of crop development.

A second type of data assembled in support of this task included tables and summaries regarding weather and crop conditions and historical wheat yield and development patterns. Specific items in this category were:

- U.S. and Canada Meteorological Summaries of precipitation, freeze dates, crop development, and disease and insect infestation;
- Universal Strata Descriptors of climate, soil conditions, agricultural practices, and other crop-related variables;
- LACIE County-Level Historical Agricultural Statistics listing percent of agricultural lands within counties having LACIE segments and estimates of each crop type harvested in that county over the past two years;
- Wheat Yield Information for each county in each of the wheat growing states of the U.S.;
- Crop Calendar for each crop reporting district (CRD) in the wheat-producing states showing the onset and completion of each biostage for each of the crops grown within that district.

All of these data items were thought to be of assistance in enabling the AIs to label the segment training samples using the LIST procedure. It should be noted, however, that these materials came from diverse sources and were therefore not compiled or designed to be the most accessible or convenient in format for use by the AIs. Valuable data had to be separated from extraneous sections of other information within each set of data. This was not only time-consuming but also a non-productive activity for the AIs.

In addition to the photographic materials, tables and summaries, there were generated at LARS some quantitative analysis aids to support the LIST analysis. These included trajectory plots of greenness values versus acquisition date for each pixel to be labeled, and generalized "typical" trajectory plots for wheat in Kansas and North Dakota. Examples of these plots are given in Figure A-2. The typical plots were utilized by the AIs in forming a mental trajectory image to compare against when encountering the plot of each training sample to be labeled. It was found that variations in acquisition dates and agricultural conditions from segment to segment made straight correlations between the "typical" and sample plots to be unrealistic.

Another quantitative aid examined for implementation for this task was an automatic screening of the segment Landsat data in order to locate features in the data of a distinctly non-agricultural nature. This

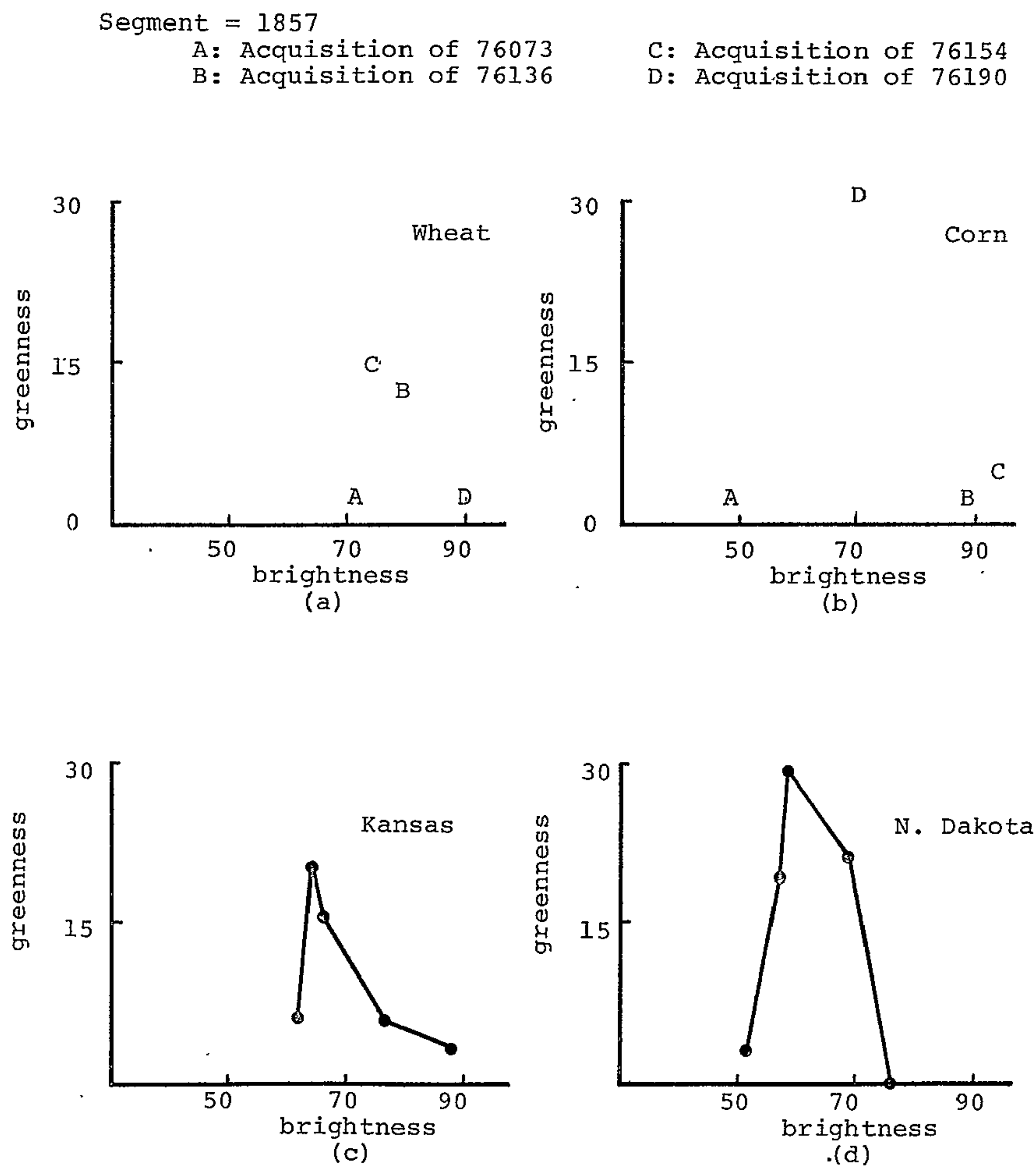

Figure A-2. a) Trajectory Plot for a Wheat Sample in Kansas, b) Trajectory Plot for a Non-wheat Sample (Corn) in Kansas, c) "Typical" Trajectory Plot for Wheat in Kansas, d) "Typical" Trajectory Plot for Wheat in North Dakota.

technique, developed at ERIM, involved delineating the "designated other" (DO) areas (water, woods, urban areas) and "designated unidentifiable" (DU) (clouds, cloud shadows, haze, snow, flooded areas) by applying thresholds to the data and printing the resultant maps [5].

The results were judged by the analysts to be unsatisfactory due to the appearance of small scattered areas of "bad data" or "shadow" which did not agree with visual examination of the film products. The ERIM documentation included a warning that the algorithm is very sensitive to the threshold settings, so the areas where errors occurred were examined and the thresholds adjusted to eliminate these errors. With the new thresholds a different problem occurred; areas of actual shadow or water were not completely delineated. Examination of the data values in problem areas to determine optimal thresholds revealed that the thresholds which minimized the error on segment 1633 would not minimize the error on segment 1637 and that the overall error occurrence for segment 1637 could never be as low as on segment 1633. It was judged that the automatic screening procedures would not produce a gain in accuracy or saving of analyst time in delineating the DO and DU areas. As a result the AIs screened the false color images visually to locate the readily recognizable DO and DU areas.

The final type of data to be included in the data base was a complete set of ground truth information for the 13 segments to be labeled. The ground truth was initially available as photo-interpreted blue print copies of high-altitude aerial photography. However, this data was later replaced by Universal format data tapes in which every Landsat pixel had been labeled as one of 101 possible crop types or conditions. By accessing these tapes using the EOD-LARSYS $HIST and $GRAYMAP processors, detailed maps were generated which could be used to evaluate analyst labeling performance. The data base was subsequently augmented to include files containing both the ground truth and the analyst labels for the specific pixels labeled by the AIs. These files were utilized to evaluate the LIST method of labeling. This portion of the task will be discussed in greater detail in a later section of this report.

In summary, a valuable data base was assembled for 13 LACIE segments in support of evaluating the LIST procedure. Compilation of the data base involved acquiring, handling, storing, and accessing a great variety of data types. It is felt that this data base is sufficiently extensive and well-documented to be incorporated in further studies requiring a data base of this type. Application will be made to have the data placed in the public domain.

Implementation of the LIST Process.

Three analysts were assigned the task of applying the LIST process to the thirteen LACIE segments described above. Two objectives were involved: to make the analysts as familiar as possible with the process in order to provide a means of evaluating the process subjectively; and to develop a data base to be used for evaluating the process objectively.

Two of the analysts were graduate students in electrical engineering having some experience in digital analysis of multispectral imagery. The third analyst was a geologist with extensive remote sensing experience. Each analyzed the data as independently as possible given their day-to-day proximity in the LARS environment. All three completed labeling of the seven Kansas segments; two completed thirteen segments.

Effective implementation of the LIST process at LARS required familiarity with the Universal Format for data tapes and conversion to LARSYS format (the conversion facilitated computation of statistics using existing software). Computer programs were also developed for generation of greenness trajectory plots for the pixels to be labeled. In general, these pixels were the seventy random "dots" specified by the LACIE Phase III type 1 and type 2 overlays [6].

Having labeled the seven Kansas segments, the analysts felt sufficiently experienced to evaluate the LIST questionnaire. Some questions were found too general to be of real value. Other questions were ambiguous and could not be interpreted. Some were judged not helpful to the decision process. In some instances, it was felt that the addition of one or two questions would contribute to a better judgement. Thus, a revised LIST questionnaire was formulated by the analysts. Both the original and revised questionnaires appear in the Appendices. The revised questionnaire was used for processing the segments not located in Kansas.

The following changes were recommended:

1. Questions 19-23 and Question 25 were thought to be too general to apply to specific pixels and were not considered helpful. They were merged, therefore, into Question 19 in the new list, in which the analyst is asked to give an overall evaluation of the crop condition based on the meteorological data available.

2. Question 32 was modified, becoming Question 27 in the new list. It was the analysts' experience that a pixel might still be fallow even though there were some indications of vegetation in it. Hence, the new question asks the analyst to decide on the pixel based on an overall judgement rather than on the vegetation indication alone.

3. A new question was inserted between Questions 33 and 34 in the old questionnaire (29 in the new list). It requires the analyst to determine whether fallowing is practiced in the segment. This helps the analyst decide whether the pixel is a fallow or a non-agricultural pixel.

4. Question 39 in the old questionnaire was reworded to Question 34 in the new list. The phrase "all available data" should be emphasized as the analyst might otherwise base judgement on only the false color imagery.

5. Two questions were inserted between Questions 39 and 40 in the old questionnaire (new Questions 35 and 36). These require the analyst to consider whether the pixel is representative of the field it is in. If it is not, the next question checks to see if the field containing that pixel follows a small grain development pattern. The idea is to label the pixel according to its field in case it is not representative of the field.

6. Questions 40 and 41 in the old questionnaire were merged into Question 37 in the new. The two old questions basically have the same meaning and a single question instead was felt to be adequate.

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7. Question 43 in the old questionnaire was deleted. It does not contribute to the decision and serves only to add confusion, as no guidance is given as to how closely or in what manner the percentages must match to motivate a particular choice of answer.

8. It was felt that Questions 45-51 in the old questionnaire must be altered in some way to be of any value to the analyst in distinguishing wheat from other small grains. However, the analysts did not feel sufficiently knowledgeable of the wheat-growing process to suggest an appropriate alteration.

A number of additional points related to the LIST processing and the analysts' experience with it are pertinent to the evaluation. These are summarized as follows:

1. The "Kraus Product" PFC imagery is intended to provide "normalized" color as a basis for acquisition-to-acquisition comparisons of imagery. However, in many cases, the analysts did not feel confident that the "redness" of a field in the Kraus product could be taken as a reliable quantitative indication of the vegetative state or quality of the field. This was particularly true in the 1976 data; the Kraus products were thought to be more reliable in the 1977 data. The analysts felt that the "Product 1" imagery was still the most interpretable and information-bearing.

2. Interpretation keys were not made available by JSC. Consequently, the answers to Question 34 were necessarily very subjective, and, though this did not create a serious problem, the need for the keys was definitely felt in some cases.

3. The available meterological data was found to be incomplete and, in many instances, not helpful. The data on 3-days-prior precipitation (Question 18) was not provided for 1976, although it was provided for 1977. In any case, the information on prior precipitation was found too general to be of significant value. The data was based on the city nearest to the county containing the segment being labeled. The nearest city almost always proved to be too distant to provide reliable information about the segment itself.

4. The analysts felt that accurate crop calendar information was absolutely essential in assessing the wheat growing stage.

5. The "typical" trajectory plots were found inadequate for precise numerical comparison with trajectory plots of pixels to be labeled. The shape of the plots, however, was clearly helpful, but the judgement of the analysts as to whether a pixel followed a small grains trajectory plot was very subjective. In many instances, the analysts were confronted with pixel trajectory plots that were ambiguous and could be interpreted different ways.

6. In the original LIST questionnaire, the analysts were directed to omit answering a number of questions when a pixel was temporally misregistered. However, a labeling decision was still sought. The analysts felt strongly that these pixels should be deleted from consideration altogether due to the unavailability of the important trajectory plot information. Certainly, the reliability and utility of data under such circumstances is doubtful.

7. Data could not be automatically screened for DO and DU prior to analysis because the available screening process was found to be ineffective. Thus, the analysts had all to agree jointly on DO and DU areas in a given segment.

8. A very serious problem encountered by the analysts was the "unanswerability" of Questions 45-51. The analysts felt strongly that, with the given information, they could not discriminate between wheat and other small grains. Furthermore, some of these questions (46, 47) are unclear. For all cases in which there were small grains other than wheat in the segment, the analysts were unable to discriminate the wheat.

9. In some cases the acquisition dates provided were not "typical" in the sense that they did not adequately cover the different stages of wheat growth. The analyst had to settle sometimes for whatever dates were available, some of which may have been little information-bearing. Further, because of these temporal shifts, the pixel trajectory plot shapes were altered, and the analyst had to interpolate mentally to decide whether a pixel trajectory plot was similar to that of small grains.

The analysts felt that a significant handicap was their inexperience with the wheat growing process and that such a background would definitely contribute to better understanding of the LIST process and the rationale behind the questions. This could lead to better labeling accuracies. Another factor mentioned was the length and tediousness of the process. The analysts felt that an effort should be directed at automating at least a part of the process, although they also observed that the analyst's role is of such importance that they doubt whether the process can be completely automated.

Labeling Performance. JSC-supplied ground truth tapes were used to evaluate the labeling results. Using these ground truth tapes and the EOD-LARSYS program $GRAYMAP, a map of each segment was generated. These maps identified the fields in the segment down to the subpixel level, each pixel divided into six subpixels. The ground cover classes were grouped into the following categories: wheat, small grains, non-small grains, fallow, and non-ag. The pixels were then assigned a ground truth label as follows: if all subpixels were of one class (e.g., wheat, fallow, etc.), the ground truth label was that class; if the pixel was partially wheat or small grains and partially one of the non-small grain types, the pixel was labeled edge point.

The analyst-labeled pixels were then compared to the corresponding pixels on the ground truth map. The LIST questionnaire limited analyst labels to the following categories: wheat, small grains, non-small grains, fallow, non-ag and edge. Each pixel label was called correct or not according to the following rules:

1. If the analyst answered wheat or small grains and the ground truth label also was wheat or small grains, the answer was considered correct.
2. If the analyst's answer was any non-small grains category and the ground truth label was also, the answer was considered correct.
3. If the ground truth label for the pixel was edge, the pixel was disregarded, since it was partially small grains and partially non-small grains.
4. Anything else was considered an error.

The accuracy of each analyst was then found by dividing the number of correctly labeled pixels by the total number of pixels labeled (disregarding edge pixels).

The labeling results for seven Kansas, one South Dakota, and five North Dakota segments are plotted in Figures A-3 to A-5. The accuracy figures for each analyst and each segment are shown in Table A-2. The general trend of these results suggests that which segment is being analyzed has more influence on the results than which analyst is producing the results. There is further evidence to support this conclusion. Table A-3 characterizes the major sources of error for the segments processed by the analysts. For the most part, although the types of errors vary from segment to segment, all analysts tended to make the same type of error on a given segment.

A more complete study of the analyst and segment effect was provided by an analysis of variance of the results. To test the significance of the effects of the analyst, the segment, and the analyst x segment interaction, an analysis-of-variance of the results was done using the SPSS ANOVA procedure. The ANOVA results produced are shown in Table A-4. A qualitative look at the results shows that analyst effects and analyst x segment interaction effects are not significant; however, segment effects are significant.

The major points to note are:

1. The area being analyzed has an effect on the labeling accuracy of the analyst. Note the much lower accuracy for the Dakota states as compared to Kansas. Also note the segment-to-segment variation in accuracy. This effect may be due to:

- Cropping practices that vary from area to area (e.g., strip cropping, contour farming, irrigation).
- Confusion crops grown in a particular area (e.g., hay and pastureland are sometimes difficult to differentiate from wheat).
- Unusual growth patterns for a given area (e.g., late planting, effects of drought or disease, early harvest).

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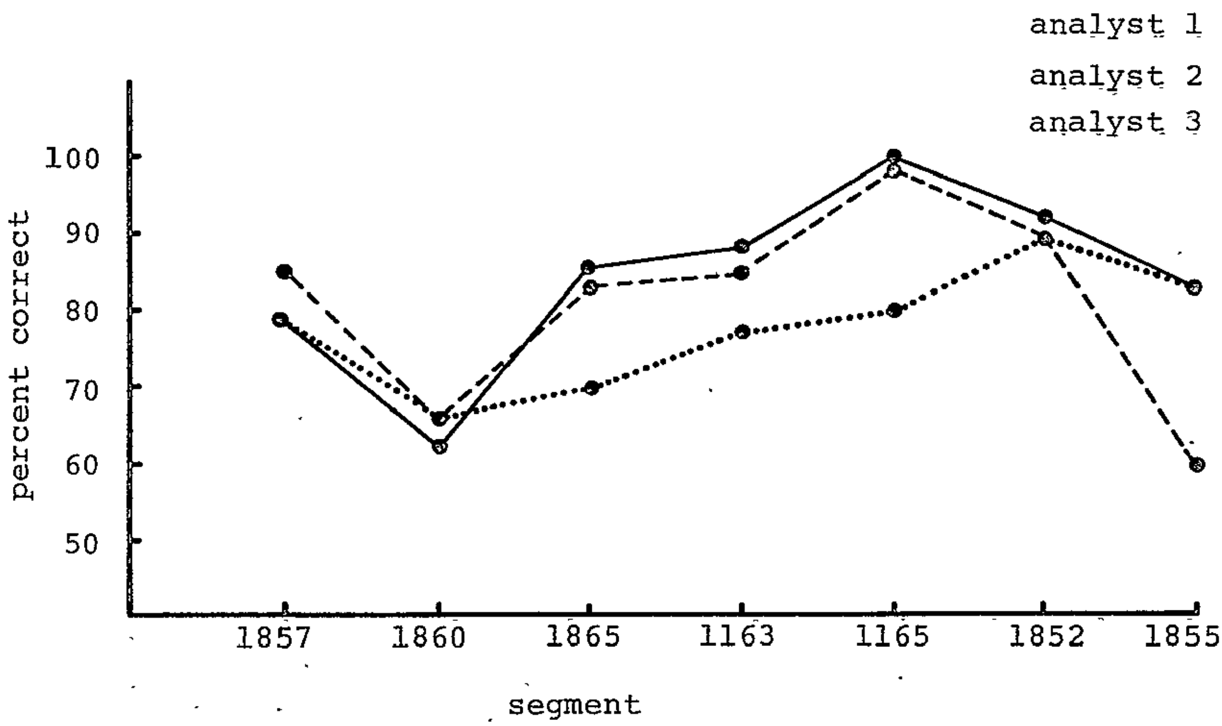

Figure A-3. Wheat/Non-Wheat Accuracy vs. Segment: Kansas, 1976.

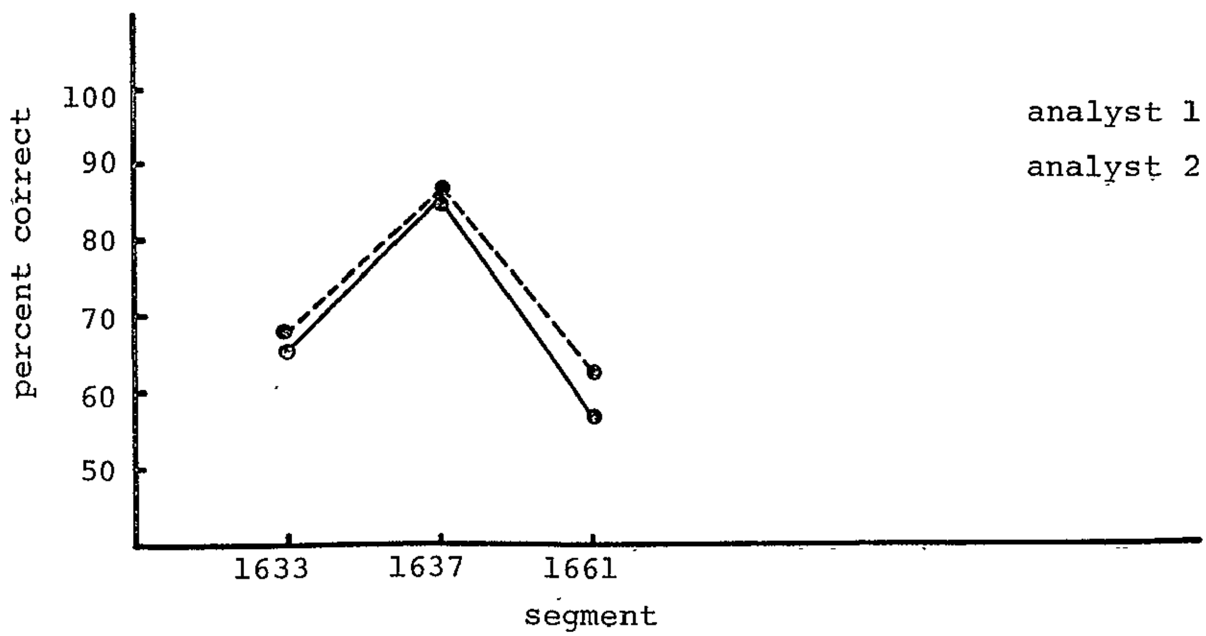

Figure A-4. Small Grains/Non-Small Grains Accuracy vs. Segment: North Dakota, 1976.

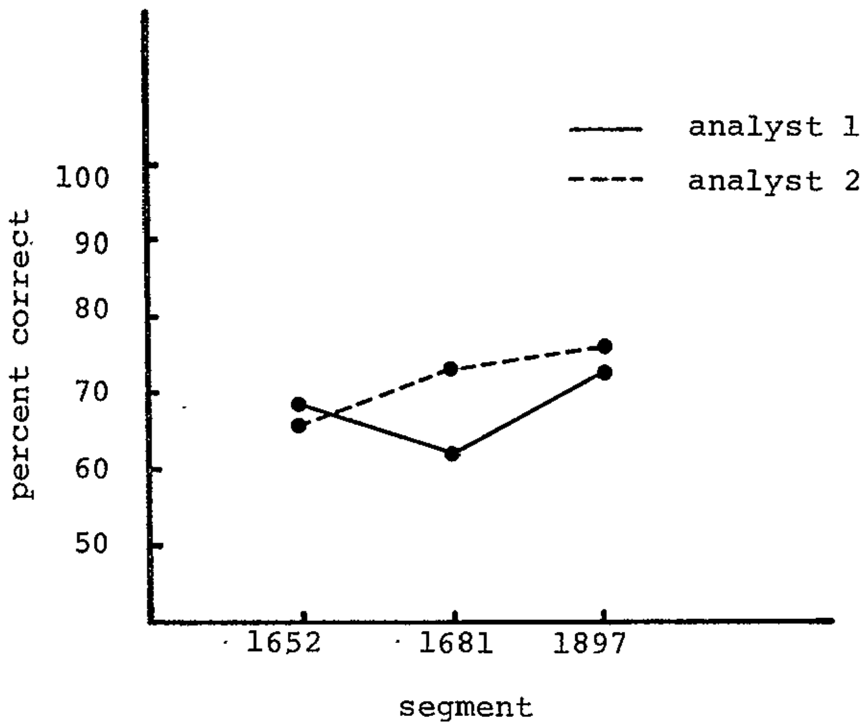

Figure A-5. Small Grains/Non-Small Grains Accuracy vs. Segment:

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Table A-2. Labeling Accuracy

Kansas (1976 data)

By Analyst Analyst	Accuracy	By Segment Segment	Accuracy
1	80.7 %	1857	80.8 %
2	84.2 %	1860	64.6 %
3	77.5 %	1865	79.0 %
Overall	80.8 %	1163	83.1 %
		1165	92.7 %
		1852	90.5 %
		1855	75.0 %
		Overall	80.8 %

North Dakota (1976 data)

By Analyst Analyst	Accuracy	By Segment Segment	Accuracy
1	72.0 %	1633	66.2 %
2	69.1 %	1637	86.0 %
Overall	70.5 %	1661	59.5 %
		Overall	70.5 %

North and South Dakota (1977 data)

By Analyst Analyst	Accuracy	By Segment Segment	Accuracy
1	67.9 %	1652	67.1 %
2	72.0 %	1681	68.1 %
Overall	70.0 %	1897	74.8 %
		Overall	70.0 %

Summary: Analyst 1 average = 75.7 %
Analyst 2 average = 77.8 %
Analyst 3 average = 77.5 %
Overall average = 77.0 %

Table A-3. Major Contributions to Labeling Error

Analyst/ Segment	1	2	3
1857	Wheat low Fallow high	Wheat low Fallow high	Wheat low Fallow high
1860	Wheat high Fallow low	Wheat/Non-small grains confusion	Wheat high Fallow low
1865	Small grains high Fallow low	Small grains high Fallow low	Small grains high Fallow low
1163	Wheat/Non-small grains confusion Fallow high	Wheat low Fallow high	Wheat high, Edge high, Fallow low
1165	Fallow high	Fallow high	Small grains high, Fallow high, Edge high
1852	Wheat high Fallow high	Fallow high	Wheat high Fallow high
1855	Wheat high	Wheat/Non-small grains confusion, Fallow high	Wheat high Fallow high
1633	Small grains high	Small grains high	
1637	Small grains high	Small grains high	
1661	Small grains/Non-small grains confusion	Small grains/Non-small grains confusion	
1652	Small grains/Non-small grains confusion	Small grains/Non-small grains confusion	

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Table A-3 (con't.)

Analyst/ Segment	1	2	3
1681	Small grains low	Small grains low	
1897	Small grains/Non-small grains confusion, Fallow low	Small grains/Non-small grains confusion, Fallow low	

Table A-4. Anova Tables for Kansas and Dakotas

Kansas (1976 Data)

Source	df	SS	MS	F
Analyst	2	153.859	76.930	1.369
Segment	6	1623.805	270.634	4.817*
Anal x Seg	1	98.632	98.632	1.756
Error	11	618.014	56.183	---

North Dakota (1976 Data)

Source	df	SS	MS	F
Analyst	1	12.615	12.615	7.994
Segment	2	756.372	378.186	239.662*
Anal x Seg	1	2.45	2.45	1.553
Error	1	1.578	1.578	---

Dakotas (1977 Data)

Source	df	SS	MS	F
Analyst	1	25.216	25.216	.504
Segment	2	70.505	35.253	.705
Anal x Seg	1	.04	.04	.001
Error	1	50.029	50.029	---

* significant at the $\alpha = .05$ level

2. Analyst effects in this study were not significant. However, we cannot conclude that this would be true in general, since all three analysts had similar amounts of related experience and knowledge of wheat growth.

3. The revised LIST questionnaire was used by the analysts to label the 1977 blind sites in North and South Dakota. Note that there is no significant change in accuracy compared to the analysis of 1976 sites in North Dakota using the original LIST.

Assessment of the LIST Characteristics.

We examined the pattern of analyst responses to the pixel-specific questions of LIST in order to determine which questions have important discriminatory power and how accurately these questions were answered. Our objectives were to understand the actual workings of the current process, hoping thereby to be able to modify it to become more quantitative and possibly have more (or all) of the work done by a computer.

The evaluation was based on 1976 Landsat and ancillary data from seven blind-site segments in Kansas. Three analyst-interpreters (AIs) at LARS filled out the LIST questionnaires. Their answers to all the questions were then keypunched to create a computer-readable data set, which contained the responses of

- 3 AIs for segments 1163, 1855, 1857, 1860, 1865
- 2 AIs for segments 1165, 1852.

Ground truth for each labeled pixel was added to the file of AI data to form the basic data set, which contained information on 1359 pixels. Of these, 146 had ground-truth (GT) codes for "edge between wheat or small grains and something else." Another 11 pixels were "designated unidentifiable" (DU) by the analyst, probably due to haze or clouds. The analysts labeled an additional 15 pixels "edge;" it is not determinable from available ground truth whether these are in fact field edges or errors. This left 1187 pixels with unequivocal AI and GT codes: Non-agricultural; Fallow; Non-small grains; Wheat; Small grains.

There is however, variability in the meaning of the label "small grains." For the ground truth label, "small grains" means "small grains other than wheat;" for the AI label, "small grains" means "small grains which may be wheat but could also be oats, barley, or rye."

Figure A-6 shows the flow of all the pixels through the LIST questionnaire, and Fig. A-7, A-8, and A-9 show the paths taken by pixels with GT labels of "wheat/small grains," "non-small grains," and "non-ag/fallow," respectively.

Questions 31 and 32 form the basis of the first major branching point. They ask the analyst to judge the presence and development stage of vegetative canopy based on the color of the pixel on each of two production film converter (PFC) images -- Product 1 and Product 3 (or Kraus product). For all 4 acquisitions the pattern of responses to Questions 31 and 32 were similar. Thus, either the two images gave almost the same information, or the AI combined his impressions from both images before answering either question. For the earliest acquisition (which ranges from March 10 to April 18, depending on segment) the answers to these questions, grouped by ground truth category, are shown in Table A-5. For the third acquisition the responses to Question 31 are shown in Table A-6.

Table A-5. Analyst Responses to LIST Questions 31 and 32, First Acquisition.

	Question 31				Question 32			
AI Response	Non-Ag	Fallow	Non-Sm Grain	Wheat or Sm Grain	Non-Ag	Fallow	Non-Sm Grain	Wheat or Sm Grain
No Vegetation -1	3	208	602	92	3	197	567	90
Indeterminate 0	0	2	54	20	0	9	70	23
Green Vegetation 1,2,3	2	9	85	110	2	13	104	109

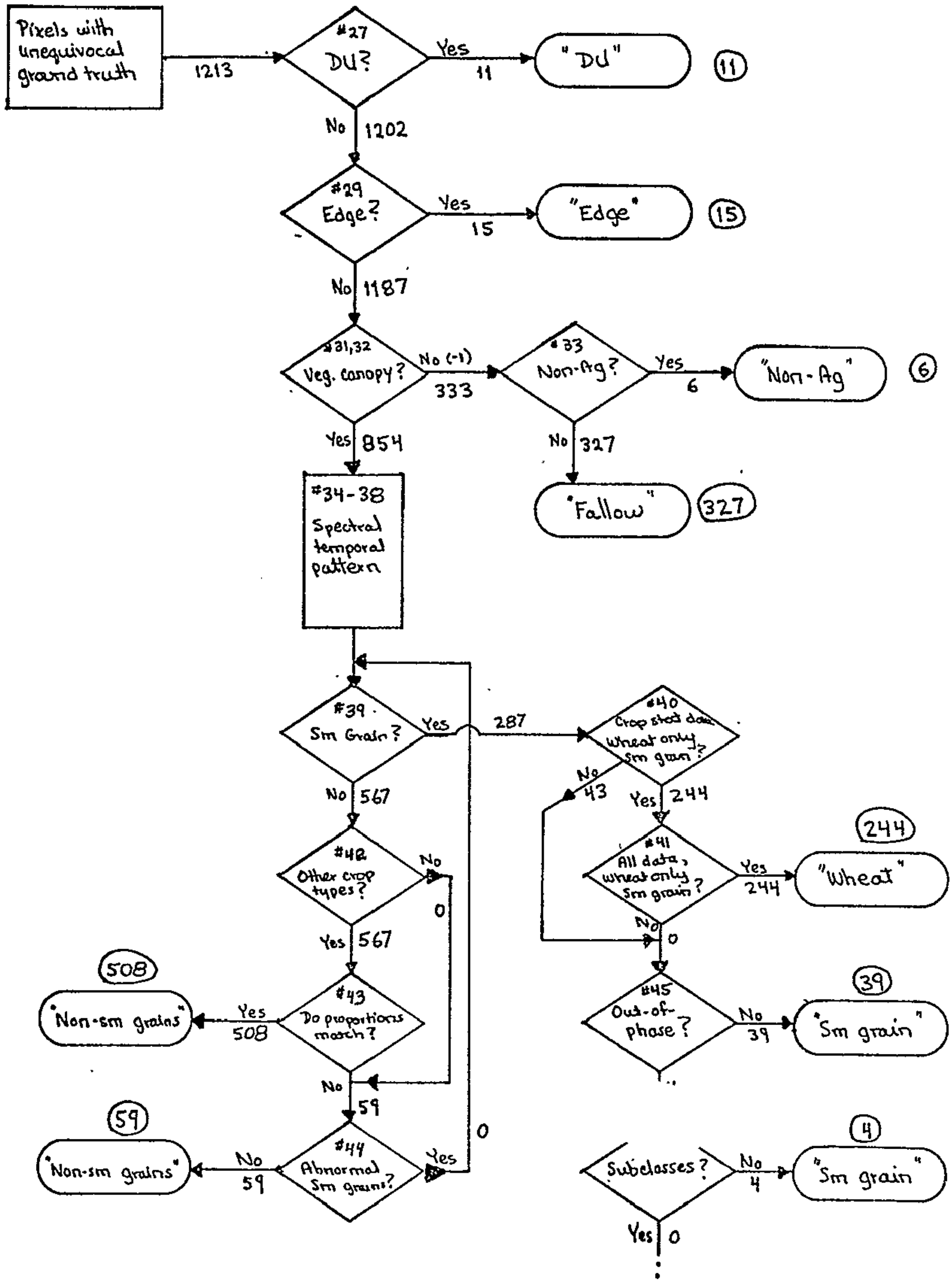

Figure A-6. Flow of all Pixels through LIST.

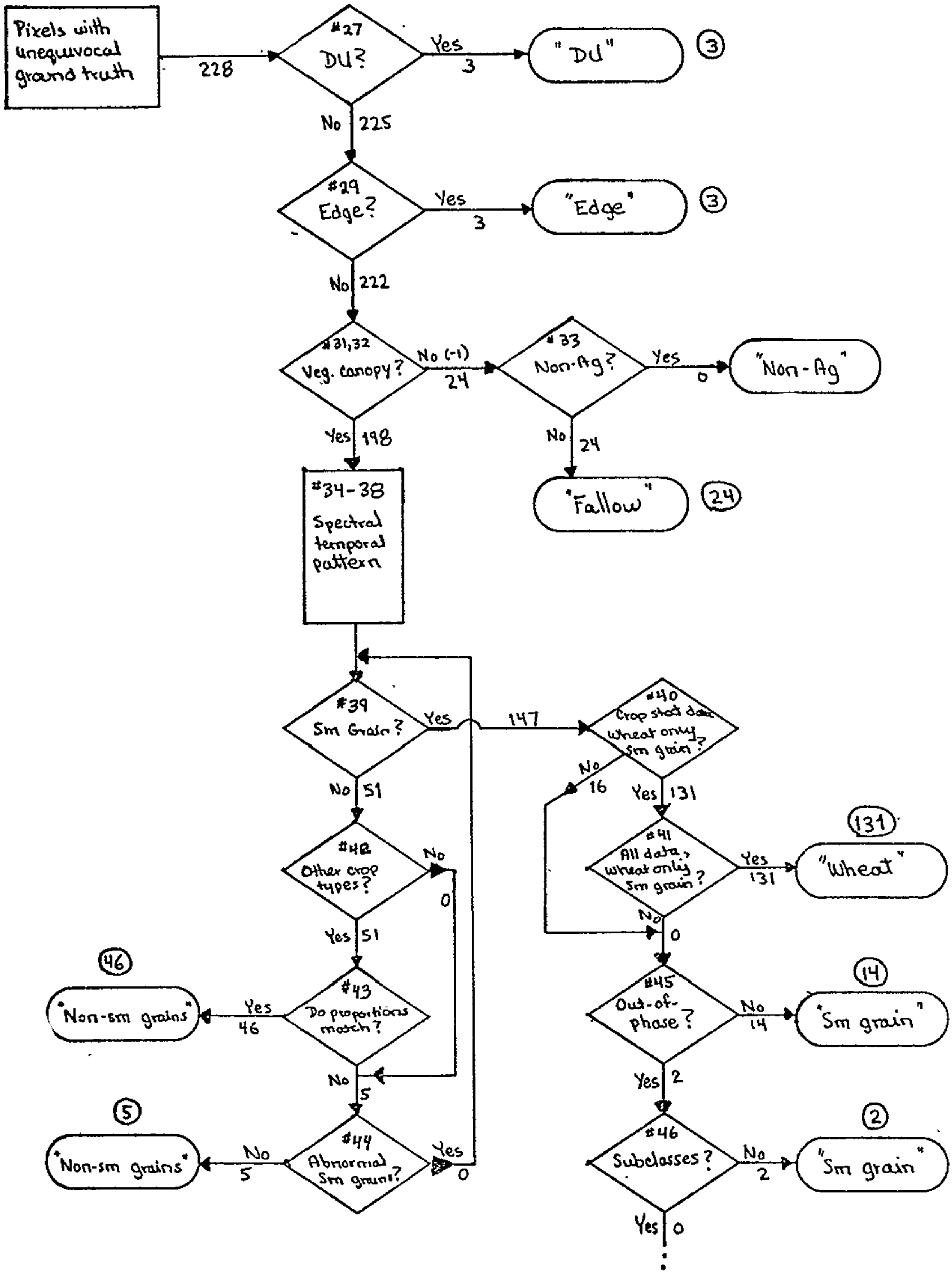

Figure A-7. Flow of Wheat/Small Grains Pixels through LIST.

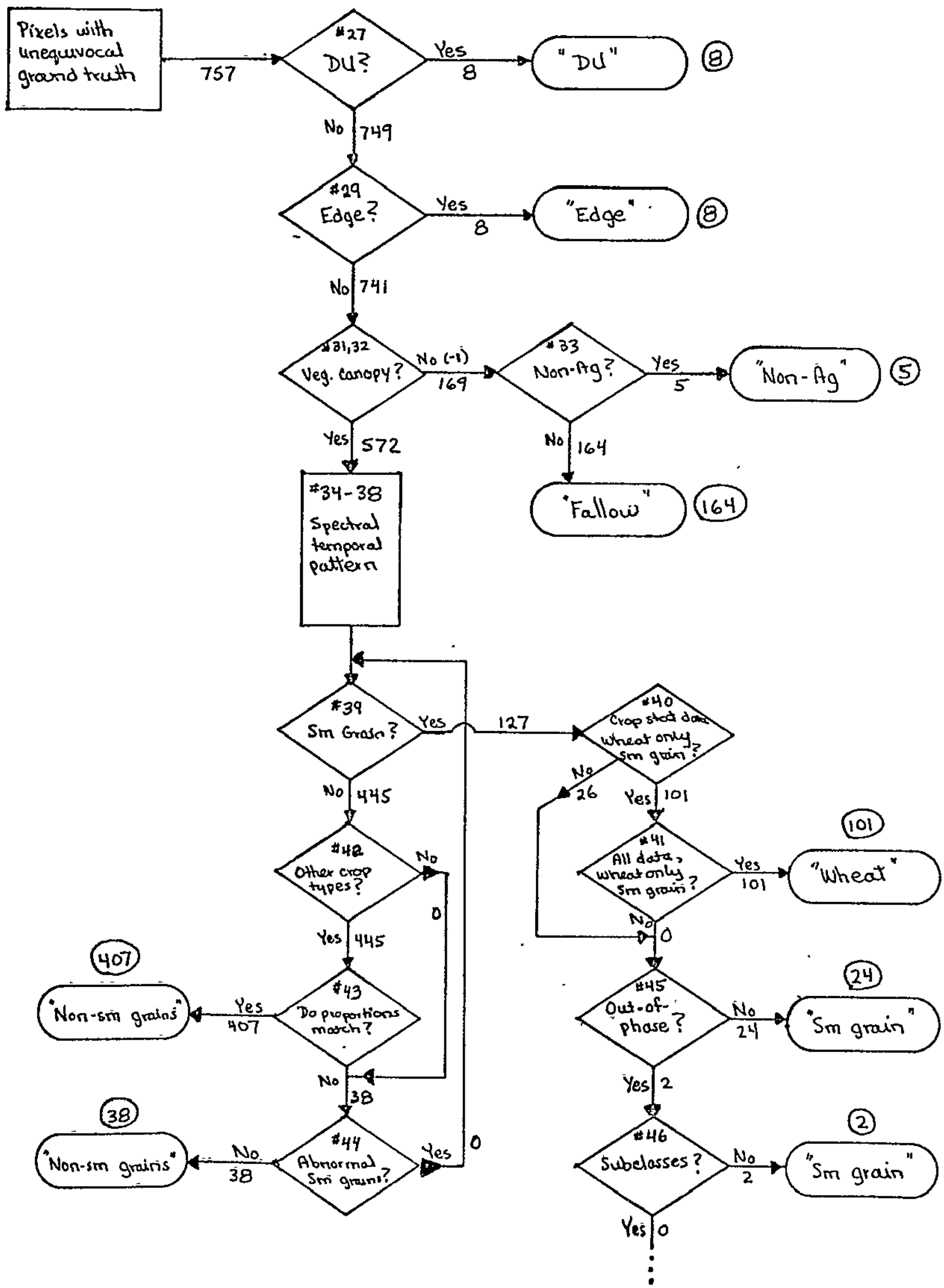

Figure A-8. Flow of Non-Small Grain Pixels through LIST.

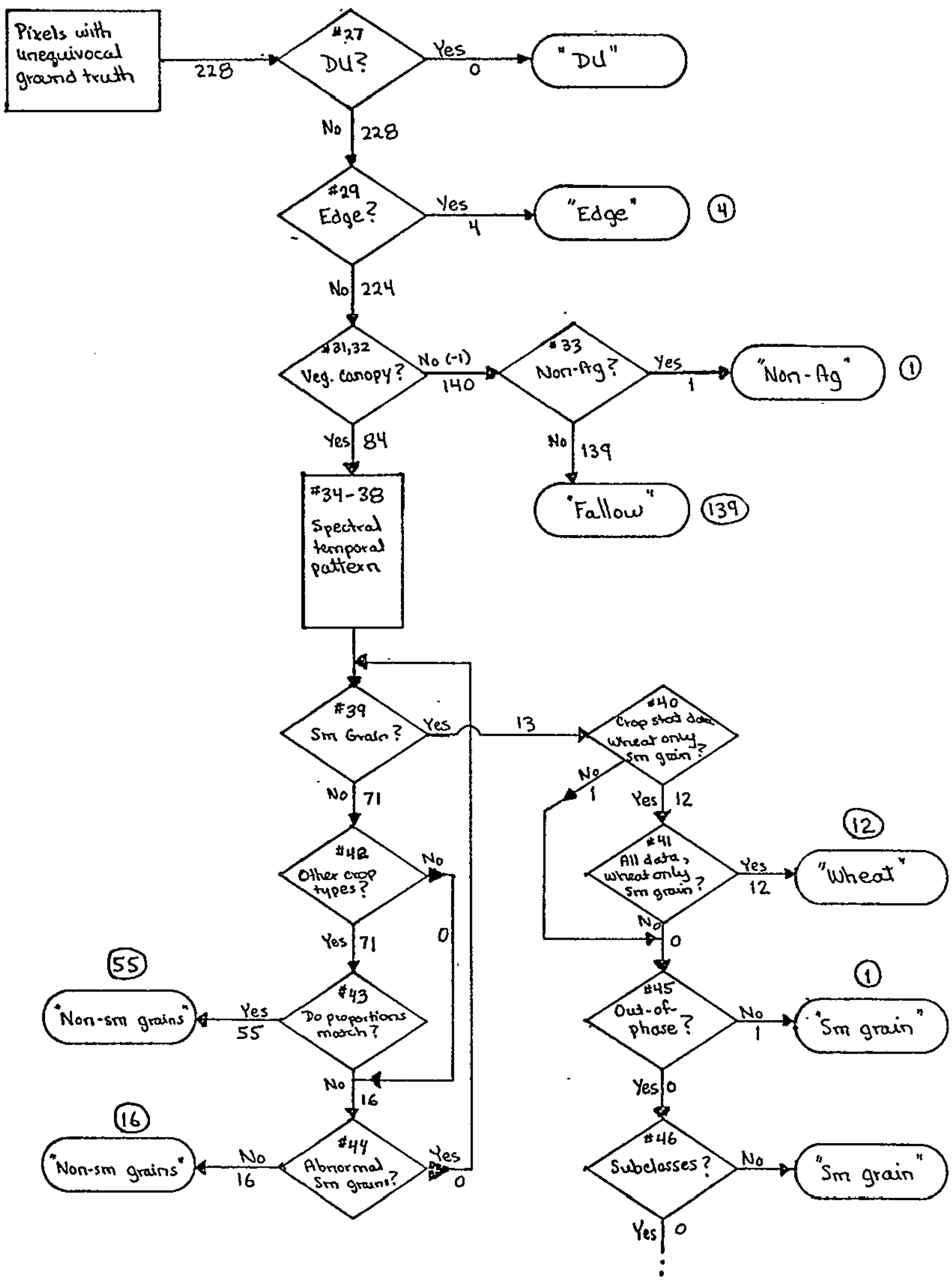

Figure A-9. Flow of Non-Ag/Fallow Pixels through LIST.

Table A-6. Analyst Responses to LIST Question 31, Third Acquisition.

AI Response		Non-Ag	Fallow	Non-Sm Grain	Wheat or Sm Grain
No vegetation	-1	4	185	364	47
Indeterminate	0	0	3	41	10
Green vegetation	1,2,3	1	27	251	82
Senescing/Harvested	4,5	0	4	55	83

Even as late as the fourth and final acquisition there were 269 "non-small grain" and 56 "wheat/small grain" pixels for which Question 31 was answered "no vegetation." Many of these pixels were misclassified as "fallow." When the AI answered both Questions 31 and 32 by -1 for all four acquisitions, he is instructed to take a path (Question 33) which leads to a non-crop (non-ag or fallow) label. Otherwise he follows a path (Question 34) which leads to a crop label (wheat, small grain, non-small grain). The correct path was followed for 910 of the 1187 pixels, as shown by the accompanying matrix.

		Ground Truth: crop	Ground Truth: non-crop	
AI Decision	crop	770	84	854
	non-crop	193	140	333
		963	224	

Thus we have:

$$P(\text{decide "crop"} \mid \text{"crop"}) = .800$$

$$P(\text{decide "crop"} \mid \text{"non-crop"}) = .375$$

$$P(\text{decide "non-crop"} \mid \text{"non-crop"}) = .625$$

$$P(\text{decide "non-crop"} \mid \text{"crop"}) = .200.$$

The largest percentage error comes from calling a pixel "crop" when in fact it is non-ag or fallow. The largest absolute error (193 pixels) comes from calling a pixel "non-ag" or "fallow" when in fact it is a "crop." Question 33 was answered for 333 pixels -- all those that got straight -1's on Questions 31 and 32. Of these, only 140 deserved straight -1's, so the answer to Question 33 was bound to be "wrong" for the other 193. For the 140 on which the analyst had a chance to be right, he was correct for all of them.

The next question that leads to a parting of ways is 39:

Does pixel follow a small grains spectral development pattern?

If answered "yes" this leads to "wheat" or "small grain" choices. If answered "no" it leads to "non-small grain." (There is a possible loop back to re-evaluate, but the loop was never taken.) This question was answered for 854 pixels, 770 of which really were "crop" and 84 were "non-crop." If we look at all responses from the standpoint of interest only in "small grain" versus "everything-else" we have:

		Ground Truth: small grain	Ground Truth: everything else	
AI Decision	small grain	147	140	287
	other crops	51	516	567
		198	656	

Remember that the "everything else" category includes 84 pixels that are not any kind of crop; therefore, all of these must be misclassified at this stage, as either "small grain" or "other crops." A more detailed breakdown is shown in Table A-7.

Table A-7. Results of Analyst Response to Question 39.

		Ground Truth: Small Grain	Ground Truth: Other Crops	Ground Truth: Non-Crop	
AI Decision	Small Grain	147	127	13	287
AI Decision	Other Crops	51	445	71	567
Pixels for which question was not answered		24	169	140	333
		222	741	224	1187

Which table is more useful depends on what it is important to identify correctly -- if a pixel is not wheat, we may or may not care what it really is. We have:

$$P(\text{deciding "small grain"} \mid \text{it really is small grain and Q39 was reached}) = \frac{147}{198} = .74$$

$$P(\text{deciding "small grain"} \mid \text{it really is small grain}) = \frac{147}{222} = .66$$

The second probability is lower because of the 24 small grain pixels that were earlier classified as "non-crop."

If Question 39 was answered "no," the AI proceeds to Questions 42, 43, and 44. If Question 44 is reached and answered "yes," the AI is directed to "go to Question 39 and re-evaluate." This path was never followed -- question 44 was reached for 59 pixels, but was answered "no" for all of them. All other paths in this section lead to a "non-small grains" label (which means "crop other than small grain"). Thus,

$$P(\text{deciding "non-small grain"} \mid \text{it really is "non-small grain" and Q39 was reached}) = \frac{445}{572} = .78$$

$$P(\text{deciding "non-small grains"} \mid \text{it really is "non-small grains"}) = \frac{445}{741} = .60$$

If question 39 was answered "yes," the AI goes to a series of questions designed to decide whether the pixel can be determined to be specifically "wheat" or must be left with the more general "small grains" label. The key question here is 41:

> Does all available data indicate wheat is the only small grain in this area?

Of 287 times this question was reached, it was answered "yes" 244 times and those pixels were subsequently labeled "wheat." The remaining 43 pixels led on to Questions 45 and 46 and were then labeled "small grains." Questions 47 to 51 were never reached.

Table A-8. Results of Analyst Response to Question 41.

		Ground Truth: wheat	Ground Truth: small grain	Ground Truth: other	
AI Decision	wheat	128	3	113	244
AI Decision	small grain	16	0	27	43
Pixels for which question was not answered		72	3	825	900
		216	6	965	

Looking at the overall labeling results, the AI and ground truth never agreed on a "small grains" pixel but since there were only 6 real "small grains" other than "wheat" pixels, this is not surprising. (Note that the AI category "small grains" includes those pixels that may be wheat but which are in areas where wheat can't be distinguished from other small grains. The GT category "small grains" contains only "non-wheat small grains.")

If we redefine "small grains" to include wheat for both AI and ground truth we have the results shown in Table A-9.

Table A-9. Two-Way Comparison of Analyst Labels and Ground Truth.

		Ground Truth: small grain	Ground Truth: everything else
AI Decision	small grain	147	140
	everything else	75	825

This gives:

$$P(\text{correct decision} = \frac{147 + 825}{1187} = .82$$

$$P(\text{decide "small grain"} | \text{it really is "small-grain"})$$

$$= \frac{147}{222} = .66$$

$$P(\text{decide "small grain"} | \text{it really is something else})$$

$$= \frac{140}{965} = .15$$

$$P(\text{decide "something-else"} | \text{it really is "small grain"})$$

$$= \frac{75}{222} = .34$$

P(decide "something-else"|it really is "something-else")

$$= \frac{825}{965} = .85$$

The actual percentage of labeled pixels that are "small grain" is 100(222/1187) = 18.7%. However, the AI decided "small grain" for 100(287/1187) = 24.2% of the pixels, thus overestimating the proportion of "small grains" by a factor of

$$24.2/18.7 = 1.3$$

Note that the proportion of correct decisions depends on the definition of "correct." Above we used a two-way criterion: small grains vs. everything else. A three-way criterion -- small grains vs. non-small grain crops vs. non-crops -- gives a lower proportion of correctness," as shown in Table A-10.

Table A-10. Three-Way Discrimination

		Ground Truth		
		small grain	non-sm grain	non-crop
AI Decision	small grain	147	127	13
	non-sm grain	51	445	71
	non-crop	24	169	140

$$\text{P(correct decision)} = \frac{147 + 445 + 140}{1187} = .62$$

Recall that a key point in the decision making process comes at Question 39, where "small grains" and "non-small grains" paths divide.

The answer given to this question depends heavily on the answers that were given to Questions 34, 35, 37, and 38. Questions 34 and 35 are parallel questions that ask:

> Is the vegetation indication of the pixel on PFC Product 1 (Product 3) valid for the Robertson biostage of wheat for the acquisition?

The pattern of response to each question is similar, so we will look only at Question 34. This question is answered separately for each acquisition, either "yes," "no," or "indeterminate." Let us for each pixel count the number of times the question was answered "yes." This can range from 4 (since there are 4 acquisitions) down to 0 (answered "no" or "indeterminate" for each date). Note that 1 could represent response patterns YNNN, NYNI, INYI, etc., but in each case the question is answered "yes" for exactly one of the four dates. Similarly, categories 2 and 3 contain many possible patterns of response.

Table A-11. Pattern of Responses to Question 34

	Ground Truth			AI Label		
No. of "yes" answers	Sm Grain	Non-sm Grain	Non-Crop	Sm Grain	Non-sm Grain	Non-Crop
0	3	49	19	8	63	0
1	21	198	32	15	236	0
2	39	154	19	41	171	0
3	47	103	10	77	83	0
4	88	68	4	146	14	0

There were 160 pixels for which Question 34 was answered YYYY; 88 of these were really small grain, 68 non-small grain, and 4 were non-crop. However, the AI labeled 146 of them small grain, and 14 non-small grain. (He could not label any of them non-crop since that path had branched off earlier.) Thus the AI decision is highly correlated with the answer to this question. The likelihood that a pixel is really small grain shows moderate correlation to the answer, but there are 21 small grain pixels that received only one "yes." Also, 72 non-small grain or non-crop pixels received four "yes" responses and 113 received three "yes" responses; many of these were later misclassified as "small grains."

Question 37 asks:

Is the green number of pixel within the range for small grains?

It too is answered once for each acquisition, and we use the same technique as above to display the results in Table A-12.

Table A-12. Pattern of Responses to Question 37

	Ground Truth			AI Label		
No. of "yes" answers	Sm Grain	Non-sm Grain	Non-Crop	Sm Grain	Non-sm Grain	Non-Crop
0	4	60	14	1	17	0
1	11	102	29	16	126	0
2	44	142	24	53	157	0
3	56	234	14	106	198	0
4	83	34	3	111	9	0

Question 37 was answered YYYY for 120 pixels, 83 of which were really "small grains." So the "typical small grain green number pattern" is followed by some non-small grain pixels and is not followed by some small grain pixels. There were 59 small grain pixels that had 0, 1, or 2 "yes" answers, and 285 "everything else" pixels with 3 or 4 "yes" answers. Once again, the AI labels are correlated highly with the answer to the question.

Question 38 asks:

Does the trajectory plot of this pixel match a small grains trajectory plot?

Since the plot incorporated information from all four acquisitions, the question is answered only once for each pixel. The results are summarized in Table A-13.

Table A-13. Results of Analyst Response to Question 38

	Ground Truth			AI Label		
	Sm Grain	Non-sm Grain	Non-Crop	Sm Grain	Non-sm Grain	Non-Crop
No	70	460	67	61	536	0
Ind.	18	53	6	55	22	0
Yes	110	59	11	171	9	0

Again, the AI label agrees closely with the answer to the question. The actual situation is less neatly defined. There were 180 "yes" answers, 171 of which were labeled "small grains," but only 110 of which were really "small grains."

<u>Conclusions</u>. In the LIST questionnaire, the decision between "crop" and "non-crop" comes early, and is based primarily on the appearance (color) of the pixel on the PFCs. Out of a total of 1187 pixels analyzed, the AIs followed the path leading to "non-crop" labels 333 times, but only 140 of these pixels actually were "fallow" or "non-agricultural." (However, the 1976 drought in Kansas may have made some planted fields appear fallow. Some fields may have been plowed under after being planted. We do not know how the "ground truth" labeled such fields.) If the "ground truth" reflects the actual condition of the fields during the growing season, then the low accuracy of the "crop" vs. "non-crop"

decision suggests that more than just the available information used by the LIST is required to make this discrimination accurately. The present decision criterion (spectral image interpretation) requires human capabilities and is not directly amenable to machine implementation. Since the color images were created from digitized data, it would be desirable to find an alternative method of structuring and categorizing the data in a multitemporal, computer-oriented form.

After careful study of the LIST process, it is not surprising that the analyst decision (Question 39) between "small grains/wheat" and "other crops" is highly influenced by and correlated with the answers to Questions 34, 35, 37, and 38. Any improvement in methods (e.g., quantitative aids) for judging green numbers or assessing trajectory plots should lead to more accurate decisions. Questions beyond 39 had little pixel-dependent discriminatory power for the data set used in this analysis. (There was segment-dependent discrimination between "wheat" and "small grains" in Questions 40 and 41.) The next section of the report will discuss machine-implemented methods of dealing with Questions 34-38.

Summary.

We draw together here the key observations concerning our analysis of the LIST process.

The training sample labeling process systematized in the LIST method is still very subjective. It is not surprising, then, that prior knowledge of the wheat-growing process is felt to be a considerable asset to the analyst, permitting him/her a more insightful understanding of the questions and a better ability to recognize abnormal situations in the data. Such analysts would also be more likely to provide effective guidance with respect to further improvement of the LIST process.

The length and tedium of the process are clearly problematical. The analysts felt that certain portions of the process could be automated to alleviate this situation, although they added that the level of subjectivity dictates against total automation. We shall show later, however, that accuracies at least comparable to those of the participating analysts may be obtainable by appropriate quantification of key features used in the LIST process.

It was interesting to discover that the major differences in LIST labeling results were attributable to segment variability. Analyst and segment/analyst interaction effects were statistically insignificant. Also, no significant performance difference was observed when the questionnaire was revised based on analyst recommendations. The full implications of these observations should be further explored. However, one conclusion which may be inferred is that the quality of the classification results, known to be sensitive to the quality of the training sample labeling, depends more on segment-to-segment variations of the data than on the analyst selected to perform the labeling. Efforts to stratify the data may still pay dividends, therefore, especially when one attempts to automate the labeling process using methods based on parameterization of data characteristics.

As it now stands, the LIST process depends heavily on the ability of the AI to quantify the spectral response of the pixels to be labeled and effectively compare the spectral response to some rather loosely defined standards for discriminating wheat from nonwheat. Basically, he/she is expected to do a very quantitative job using tools which at best are only quasi-quantitative. The impact of this situation is reflected in the level of analyst-dependent variability in the results for any given segment (not withstanding that we have already shown that this variability is relatively insignificant as compared to the variability resulting from segment-to-segment variation in the data). There is clearly room for improvement in the process through development of more quantitative tools.

2.2 Toward Computer Implementation of a LIST-like Labeling Process

A recent technical report by Abotteen and Pore [4] discussed a method to automate a portion of the LIST questionnaire. In that report a revised LIST questionnaire incorporating the automation was presented and evaluated over two LACIE spring wheat segments in North Dakota. The high classification accuracies reported by Abotteen and Pore for these two segments encouraged further investigation into their method and evaluation of it over additional LACIE segments. We anticipated that such an investigation would point to a still more quantitative and "automatic" implementation of a LIST-like labeling process.

Approach

Questions 34 and 35 from the LIST questionnaire ask:

34. Is the vegetation indication of the pixel on PFC Product 1 valid for the Robertson biostage of wheat for the acquisition?

35. Is the vegetation indication of the pixel on PFC Kraus product valid for the Robertson biostage of wheat for the acquisition?

The vegetation indication mentioned in Questions 34 and 35 is the response to the LIST Questions 31 and 32, respectively (see Appendix A-1). These responses are coded evaluations of the nature of vegetation canopy indicated to the analyst by the Product 1 image (Question 31) and the Kraus product image (Question 32).

Abotteen and Pore describe a rule for answering Questions 34 and 35 based on the analyst response to Questions 31 and 32. They combined Question 31 with 32 and Question 34 with 35, but their report is not clear as to how this combination was done. Because of this ambiguity, the implementation described here answers Questions 34 and 35 separately.

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The vegetation canopy indication code used by Abotteen and Pore in Questions 31 and 32 is slightly different from the code used by the analysts in this study. Abotteen and Pore use code 0 to indicate "no vegetation canopy," whereas this study used code 0 to indicate "indeterminate," and code -1 to indicate "no vegetation canopy." This is accounted for here by assuming analyst responses -1 and 0 to both be equivalent to code 0 of Abotteen and Pore.

Except for minor modifications mentioned, our computer implementation of Questions 34 and 35 followed Abotteen and Pore exactly*:

> ...Figure A-10 describes the automation technique. It is a chart of the Robertson biostage on the horizontal axis versus the vegetation canopy (Question 31/32) on the vertical axis. ...For each acquisition, a point is located in Figure A-10 with the horizontal axis coordinate corresponding to the Robertson biostage for wheat for the acquisition and the vertical axis coordinate corresponding to the answer (for a given pixel) to Question 31/32. If the point is in the blank or the dotted area, Question 34/35 is automatically answered with a yes. If the point is in the shaded (barred) area, the answer is no (for that pixel and acquisition). Vertical borders belong to the class on the left. [4]

Question 39 from the LIST questionnaire asks:

39. Does pixel follow a small grains spectral development pattern?

Again referring to Figure A-10, Abotteen and Pore suggest the following rule for answering the question:

> Question 39 is answered with a yes if the points corresponding to the four acquisitions are all in the blank or dotted regions [with] at least two in the blank region. ...Hence, the dotted region in Figure A-10...is used as a different designation from the blank region...for answering Question 39 only. [4]

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* The inset material is taken directly from [4] except that figures numbers are adapted to this report.

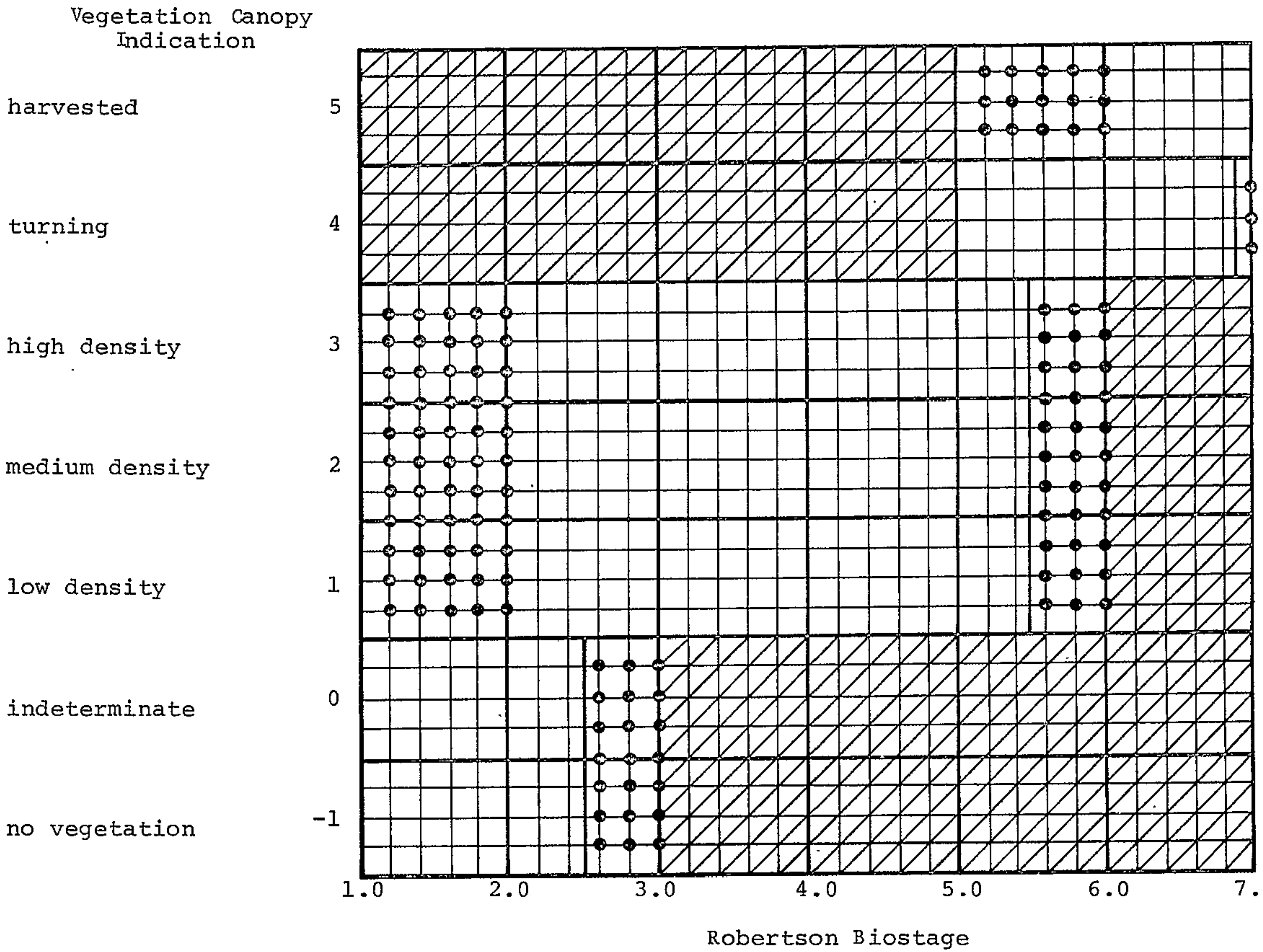

Figure A-10. Expected Vegetation Canopy as a Function of Robertson Biostage.

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An alternative rule for answering Question 39 is discussed later.

The computed results corresponding to Questions 34, 35, and 39 depend directly on the analyst responses to Questions 31 and 32 (i.e., on the perceived vegetation canopy indication). This dependence poses problems when further automation of the process is considered. Also, since the answers to Questions 31 and 32 depend on the analyst's subjective interpretation of the imagery, they are not necessarily consistent from analyst to analyst.

LIST Question 37 asks:

37. Is the green number of the pixel within the range for small grains?

Abotteen and Pore suggest that a green number grand mean and standard deviation for small grains be used at each Robertson biostage to determine a standard range for small grains. Our implementation of this idea answers Question 37 "yes" if the green number lies within one grand standard deviation of the mean; the response is "indeterminate" if the green number lies between one and two grand deviations from the mean and "no" if two standard deviations or beyond. But if an overall green number mean and standard deviation must be calculated, what samples should be used for the calculation? Abotteen and Pore used 34 unspecified LACIE segments to calculate a green number mean and standard deviation for all winter small grains and spring small grains. However, one might expect that more accuracy would be obtained if separate green number means and standard deviations were used for spring and/or winter small grains in certain geographical areas (such as universal strata).

Abotteen and Pore introduce what they term the PCG (Principal Component Greenness) statistic as another feature for separating small grains from non-small grains. It is calculated by taking the inner product of the first greenness image eigenvector (see Abotteen [7]) with the green number vector for the pixel under consideration. (The green number vector for a pixel is defined by $\overline{G} = [g_1, g_2, g_3, g_4]^T$, where g_i is the green number for the pixel at the ith acquisition.)

The first greenness image eigenvector plotted versus Robertson biostage has a shape similar to an "ideal" small grains temporal trajectory. The PCG statistic is therefore an appropriate feature to use in answering LIST Question 38:

38. Does the trajectory plot of this pixel match a small grains trajectory plot?

This PCG statistic is, however, influenced by the size of the elements of the green number vector. For example, given $\overline{G} = [24, 45, 10, 43]^T$ and the first greenness image eigenvector = $[.59, .69, .53, -.25]^T$, the PCG statistic is 39.8, a rather large value; however, the green numbers definitely do not follow a typical small grains temporal trajectory, and the ground truth label for this pixel is "non-small grains." Because of this problem it was decided to normalize the PCG statistic by dividing by the 2-norm of the green number vector and multiplying by 40 (to maintain a convenient magnitude). See Table A-14 for further examples. This normalization does not always reduce the PCG statistic for non-small grain pixels (and vice versa), but it does guarantee that the PCG statistic is uninfluenced by green number size and is thus a measure of trend only. The implementation described herein uses the normalized PCG statistic.

Table A-14. Comparison of Unnormalized and Normalized PCG Statistic.

$\overline{G}$	Unnormalized PCG Statistic	Normalized PCG Statistic	Ground Truth
$[24, 45, 10, 43]^T$	39.8	23.6	Non-Small Grains
$[2, 11, 6, 1]^T$	11.7	36.8	Winter Wheat
$[4, 6, 6, 4]^T$	8.7	34.0	Winter Wheat
$[4, 18, 24, 13]^T$	32.6	39.2	Winter Wheat
$[3, 17, 18, 12]^T$	20.0	29.0	Non-Small Grains

Abotteen and Pore used four acquisitions each of seven unspecified winter small grains LACIE segments acquired in the 1976 crop year to calculate the components of the first greenness image eigenvector for various Robertson biostages. Six unspecified LACIE segments were used in the calculation for spring small grains. As with the calculation of green number mean and standard deviation, we speculate, based on analyst experience, that more accuracy might be obtained if separate calculations were performed for differing geographical areas.

Another problem with the implementation of Question 38 is related to how large the normalized PCG statistic should be before the answer is given as "yes." As discussed in the next section, a threshold value near 25 seems to be appropriate for the LACIE segments considered; but it is not known whether this value would be universally applicable.

Discussed earlier was the Abotteen and Pore rule for answering LIST Question 39:

39. Does pixel follow a small grains spectral development pattern?

An alternative rule can easily be devised based on the computed response to Questions 37 and 38: Answer Question 39 "yes" if the answer to Question 38 is "yes" and Question 37 is answered "yes" or "indeterminate" for all acquisitions, or Question 37 is "no" for only one acquisition and "yes" for the three remaining acquisitions. Both rules were implemented.

Experimental Results.

LIST Questions 34, 35, 37, 38 and 39 were implemented using a simple FORTRAN program. The program was run on the seven 1976 LACIE segments in Kansas which had been labeled earlier by three analysts. The rule for answering Question 39 based on Questions 37 and 38 was used for the evaluation discussed here. The other rule (based on 34 and 35) would really only evaluate the analyst responses to Questions 31 and 32.

The Abotteen and Pore values for the first greenness image eigenvector and for green number mean and standard deviation were used. Green number means and standard deviations were also calculated based on the seven LACIE segments considered, but use of those means and standard deviations did not significantly affect the labeling results. Of course, when the green number means and standard deviations are calculated from only the segment being labeled, the accuracy is increased (e.g., segment 1960 accuracy was increased from 87.9% to 94.8%); but that's cheating, since this would be testing accuracy on the training segment.

A convenient method by which to evaluate the effectiveness of the implementation is to interpret a positive response to Question 39 as labeling the pixel "wheat" (or "small grains") and a negative response as labeling the pixel "nonwheat" (or "non-small grains"), and to compute the resulting accuracy based on ground truth. Table A-15 lists the labeling accuracies obtained using the computed answers to LIST Question 39 and compares this to the accuracies obtained by the three analysts. The mean accuracy for the computer labeling was higher than that for any one analyst. Also, the standard deviation of the computer labeling accuracy was somewhat lower than every analyst standard deviation. Further, looking at each individual segment accuracy, the computer "won" eleven times while the analysts "won" ten times. Thus the computer labeling, based solely on green numbers, was consistently at least as accurate as labeling by analysts who had access to much more information than just green numbers.

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Table A-15. Comparison of Analyst and Computer Labeling Accuracies.

Segment	Labeling Accuracies (%)			
	Analyst			Computer Threshold = 25
	A1	A2	A3	
1163	84.5	87.9	76.9	91.2
1165	98.4	100	79.7	95.3
1852	89.7	92.4	89.4	84.8
1855	59.4	82.8	82.8	78.1
1857	85.2	78.7	78.5	77.0
1860	65.5	62.1	66.1	87.9
1865	82.4	85.3	69.4	89.0
mean	80.7	84.2	77.5	86.2
std. dev.	13.6	11.9	7.9	6.7

The results in Table A-15 were obtained using a threshold of 25 in answering Question 38 (and thus Question 39). Thresholds of 20 and 30 were also tried. The threshold of 25 was chosen, not because it gave a significantly more accurate labeling in the sense of correctly labeled pixels versus the total number of pixels (which it didn't), but because it tended to give a more accurate estimate of the total number of small grain pixels in the segment.

Discussion and Conclusions.

In Section 2.1, we demonstrated the impact of Questions 31, 32 and 34 through 38 on the results of the LIST process. These questions direct the AI to a close scrutiny of the spectral response of pixels already determined to be vegetation. They attempt to provide the AI with objective evidence on which to base the crucial decision at Question 39 which, for all practical purposes, implements the discrimination between small grains and non-small grains. Available experimental results suggest the following conclusions:

1. Given the vegetation canopy indication (AI response to Questions 31 and 32) and the Robertson biostage (Question 16) it is possible to "compute" (essentially by table look-up) the response to Questions 34 and 35 (valid vegetation canopy indication). Furthermore, the response to Question 39 can be computed based on the outcome of Questions 31, 32, 34 and 35.

2. The decisions called for in Questions 37 (green number for small grains) and 38 (small grains trajectory plot) are quantifiable provided that the necessary statistics are available and invariant over time and location. The response to Question 39 can then be computed based on Questions 37 and 38. Our experimental results support the possibility of obtaining the necessary statistics. Labeling results based on only the normalized inner product of the green number (temporal) vector and the first greenness image eigenvector rivaled those obtained by AIs using the complete LIST process.

The latter conclusion is particularly important because it suggests that the small grains/non-small grains determination can be made by machine computation just as accurately and much more efficiently than by the AI using the LIST questionnaire. This could be used to advantage to greatly reduce the tedium of the AIs task, although the AI may still be employed to monitor the results for anomalous cases and, as necessary, to discriminate wheat from other small grains.

Since the computations involved in this automated decision process are very simple, one could easily conceive of applying them to the entire segment. A map of the results (e.g., a PFC image), possibly a color-coded rendering of the normalized inner product of green number vector and greenness image eigenvector, would likely be of great assistance to the AI in the labeling process.

3. SUMMARY AND RECOMMENDATIONS

The LIST method for labeling training data (in lieu of ground observations) represents a workable approach, though it is generally recognized that substantial improvements are needed and possible. In particular, more effective use can be made of the analyst-interpreter by making the questionnaire shorter and less tedious to apply. Some of the questions need to be made more objective and additional quantitative aids should be provided to the AI. A temporal greenness trajectory function has been proposed and, in this study, shown to provide a means of objectively discriminating between the categories "small grains" and "non-small grains." Experimental results obtained by Lockheed Electronics Corp. and LARS suggest that it may be feasible to automate this discrimination.

It should be pointed out, however, that the LIST process calls for data from strategically timed acquisitions of the multispectral data, and the data base used in this study was selected to meet this requirement. The impact of poorly timed or missing acquisitions has not been assessed, but it is likely to be significant. Further research is required to find ways of minimizing this impact.

Finally, we note that the LIST process is, after all, a method for unsupervised classification--classification of the primary remote sensing data without benefit of "ground truth" for definition of training samples. As such it cannot be as powerful for achieving accurate discrimination as a supervised method would be (the latter makes more definitive associations between information classes and corresponding regions of the measurement space). This must be kept in mind as efforts are made to extend the approach in the direction of increasingly difficult discriminations. It may eventually become necessary to consider alternative strategies employing more direct information about the ground scene (such as aerial photography), thereby reintroducing a greater degree of supervision in the classifier training process. The alternative is to continue the search for highly characteristic and invariant spectral/spatial/temporal features or "signatures." The inherent variability ("noisiness") of the natural scene makes progress in this direction increasingly difficult.

4. ACKNOWLEDGEMENTS

The author wishes to express his appreciation to the LARS staff members who made substantial contributions to this investigation and final report on Task 2.2a: Barbara Davis, who was initially project manager until her departure at mid-year, Carol de Branges, Edward Crabill, Marwan Muasher, Donna Scholz and James Tilton. The reader will thank Julie Hanover for her patience and care in typing the report. Susan Ferringer drafted the figures.

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Appendix A-1

List Experiment Questions [4]

1. Segment #

2. Partition #

3. Segment Type
(winter wheat, spring wheat, mixed wheat)

4. Country

5. State

6. County

Segment Questions from Imagery

7. Is there any agricultural land present in this segment?
(Check full frame, multitemporal imagery, maps and previous year's imagery).
Yes: Go to 8
No: Stop

8. List the interpretable acquisition dates in the space provided (YDDD).

9. Acquisition date chosen by analyst as registration date is ___________.
Indicate (a) YDDD and (b) biowindow. (This is not necessarily the Goddard reference segment.)

10. Is the segment representative of the general area? (Check full frame and ancillary data)
Yes
Indeterminate
No

11. Are there strip fields in the cultivated area?
Yes
No

Cropping Practices

12. Are wheat and/or other small grains continuously cropped in this area?
Yes
Indeterminate
No

13. Is fallowing practiced in this area?
    Yes
    Indeterminate
    No

14. Are the small grains irrigated in this area?
    Yes
    Indeterminate
    No

15. Determination of potential confusion:

    a. List the most recent percent of county area occupied by each of the applicable major crops.

    b. Using the nominal crop calendar, determine the possibility of confusion between wheat (winter and/or spring) and the other major crops for each acquisition.

       +1 = No confusion
       0 = Indeterminate
       -1 = Confusion

Met Data

16. Robertson biostage for the segment for each acquisition is ___________.

17. Total precipitation (in inches) for the week prior to each acquisition as provided in the weekly meteorological summary is __________________.

18. Total precipitation (in inches) for the 3 days prior to each acquisition is _______________.

19. Is there evidence of drought conditions (from met summary)?

20. Is there evidence of winter kill (from met summary)?
    Yes
    Indeterminate
    No

21. Is there evidence of a late freeze (from met summary)?
    Yes
    Indeterminate
    No

22. Is there evidence of hail damage (from met summary)?
    Yes
    Indeterminate
    No

23. Is there evidence of insects or disease (from met summary)?
    Yes
    Indeterminate
    No

24. Expected normal yield for this segment is _______________.

25. Evaluation of crop condition for each acquisition is _______________.

    2 = Significantly above normal
    1 = Above normal
    0 = Near normal
    -1 = Below normal
    -2 = Significantly below normal
    ****
    Delineate "DO" areas. (Area must apply to all acquisitions.)
    Delineate "DU" areas where applicable.
    ****

Pixel Specific Questions

26. Is pixel a DO'd pixel?
    Yes: Non-ag STOP
    No: Go to 27

27. Is pixel a DU'd pixel?
    Yes: STOP
    No: Go to 28

28. Is pixel registered with regard to analyst_chosen registration date?
    Yes
    Indeterminate: Do not answer questions 36, 37, 38 for this acquisition.
    No: Do not answer questions 36, 37, 38 for this acquisition
    Go to 29

29. Is pixel a mixed pixel (part of more than one field or boundary)?
    Yes
    Indeterminate
    No
    Go to 30

30. Is this an anomalous pixel (not representative of most of the other pixels within the field)?
    Yes
    No
    Go to 31

31. PFC vegetation canopy indication is ____________. (Product 1)

    -1 = No vegetation canopy
     0 = Indeterminate
     1 = Low density green vegetation canopy
     2 = Medium density green vegetation canopy
     3 = High density vegetation canopy
     4 = Senescing (turning) vegetation canopy
     5 = Harvested canopy (stubble)

32. PFC vegetation indication is __________. (Kraus product)
    Same code as # 31. If -1 on 31 and 32 then go to 33. Otherwise go to 34.

33. Is pixel a non-ag pixel? (Check all available data.)
    Yes: Non-ag STOP
    No: Fallow STOP

34. Is the vegetation indication of the pixel on PFC Product 1 valid for the Robertson biostage of wheat for the acquisition? (Check keys for partition.)
    Yes
    Indeterminable
    No

35. Is the vegetation indication of the pixel on PFC Kraus product valid for the Robertson biostage of wheat for the acquisition?
    Yes
    Indeterminable
    No

36. Green number of pixel is ____________. (Refer to question 28. Correct the number to 60° latitude if appropriate.)

37. Is the green number of the pixel within the range for small grains? (Check green number/biostage chart.)
    Yes
    Indeterminable
    No

38. Does the trajectory plot of this pixel match a small grains trajectory plot? (Answer for fourth acquisition only.)
    Yes
    Indeterminable
    No

39. Does pixel follow a small grains spectral development pattern?
    Yes: Go to 40
    No: Go to 42

40. Does crop statistical data indicate wheat is the only small grain in this area?
    Yes: Go to 41
    No: Go to 45

41. Does all available data indicate wheat is the only small grain in this area?
    Yes: Wheat Go to 52
    No: Go to 45

42. Does crop statistical data indicate significant occurrence of other crop types?
    Yes: Go to 43
    No: Go to 44

43. If more than one non-small grain spectral signature is observed, do the proportions of the signatures correspond to the historical non-small grain percentages?
    Yes: Non-small grains STOP
    Indeterminate
    No: Go to 44

44. Do ancillary and met data indicate that the departure of the observed spectral signature from an expected normal small grains spectral signature could be due to an abnormal small grains signature development?
    Yes: Go to 39 and re-evaluate
    No: Non-wheat STOP

45. Does the nominal crop calendar indicate an out-of-phase relationship between wheat and other confusion small grains?
    Yes: Go to 46
    No: Small grains STOP

46. Can subclasses of small grains be identified on PFC products or spectral plots as early, medium, or late developing?
    Yes: Go to 47
    No: Small grains STOP

47. Does the stage of development of any of these subclasses correspond to the indicated stage of development for the out-of-phase confusion small grain/s?
    Yes: Go to 48
    No: Small grains STOP

48. Do the proportional distributions of the small grain subclasses correspond to the historical percentage of confusion small grains?
    Yes: Wheat Go to 52
    No: Go to 49

49. Is the proportional distribution of the small grains subclass consistent with the historical percentage of wheat?
    Yes: Go to 50
    No: Small grains STOP

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50. Is the small grains subclass a relatively pure wheat class?
    Yes: Go to 51
    No: Small grains STOP

51. Does the pixel belong to the above mentioned subclass?
    Yes: Wheat Go to 52
    No: Small grains STOP

52. Analyst estimate of pixel's growth stage is ______________.

Appendix A-2
Revised List Experiment Questions

1. Segment #

2. Partition #

3. Segment Type
   (winter wheat, spring wheat, mixed wheat)

4. Country

5. State

6. County

Segment Questions from Imagery

7. Is there any agricultural land present in this segment?
   (Check full frame, multitemporal imagery, maps and previous year's imagery.)
   Yes: Go to 8
   No: Stop

8. List the interpretable acquisition dates in the space provided (YDDD).

9. Acquisition date chosen by analyst as registration date is ____________.
   Indicate (a) YDDD and (b) biowindow. (This is not necessarily the Goddard reference segment),

10. Is the segment representative of the general area? (Check full frame and ancillary data).
    Yes
    Indeterminate
    No

11. Are there strip fields in the cultivated area?
    Yes
    No

Cropping Practices

12. Are wheat and/or other small grains continuously cropped in this area?
    Yes
    Indeterminate
    No

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13. Is fallowing practiced in this area?
    Yes
    Indeterminate
    No

14. Are the small grains irrigated in this area?
    Yes
    Indeterminate
    No

15. Determination of potential confusion:

    a. List the most recent percent of county area occupied by each of the applicable major crops.

    b. Using the nominal crop calendar, determine the possibility of confusion between wheat (winter and/or spring) and the other major crops for each acquisition.

       +1 = No confusion
       0 = Indeterminate
       -1 = Confusion

Met Data

16. Robertson biostage for the segment for each acquisition is ___________.

17. Total precipitation (in inches) for the week prior to each acquisition as provided in the weekly meteorological summary is ___________

18. Expected normal yield for this segment is ___________________________

19. Evaluation of crop condition for each acquisition is (check met summary) _______________.

    2 = Significantly above normal
    1 = Above normal
    0 = Near Normal
    -1 = Below normal
    -2 = Significantly below normal

Pixel Specific Questions

20. Is pixel a DO'd pixel?
    Yes: DO STOP
    No: Go to 21

21. Is pixel a DU'd pixel?
    Yes: DU STOP
    No: Go to 22

22. Is pixel registered with regard to analyst chosen registration date?
Yes: Go to 23
Indeterminate: STOP
No: STOP

23. Is pixel a mixed pixel (part of more than one field or boundary)?
Yes (on all 4): Edge STOP
Indeterminate: Go to 24
No: Go to 24

24. Green number of pixel is ______________.

25. Is this an anomalous pixel (not representative of most of the other pixels within the field)?
Yes
No
Go to 26

26. PFC vegetation canopy indication is ______________. (Product 1)

-1 = No vegetation canopy
0 = Indeterminate
1 = Low density green vegetation canopy
2 = Medium density green vegetation canopy
3 = High density vegetation canopy
4 = Senescing (turning) vegetation canopy
5 = Harvested canopy (stubble)

27. PFC vegetation indication is ____________. (Kraus Product)
Same code as 26. If all available data indicates no vegetation, go to 28. Otherwise, go to 30.

28. Is pixel a non-ag pixel? (Check all available data.)
Yes: Non-Ag STOP
No: Go to 29

29. Is Question 13 affirmative?
Yes: Fallow STOP
No: Non-small grain STOP

30. Is the vegetation indication of the pixel on PFC product 1 valid for the Robertson biostage of wheat for the acquisition? (Check keys for partition.)
Yes
Indeterminate
No

31. Is the vegetation indication of the pixel on PFC Kraus product valid for the Robertson biostage of wheat for the acquisition?
Yes
Indeterminate
No

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32. Is the green number of the pixel within the range for small grains? (Check green number/biostage chart.)
    Yes
    Indeterminate
    No

33. Does the trajectory plot of this pixel match a small grains trajectory plot? (Answer for fourth acquisition only.)
    Yes
    Indeterminate
    No

34. Does all available data indicate pixel follows a small grains development pattern?
    Yes: Go to 37
    No: Go to 35

35. Is Question 25 affirmative?
    Yes: Go to 36
    No: Go to 38

36. Does field around pixel follow a small grain development pattern? (Check available data.)
    Yes: Go to 37
    No: Go to 38

37. Does all available data indicate wheat is the only small grain in this area?
    Yes: Wheat Go to 47
    No: Go to 40

38. Does crop statistical data indicate significant occurrence of other crop types?
    Yes: Non-small grain STOP
    No: Go to 39

39. Do ancillary and met data indicate that the departure of the observed spectral signature from an expected normal small grains spectral signature could be due to an abnormal small grains signature development?
    Yes: Go to 34 and re-evaluate
    No: Non-wheat STOP

40. Does the nominal crop calendar indicate an out-of-phase relationship between wheat and other confusion small grains?
    Yes: Go to 41
    Indeterminate: Small grains STOP

41. Can subclasses of small grains be identified on PFC products or spectral plots as early, medium, or late developing?
    Yes: Go to 42
    No: Small grains STOP

42. Does the stage of development of any of these subclasses correspond to the indicated stage of development for the out-of-phase confusion small grains?
    Yes: Go to 43
    No: Small grains STOP

43. Do the proportional distributions of the small grain subclasses correspond to the historical percentage of confusion small grains?
    Yes: Wheat Go to 47
    No: Go to 44

44. Is the proportional distribution of the small grains subclass consistent with the historical percentage of wheat?
    Yes: Go to 45
    No: Small grains STOP

45. Is the small grains subclass a relatively pure wheat class?
    Yes: Go to 46
    No: Small grains STOP

46. Does the pixel belong to the above mentioned subclass?
    Yes: Wheat Go to 47
    No: Small grains STOP

47. Analyst estimate of pixel growth stage is ______________.

B. Application and Evaluation of Landsat Training, Classification, and Area Estimation Procedures for Crop Inventory*

The need for accurate and timely crop production information on a global basis is increasing each year as the world's growing population increases the demand for food. In mid-1972, the world food situation changed as production declined for the first time in many years at a time of rapidly increasing demand. The importance of crop production information has been recently highlighted by severe drought in the Soviet Union causing large purchases of wheat and increased grain exports by the U.S. to all parts of the world.

Considerable evidence has developed that multispectral remote sensing from satellites combined with computer-aided data analysis can provide the data necessary for upgrading our capability to monitor and inventory the world's croplands. The first milestone in the development of the technology was collection in 1964 of multispectral photography for the first time over agricultural fields and recognition of the potential of the multispectral approach for crop identification [4]. In 1967 a crop classification was made of multispectral scanner data using pattern recognition methods implemented on a digital computer [5]. The Corn Blight Watch Experiment, conducted in 1971 over seven Corn Belt States, provided a prototype remote sensing system which successfully integrated techniques of sampling, data acquisition, processing, analysis, and information dissemination in a quasi-operational system environment [10]. Multivariate pattern recognition methods implemented on a digital computer were used to classify Landsat-1 data acquired over a three-county area in northern Illinois and the area estimates obtained for corn and soybeans were within 1.5 and 1.1 percent, respectively, of those made by the U.S. Department of Agriculture [2].

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*This report, describing the work of Task 2B, Application and Evaluation of Landsat Training, Classification, and Area Estimation Procedures for Crop Inventory, was written by Marilyn Hixson.

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Based on these and other results, the Large Area Crop Inventory Experiment (LACIE) was initiated in 1974, using the remote sensing technology available at that time, to estimate wheat production at the country level [9]. In LACIE, training and classification were typically performed on each 5 x 6 nm segment of Landsat MSS data. Large area estimates for wheat were made by aggregating the proportion of wheat in the individual segments, which together represented about two percent of the total land area. Since the estimates were based on a relatively small number of segments, the sampling errors associated with estimates were quite large (more than 4% at the country level).

Since the LACIE system was designed, new information has been acquired on scene stratification, training sample selection, classification algorithms, and area estimation methods. This research task will build upon these recent developments to improve future crop inventory systems.

In particular, three classification algorithms developed at LARS, ECHO (Extraction and Classification of Homogeneous Objects), cascade classifier, and layered classifier, will be tested [6,8]. The layered and cascade classifiers are both multistage classifiers which eliminate many of the difficulties encountered with the "stacked vector" or "concatenation" approach to multitemporal analysis. ECHO can also be used in an unsupervised mode as a training aid. Past studies have investigated different sampling schemes for training and different area estimation procedures [1,7].

This investigation is divided into two phases: a preliminary study and a major study. The objectives of the major study include investigations of training area selection and training, classification, and area estimation procedures. Specific objectives are:

1. <u>Training</u>

   To evaluate and extend procedures for the training area selection including factors such as size, number, and geographic location of the training areas.

To refine procedures for obtaining class statistics from multiple training areas. Training methods include ISOCLS, multi-block clustering, and ECHO.

2. Classification

To assess the accuracy of the area estimates of corn and soybeans obtained by different classification algorithms: per point maximum likelihood, ECHO, and sum of densities.

To assess the accuracy of multitemporal classification (including LACIE Procedure 1) as compared to the unitemporal classifications.

3. Area Estimation

To compare the accuracy and precision of area estimates for corn and soybeans obtained by different estimation methods; specifically, to compare estimates obtained by classification and aggregation of a systematic sample of pixels with estimates made from a sample segment approach.

To compare methods of obtaining unbiased estimates such as stratified area estimates and the regression approach.

At the request of NASA/JSC, the implementation plan for this task was revised in mid May. This revision was to reflect the increased emphasis on Multicrop and permit the establishment of a supporting field research task. That effort, which was conducted as part of this task, is described in Volume I, Section C, of this report.

At the time this investigation was begun, data appropriate for addressing the original objectives was not available. Therefore, during the period of data acquisition, a preliminary study was conducted using currently available data. The activites of this task during the past contract year have been in three areas:

(1) Development of the experiment design and definition of data requirements for the major study. As an extension of this objective, a stratification and sampling plan for the NASA/JSC 1978 corn/soybeans data acquisition program was defined and carried out by LARS.

(2) Recommendations for reference data acquisition. Data to be acquired as inventory and periodic observations were recommended. Flightlines and dates for aerial photography acquisition were recommended.

(3) Evaluation of the training-classification procedures used in LACIE (Procedure 1) for a corn/soybeans/"other" crop identification problem and investigation of changes to improve the performance of Procedure 1 on corn and soybeans. This study has been conducted using currently available data; results will need to be confirmed when additional sample segments become available.

These three general areas of effort are addressed in this report. Section 1 describes the stratification and sample selection work conducted for the transition year experiments. The data acquisition is discussed in Section 2 and Section 3 describes the preliminary study.

1. STRATIFICATION AND SAMPLE SELECTION FOR MULTICROP EXPERIMENTS

1.1. Introduction

In February 1978, LARS was asked to participate in the stratification and sampling tasks for the transition year experiments. The project was supported by personnel and funds from two tasks of NASA Contract NAS9-15466: "Application of Statistical Pattern Recognition to Image Interpretation" and "Application and Evaluation of Landsat Training, Classification, and Area Estimation Procedures for Crop Inventory."

The purpose of this effort was to identify the locations of the sample segments for the 1978-79 Multicrop experiments to support:

- Development and evaluation of procedures for using LACIE and other technologies for the classification of corn and soybeans.
- Identification of factors likely to affect classification performance.
- Evaluation of problems encountered and techniques which are applicable to the crop estimation problem in foreign countries as well.

In order to meet these requirements, two types of samples were selected. Low density segments were distributed throughout corn and soybean producing areas to sample all variations of conditions which could affect classification accuracy and to more completely represent conditions which might be found in other countries. High density segments were selected in smaller areas to support the investigation of training, classification, and area estimation procedures on a smaller scale for possible use in future Multicrop experiments.

In this report, the data set and methods employed in the stratification are discussed. Rationale, methods, and results for both the low and high density segments are discussed.

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1.2 Objectives

In order to support the corn and soybean experiments, two types of segments were selected: low density segments and high density segments. Different issues can be addressed using each type of segment.

The low density segments were selected to cover a wide range of conditions under which areas will have to be classified in larger Multicrop efforts to allow possible problems to be examined (e.g., in algorithms, systems, data acquisition). The low density samples were located in 14 states in the U.S. corn and soybean producing areas. This region was divided into eight strata according to the level of county production of corn and soybeans and average farm size. Twenty segments per stratum were selected. The distribution of these segments permits the calculation of variability within a stratum to predict the variability of aggregated estimates of corn and soybeans in the U.S. and to determine the optimum allocation of samples for making such estimates. The allocation of these samples was not designed for, and thus does not support, making aggregated estimates.

The high density samples are located in four test sites in high production areas of the U.S. Corn Belt. Twenty segments were selected from each test site which is approximately ten counties in size. The increased density of samples permits estimation of the local variability in high production areas. These samples support the investigation of training, classification, and area estimation procedures on a smaller scale for possible use in future Multicrop experiments. Other area estimation procedures such as regression estimation can be evaluated and county level estimates can be assessed.

1.3 Data Set Description

The data used in this study were acquired by the Statistical Reporting Service of the U.S. Department of Agriculture (USDA/SRS). Two types of data were available: the USDA/SRS county estimates for 1972-76 and the 1974 agriculture census data. The data were supplied by NASA/Johnson Space Center (NASA/JSC).

The SRS dual county estimates program data for 1972-76 were available. Under the Federal program, county estimates are prepared for specified crops, states, and counties. These estimates include the major crops produced in most states. Some of the state statistical offices prepare county estimates for a few crops not required under the Federal program in cooperation with their respective state governments, but these estimates were not available on tape.

Variables which were included in the county estimates data set were: state, crop reporting district, county, year data was punched, crop year, commodity code, acres planted, acres harvested, yield per harvested acre, and production (Figure B-1). Counties from the entire United States were represented. The commodities for which information was available are listed in Table B-1.

The 1974 agriculture census data were supplied for 14 states in the U.S. corn and soybean producing regions. These data included: number of acres in each county, average farm size by county, and the land in farms for each county.

1.4 Stratification

The first step in selection of sample segments was the stratification of the area to be studied. The variables used in the stratification, the rationale and methods employed, and the results of the stratification will be discussed in this section.

Variables Used in Stratification.

The variables available were those contained in the USDA/SRS county estimates program (Figure B-1) and the selected variables from the 1974 agriculture census which were supplied by NASA/JSC. The variables which were considered for use were: acres planted, acres harvested, yield, and production for the crops listed in Table B-1; acres in a county; percent agricultural area (land in farms) in a county; and average farm size by county. From these variables, the

		ID						DATA						
CARD NO.	SURVEY CODE	STATE	DISTRICT	COUNTY	YEAR PUNCHED	CROP YEAR	COMMODITY CODE	(1) ACRES PLANTED ALL PURPOSES	(2) ACRES PLANTED FOR HARV. OR NET ACRES SEEDED OR ACRES ABANDONED	(3) ACRES HARVESTED	(4)	(5) YIELD PER HARVESTED ACRE	(6) PRODUCTION	(7) PRODUCTION (COTTON LBS OF LINT)
1	2 5	6 7	8 9	10 12	13 14	15 16	17 26	27 34	35 42	43 50	51 54	55 58	59 68	69 78

Figure B-1. Record layout of county estimates data.

Table B-1. Crops included in the USDA/SRS county estimates program.

Winter Wheat
Durum Wheat
Other Spring Wheat
Wheat, All
Rye, All
Rice, All
Corn for Grain
Corn For Silage
Oats, All
Barley, All
Sorghum, All
Cotton, All
Cotton, Upland
Cotton, American Pima
Tobacco
Flaxseed
Peanuts
Soybeans
Dry Edible Beans - Pea (Navy)
- Great Northern
- Flat Small White
- Pinto
- Red Kidney
- Pink
- Small Red
Dry Beans (All Mich.)
Dry Peas - Smooth Green Kinds, All
- Yellow and White Kinds, All
Wrinkled Peas for Seed
Lentils, All
Austrian Winter Peas
Green Peas for Processing, All
Tomatoes for Processing, All
Bush Garden Seed Beans (Idaho)

number of agricultural acres in a county was computed by multiplying the percent agricultural area by the county acreage. Normalized production of a crop for a county was computed by dividing the five-year average production of that crop by the agricultural acres in the county.

In order to fulfill the objectives, the stratification was performed using three variables: normalized production of corn, normalized production of soybeans, and average farm size. The first two variables were selected to make strata which are homogeneous with respect to the relative importance of corn and soybeans in the agricultural scene. The average farm size was selected to represent problems which might be encountered in Landsat data classifications with different field sizes.

Methods of Stratification.

The rationale for the stratification method was based upon the objective of creating eight strata in the United States corn and soybean producing regions which were relatively homogeneous with respect to the relative importance of corn and soybeans in the agricultural scene and the average farm (or field) size. These strata, then, represent several conditions under which Landsat data will have to be classified in Multicrop studies. Samples selected from these strata will be representative of conditions found throughout the corn and soybean producing regions.

The first step in the stratification was a reduction of the data set size. Only the 14 states for which the agriculture census data were supplied were considered. Counties with neither corn nor soybeans were omitted.

The joint distributions of normalized corn and soybean productions and average farm size were examined. The average farm size was represented in two groups: small farms (average size less than or equal to 190 acres) and large farms (size greater than 190 acres).

About one-third of the counties were in the small farms category and about two-thirds were in the large farms category. The division into these two groups was somewhat arbitrary although there was a break in the continuum of data at about 190 acres.

For each farm size, the normalized corn and soybean productions were displayed in deciles to look for broad clusters of data. The strata were determined by examining tables of the distributions of these variables. Three strata of small farm counties and five strata of large farm counties were selected to represent the two farm sizes approximately proportionally to the number of counties in them.

Counties which fell in the lower 10% of all counties in both corn and soybean production were omitted from consideration. Counties which fell outside the broad clusters of data were not included in any stratum. Thirteen counties satisfying all other selection criteria were outliers from the clusters and were not included. A schematic diagram (Figure B-2) shows the methodology employed in the stratification. Table B-2 gives the definitions of stratum boundaries.

Results of Stratification.

Eight strata covering 14 states in the U.S. corn and soybean producing region were determined. The counties in each of these strata are shown in Figures 3 to 10. Lists of the counties can be obtained in a complete report of this work [3].

The large farm, highest production stratum (stratum 8) is geographically located at the center of the Corn Belt. Strata 7, 6, and 4 are located around its perimeter outward according to decreased production. In these strata of large farms, corn and soybeans are of approximately equal importance.

Stratum 5 is located geographically apart from the other strata with large farms. This stratum, in which soybeans have a greater

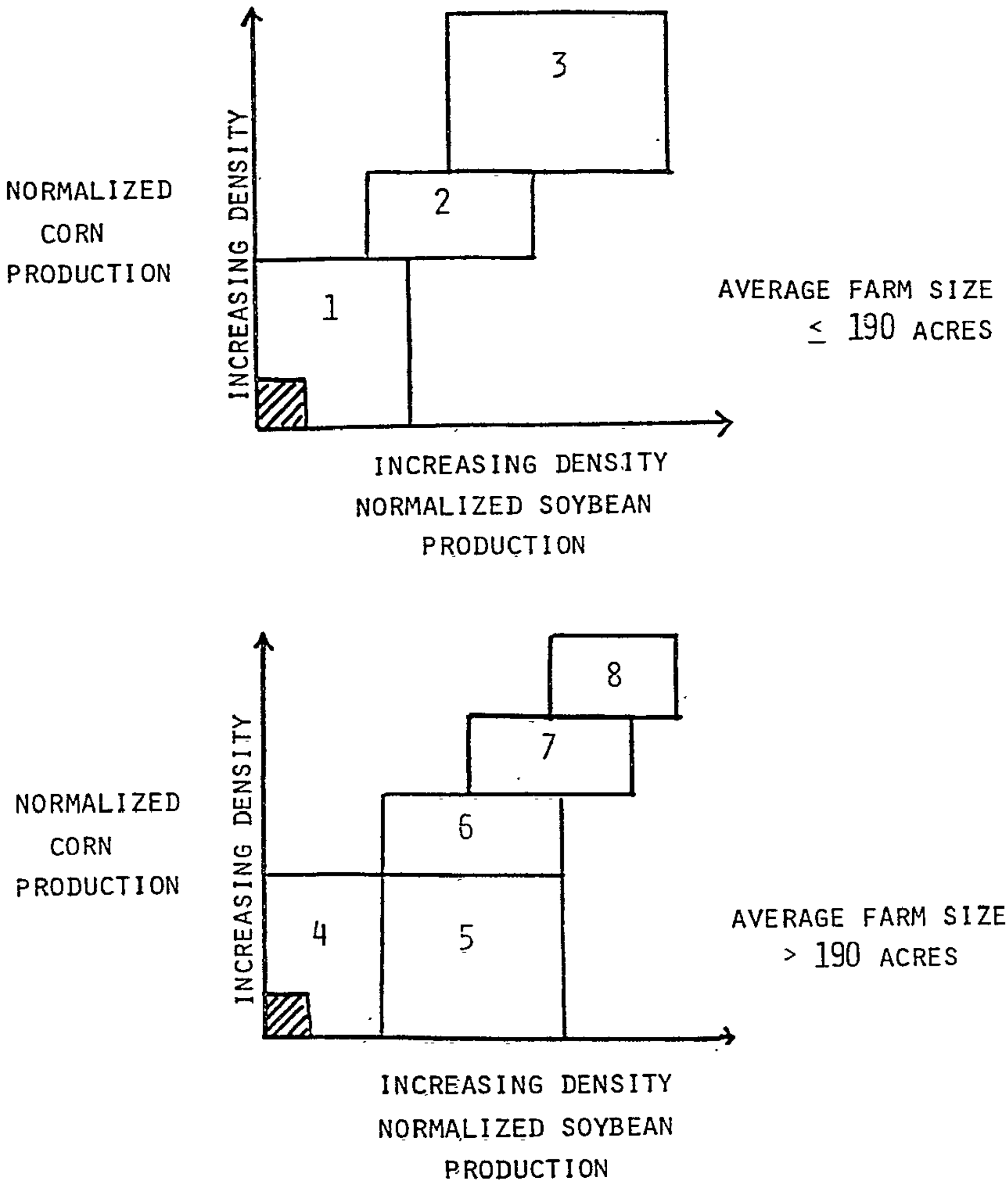

Figure B-2. Schematic diagram illustrating the determination of strata for Multicrop experiments based on normalized production of corn and soybeans and average farm size.

Table B-2. Determination of strata according to the normalized production of corn and soybeans and average farm size.

Stratum Number	Average Farm Size	Normalized Production		No. of Counties
		Corn	Soybeans	
	(acres)	(deciles)	(deciles)	
1	≤190	0-40	0-40	149
2	≤190	40-60	30-70	109
3	≤190	60-100	50-100	126
4	>190	0-40	0-30	192
5	>190	0-40	30-70	102
6	>190	40-60	30-70	126
7	>190	60-80	50-90	147
8	>190	80-100	70-100	213

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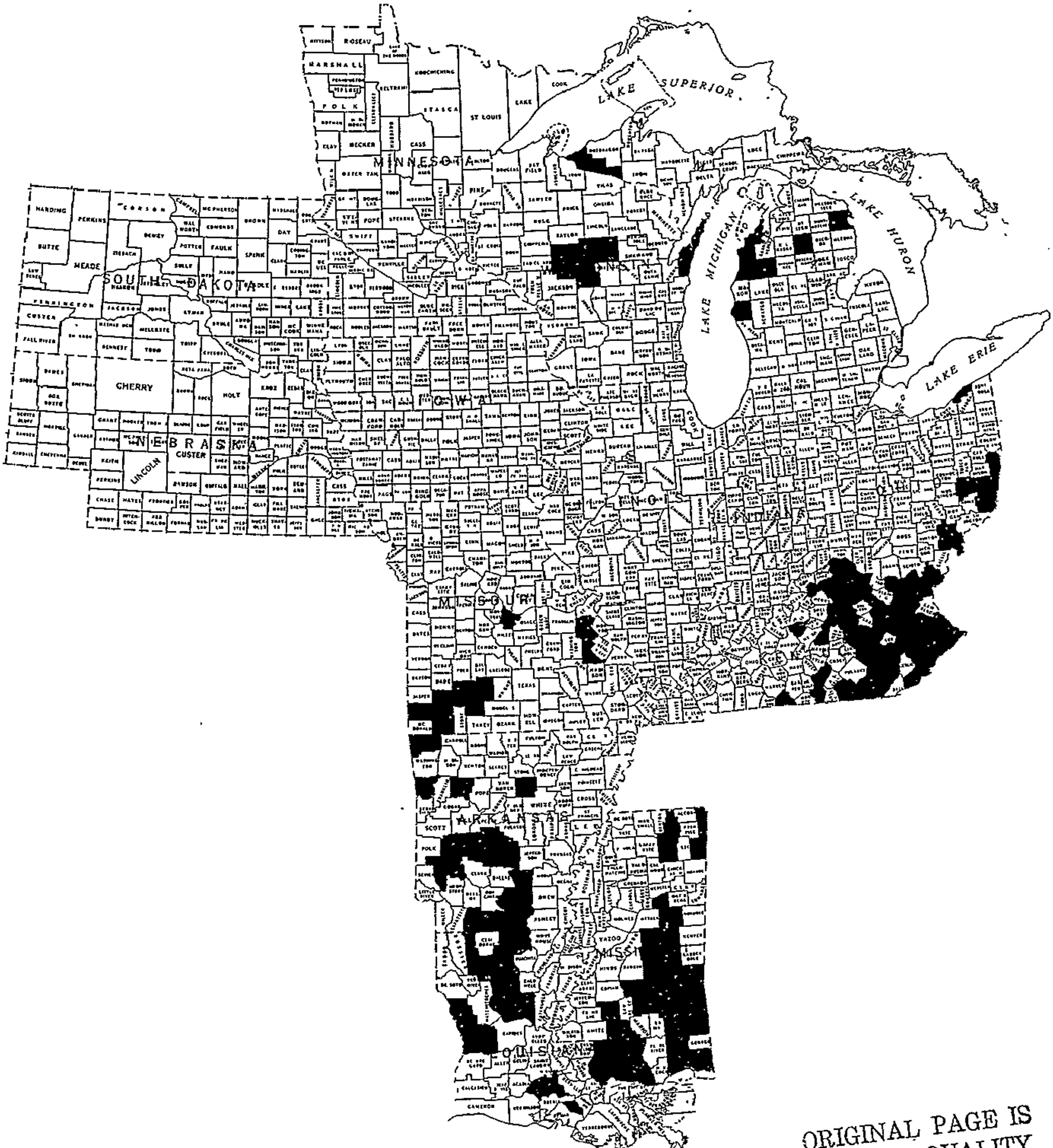

Figure B-3. Locations of counties assigned to Stratum 1, small farms, low production of corn and soybeans.

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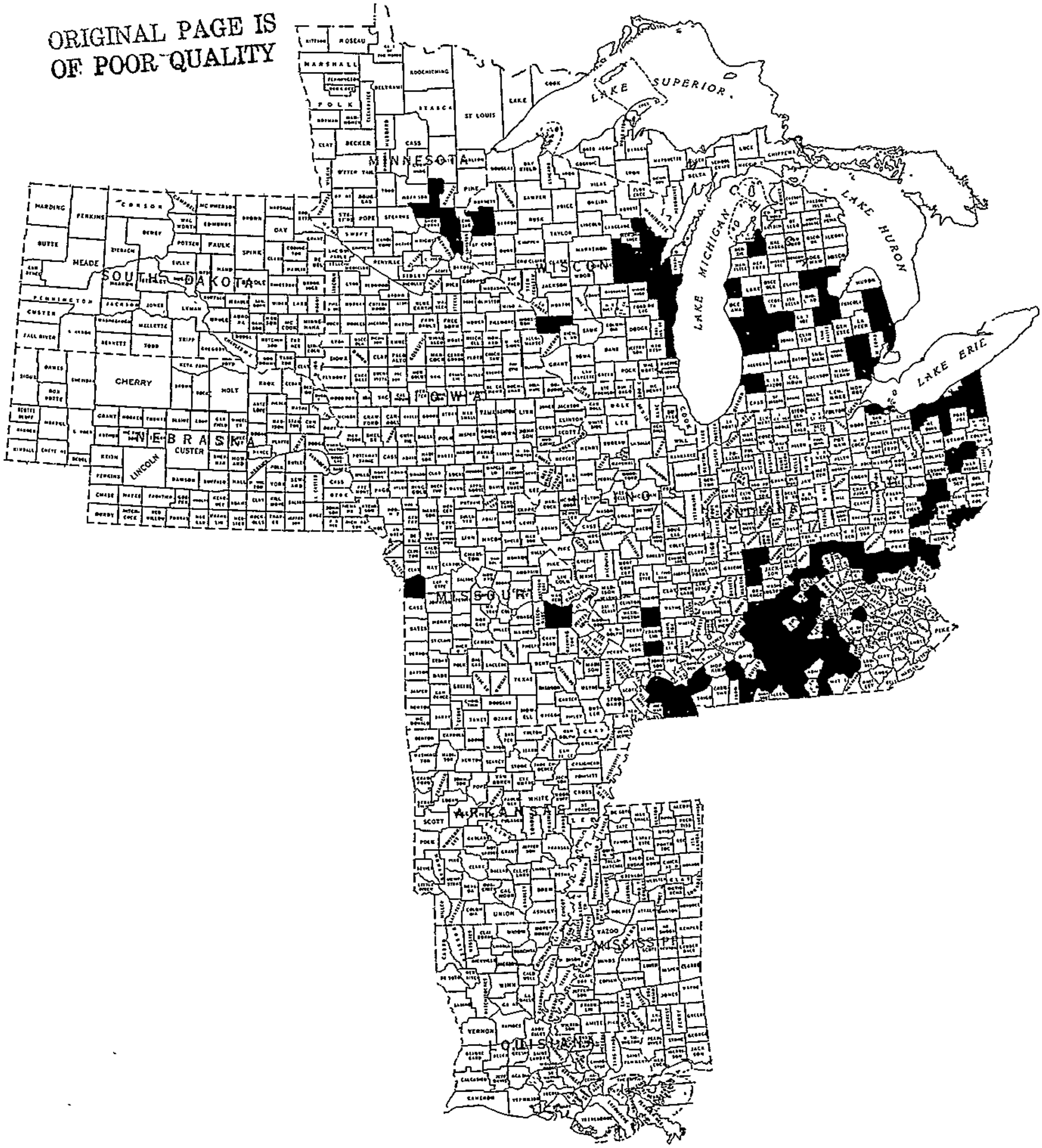

Figure B-4. Locations of counties assigned to Stratum 2, small farms, medium production of corn and soybeans.

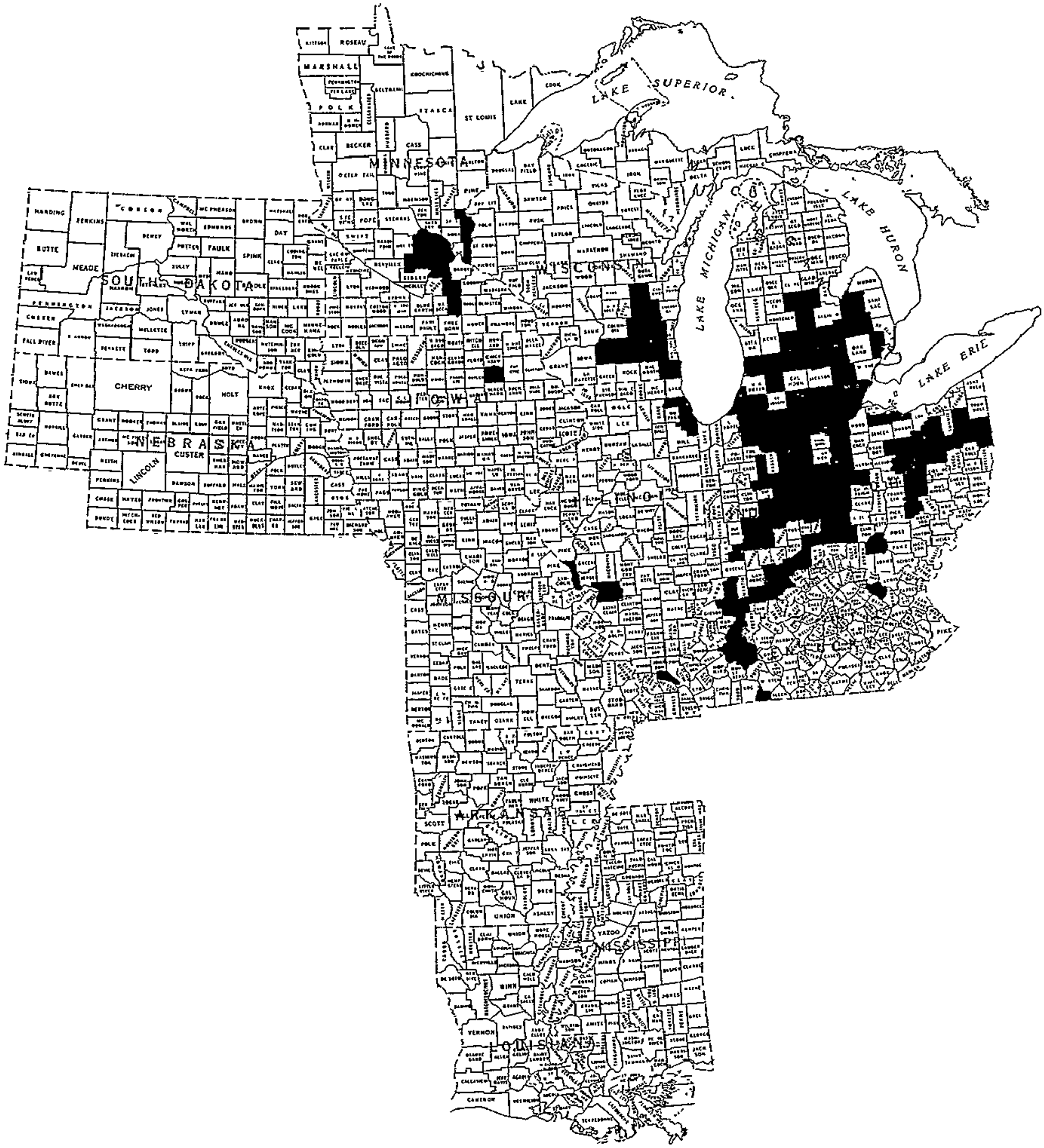

Figure B-5. Locations of counties assigned to Stratum 3, small farms, high production of corn and soybeans.

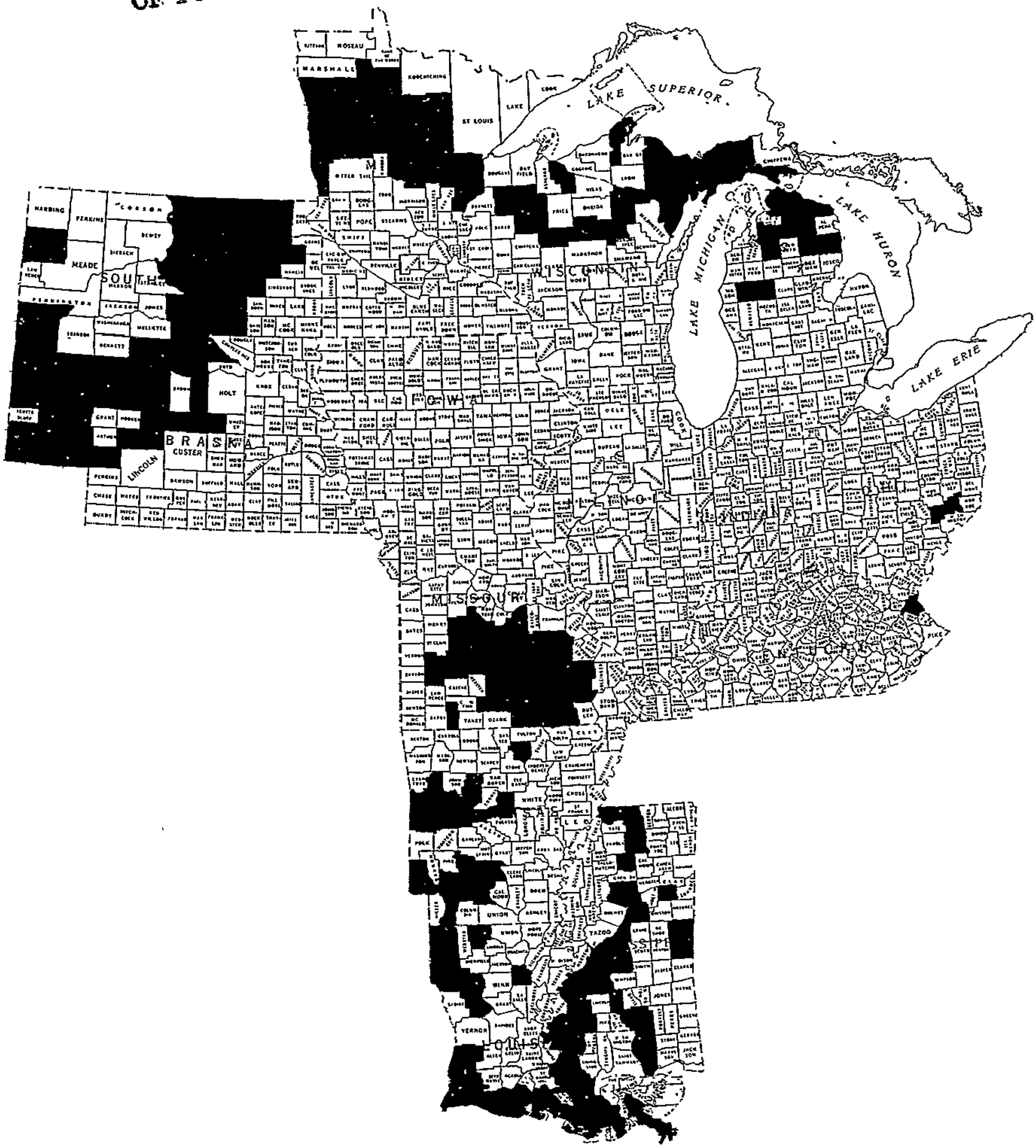

Figure B-6. Locations of counties assigned to Stratum 4, large farms, low production of corn and soybeans.

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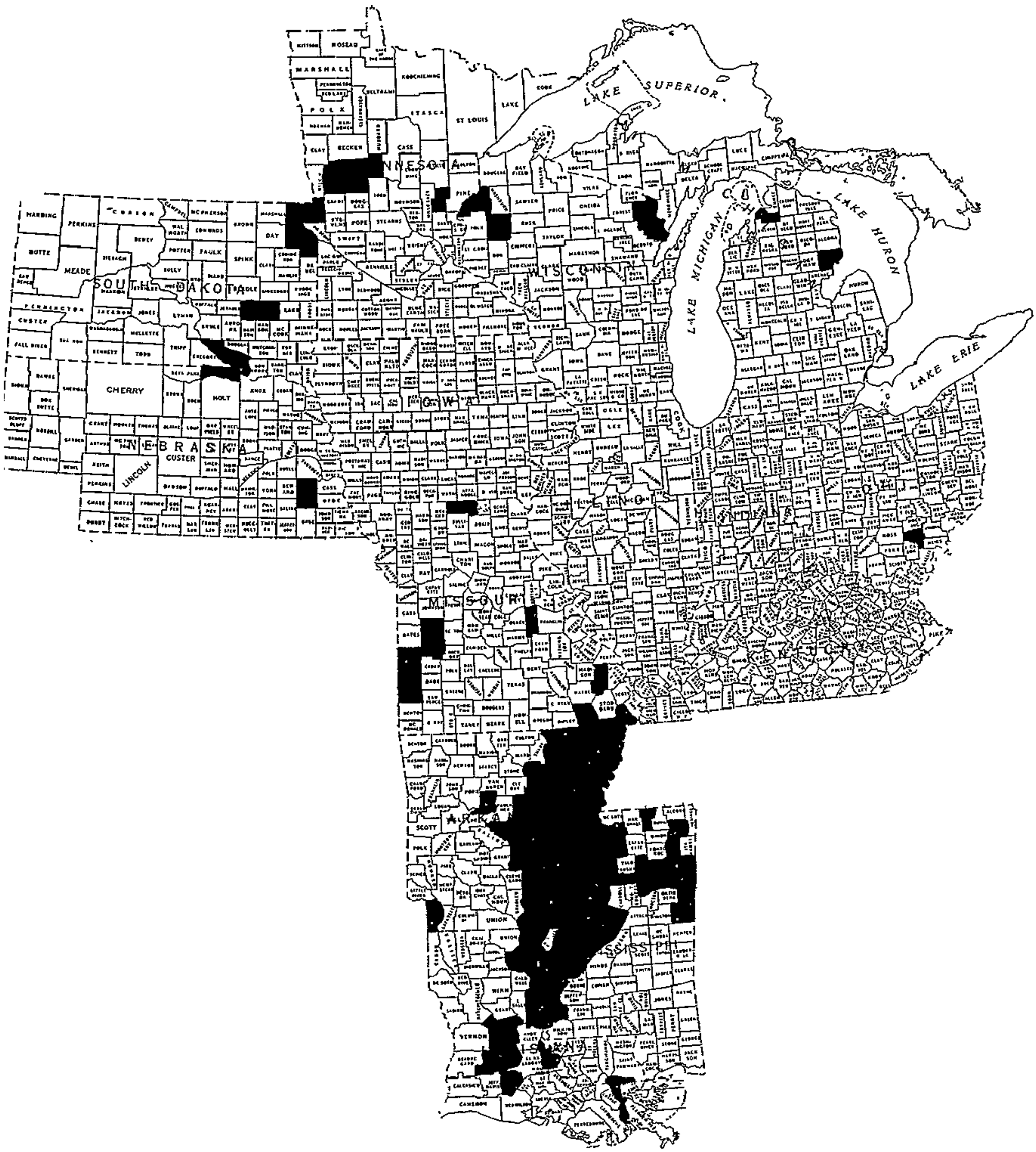

Figure B-7. Locations of counties assigned to Stratum 5, large farms, low production of corn, medium production of soybeans.

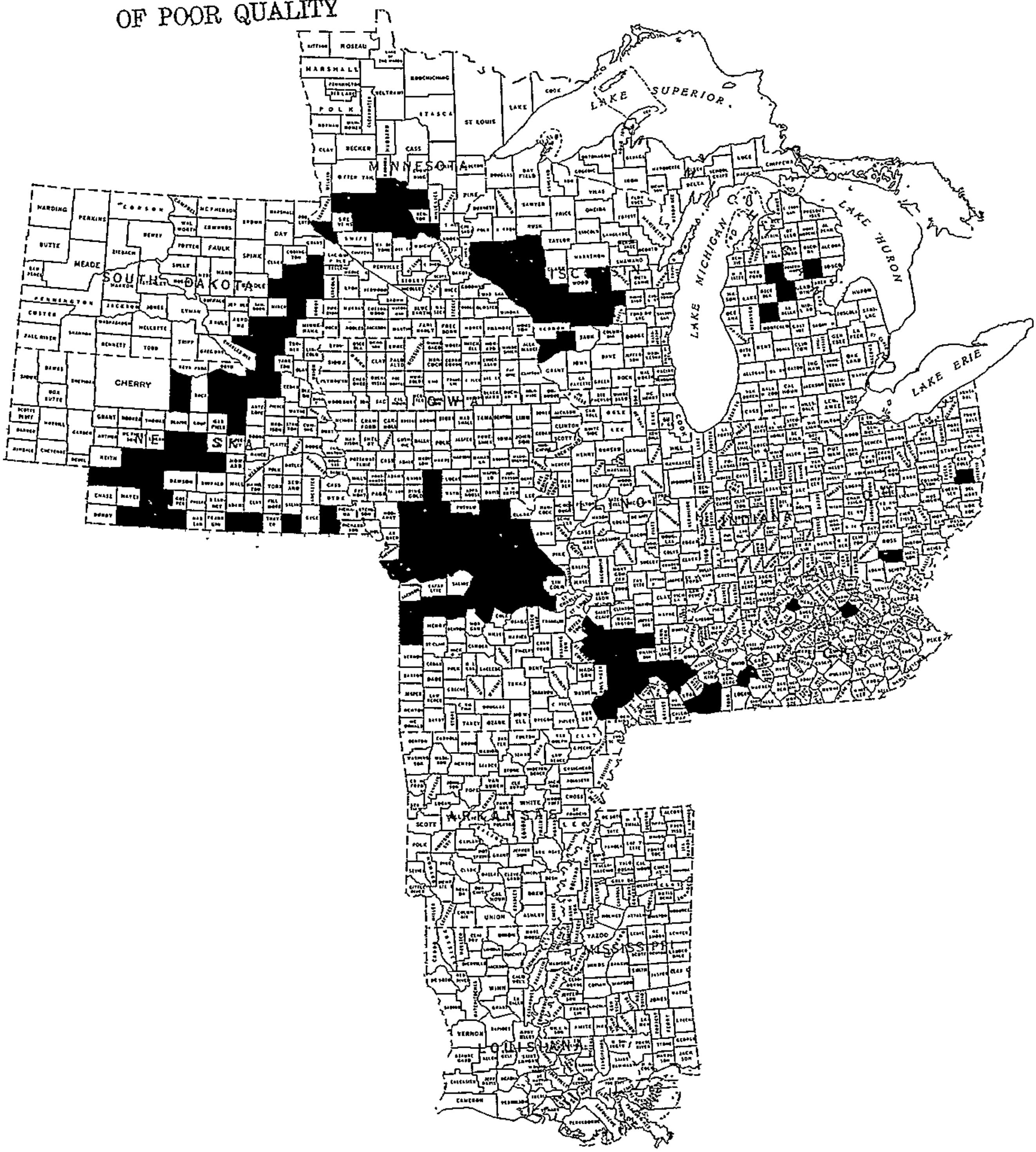

Figure B-8. Locations of counties assigned to Stratum 6, large farms, medium production of corn and soybeans.

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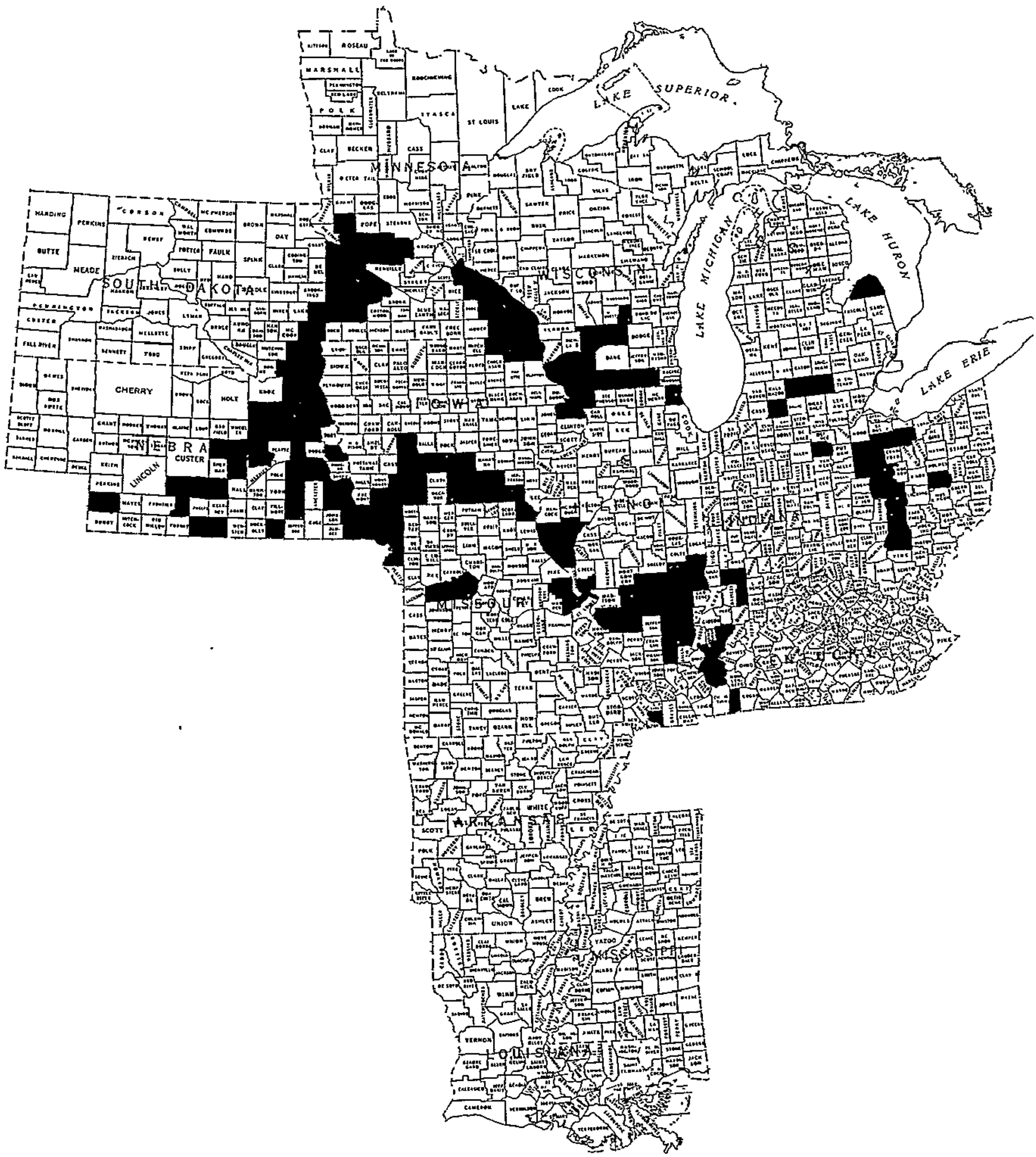

Figure B-9. Locations of counties assigned to Stratum 7, large farms, high production of corn and soybeans.

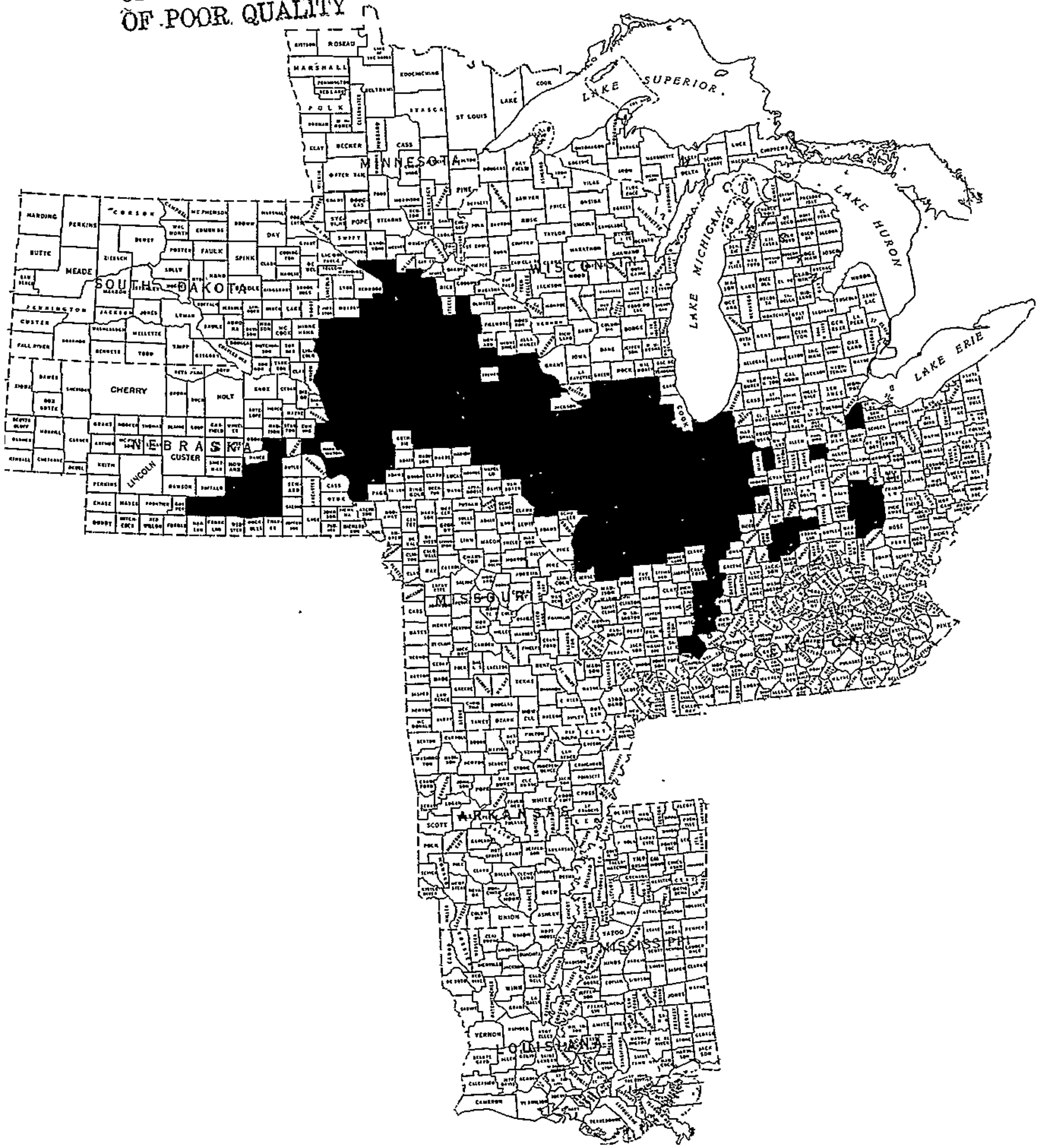

Figure B-10. Locations of counties assigned to Stratum 8, large farms, highest production of corn and soybeans.

importance than corn, is located in the Mississippi River Valley where the climate and soils are more suited to soybeans than to corn.

Stratum 3, the small farm stratum with the greatest production of corn and soybeans, is located primarily in eastern Indiana and western Ohio where the cropland is productive, but the terrain is rolling. The lesser production small farm strata (strata 1 and 2) are centered about this area on the outskirts of stratum 3.

In summary, looking at the geographic location of the strata, the system appears to be logical and the various strata seem to represent different conditions. This result is supportive not only of the variables and the methodology employed in the stratification, but also of the validity of the data sets employed.

1.5 Low Density Segments

Sample Allocation.

The low density segments were selected to sample the variability present in corn and soybean producing regions of the United States. The sample was designed to represent differences in climate, topography, field size, variety, and management practices. In order to achieve as diverse a representation as possible, an equal number of segments were allocated to each of the strata. This allocation scheme emphasizes representation of variability rather than sampling in a manner suitable for aggregation purposes.

Twenty 5 x 6 nautical mile segments were allocated to each stratum. The counties to receive sample segments were determined using a random selection procedure without replacement. Thus, all counties in a stratum had an equal probability of receiving a sample and no county could contain more than one segment. Locations of counties receiving sample segments are illustrated in Figure B-11. Latitude and longitude coordinates of the sample segments can be found in the LARS technical report on this work [3].

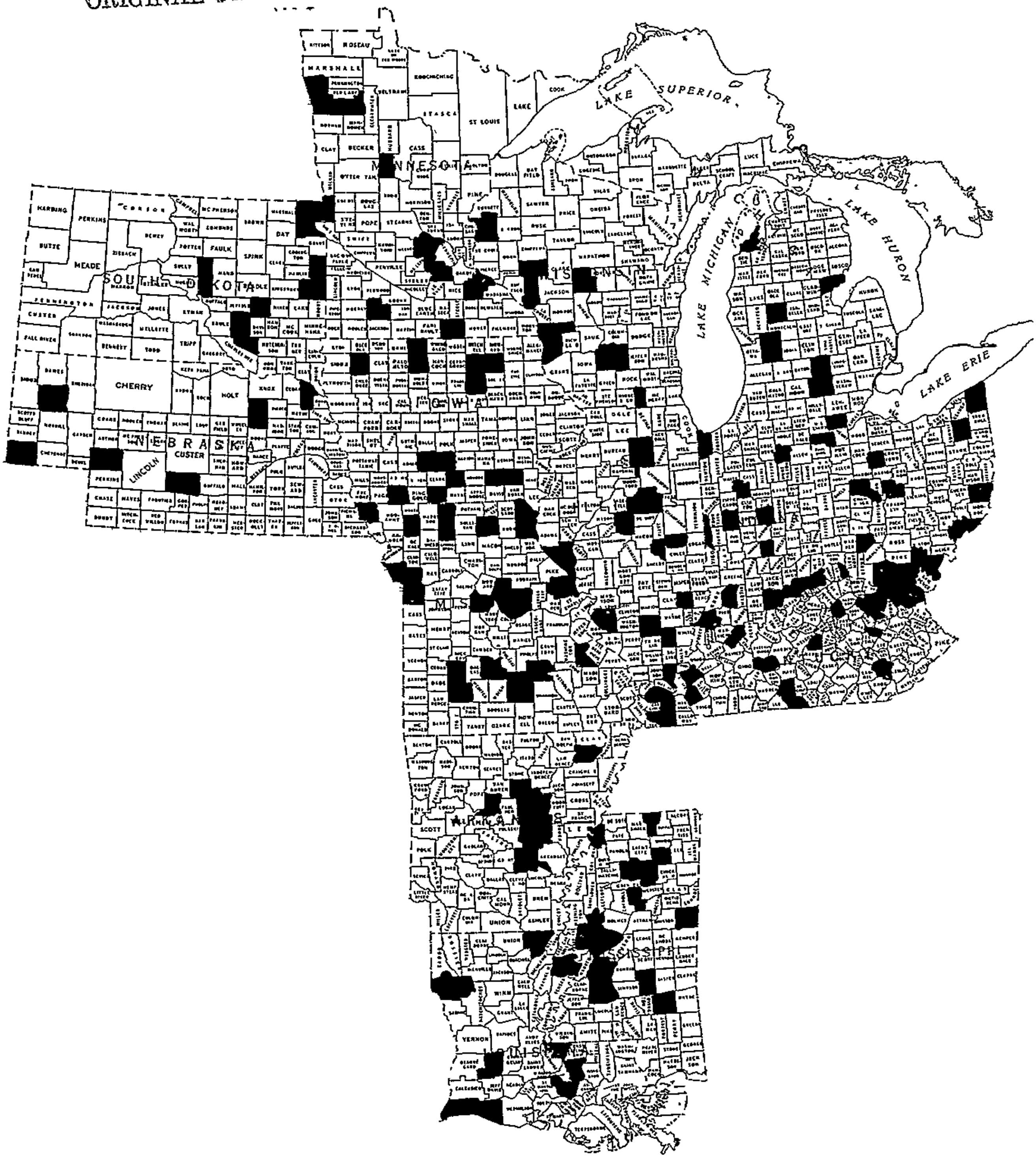

Figure B-11. Locations of counties in all eight strata receiving low density sample segments.

Segment Location.

Segment locations were selected using a modification of a computer program written for "Crop Inventory Using Full-Frame Classification", described in the final report of Contract NAS9-14970 (June, 1977). The design of the location procedure was based upon that used in LACIE. A grid was laid over each county with grid intersections five by six nautical miles apart. A random selection procedure was then used to select a grid intersection which determined the latitude and longitude coordinates of the center point of each segment.

Although only one segment was allocated to each county, several segments were selected to attain a high probability that at least one of them would be located in an agricultural area and would be accepted as a site. The number of sites to be located in each county was determined by the percent agricultural land in the county. The segment centers were randomly selected without replacement and the first segment located outside a nonagricultural area was to be used.

The ag/nonag delineation was conducted by NASA/JSC. Full-frame color composite Landsat imagery was used to delineate areas which were not agricultural. This was done on the basis of whether or not field patterns were apparent. Rangeland, forest, and urban areas were among the types of land uses which were delineated as nonag. Segment locations were compared with these boundaries and the segment was rejected if less than 5% of the segment fell into an agricultural area.

1.6 High Density Segments

Test Site Selection.

The high density segments were designed for intensive study of the remote sensing technology required for corn and soybean inventories. In order to sample more corn and soybeans, test sites were located in the Corn Belt where production of both crops is high. Test sites were placed across the Corn Belt to sample the varied climatic conditions, soil types, crop distributions, and field sizes which are present (Figure B-12). Each test site was selected to be relatively homogeneous within (same stratum, similar soil types and farming practices) to support classification studies, particularly of multisegment training. Each of the sites contained about ten counties and was approximately the size of a crop reporting district.

Test Site 1 is located in eastern Indiana which is an area of small farms. The other three test sites are located in large farm areas. Test Site 2 is comprised of counties in west central Indiana and east central Illinois. Test Site 3 is in north central Iowa and Test Site 4 is in west central Iowa.

<u>Description of Test Sites 1 and 2</u>. The climate across central Indiana and east central Illinois is continental with warm summers and cold winters. Normal mean temperature is $-1.2^{\circ}C$ in January and $31.1^{\circ}C$ in July. In this semihumid region of the U.S., the average annual precipitation is 950 to 1000 mm which does not limit crop production. Rainfall is greatest during the spring and early summer months with June typically receiving 107 to 118 mm of rain. Average precipitation in June is slightly excessive, adequate in July, and often inadequate in August for corn. The crops survive because of some moisture stored in the soil profile.

Test Site 1 is composed of two major soil associations. Soils of the northern two-thirds of this district (Allen, Wells, Adams, Blackford, Jay, and parts of Madison, Delaware, and Randolph counties) belong to the Blont-Pewano-Mortley soil association. These soils were formed on clayey glacial till and are nearly level and poorly to very poorly drained. The Brookston-Crosby-Miami-Parr assocation which predominates in the remainder of Test Site 1 was formed in thin loess (wind-blown materials) over loamy glacial till and is also poorly drained. These two soil associations are suited to intensive cropping but are subject to problems associated with wet soils unless adequate artifical drainage is provided. Typically, approximately 287,700 hectares of

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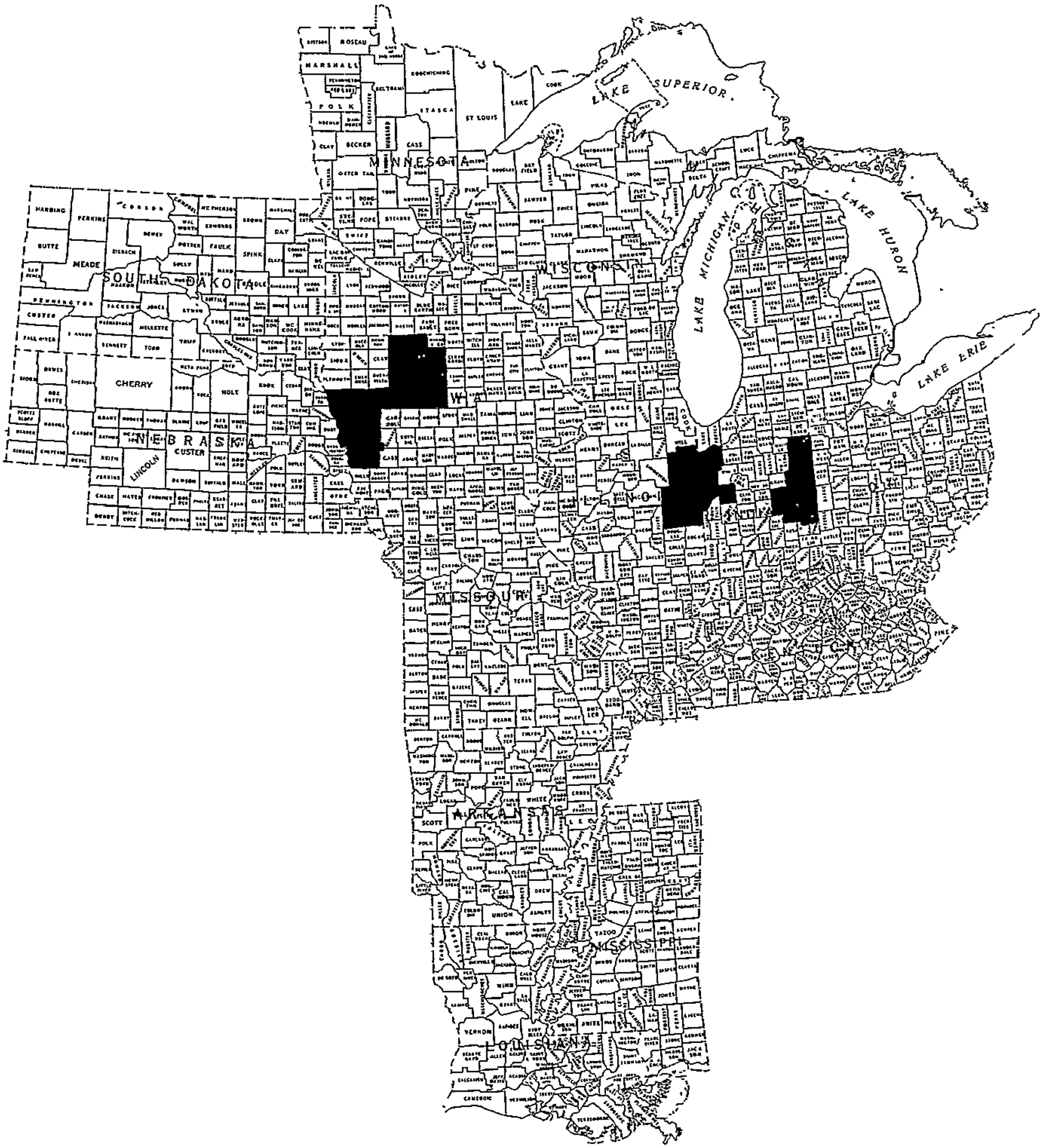

Figure B-12. Locations of high density test sites.

corn for grain; 245,300 hectares of soybeans; and 87,300 hectares of winter wheat are planted.

Test Site 2 includes dark-colored prairie soils and light-colored forest soils both of which were formed in loess-covered glacial till. Topography is generally gently rolling with short slopes and nearly level areas interrupted by depressions or potholes. The northern one-third of this district (Newton, Jasper, Kankakee, and northern Ford and Iroquois counties) has soils which are sandy and variable in subsoil development. These soils tend to be droughty, low in fertility, and require a high level of management for moderate yields. In Tippecanoe, Benton, Warren, southern Ford and Iroquois, and northern Vermilion and Champaign counties in the central portion of the district, the soils developed under prairie or mixed prairie and forest vegetation, are dark to moderately dark colored, and are generally imperfectly drained. Crop yields are moderately high to high with a high level of management. Dark-colored soils on nearly level to moderately sloping upland areas are typical in southern Vermilion and Champaign counties. These soils have high available moisture storage capacities and are very highly productive under a high level of management. Farmers in Test Site 2 typically plant 667,700 hectares of corn; 557,200 hectares of soybeans; and 39,200 hectares of winter wheat.

<u>Description of Test Sites 3 and 4</u>. The climate in western Iowa is continental, characterized by marked seasonal changes. Temperature fluctuations are extreme with winters being cold and summers warm. Thirty-year normal temperatures are -8.4^{0} C in January, the coldest month, and 23.6^{o} in July, the warmest month. Annual precipitation is 762 mm with most of it occurring in the spring and early summer. Summer precipitation is variable from year to year with the largest amount (132 mm) generally falling in June.

The Clarion-Nicollet-Webster soil association, which is the only major soil group in Test Site 3, was derived from glacial till. About 75 percent of the area has level to gently sloping topography and is well suited to intensive production of corn, soybeans, and alfalfa.

This test site has about 1,499,600 hectares of farm land and typically grows 607,300 hectares of corn (approximately 96% for grain); 477,100 hectares of soybeans; and 54,500 hectares of alfalfa and hay.

Three major kinds of parent materials (loess, glacial till, and alluvium) are found in Test Site 4. Loess (wind-blown material) from the Missouri flood plains is thickest near the Missouri River and thins and increases in clay content in a southeasterly direction. Marshall and Monona-Ida-Hamburg soil associations which occupy the central three-fourths of this district were formed from deep loess under grass vegetation. These soils are generally well-drained and have high proportions of their area used for cultivated crops. The Clarion-Nicollet-Webster soil association, which is a continuation of the predominant soil of the third test site, is the major soil in Sac County. These soils are well suited to intensive production of corn, soybeans, and alfalfa. A third major group of soils which developed primarily from alluvial materials on the nearly level flood plains of the Missouri River are the Luton-Onawa-Salix association. These soils are found primarily along the Missouri River in Woodbury, Monona, and Harrison counties and are farmed for corn, soybeans, and wheat.

High proportions of Test Site 4 are used for cultivated crops, particularly corn and soybeans. Of the 1,385,100 hectares of farm land in this district, 634,100 hectares of corn are planted annually and approximately 90 percent of this corn is harvested for grain. An additional 233,700 hectares of soybeans are typically planted. The proportions of corn and soybeans vary from year to year depending on market conditions and prices.

<u>Sample Allocation</u>.

In general, two segments per county were allocated. In the case of unusually large or small counties, three segments or one segment might be allocated. All counties indicated in Figure B-12 received segments. Table B-3 lists the number of segments allocated to each county.

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Table B-3. Allocation of sample segments to counties in each of the four high density test sites.

Test Sites	State	County	No. of Segments
1	Indiana	Adams	2
		Allen	2
		Blackford	2
		Delaware	2
		Henry	2
		Jay	2
		Madison	2
		Randolph	2
		Wayne	2
		Wells	2
2	Indiana	Benton	2
		Jasper	2
		Newton	2
		Tippecanoe	2
		Warren	2
	Illinois	Champaign	3
		Ford	1
		Iroquois	3
		Kankakee	2
		Vermilion	3
3	Iowa	Calhoun	2
		Emmet	2
		Hamilton	2
		Hancock	2
		Humboldt	2
		Kossuth	2
		Palo Alto	2
		Pocahontas	2
		Webster	2
		Wright	2
4	Iowa	Crawford	2
		Harrison	2
		Ida	2
		Monona	2
		Pottawatomie	3
		Sac	2
		Shelby	2
		Woodbury	3

C-2

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Sample Location.

The method used for sample selection was the same as described for the low density samples. More segments were located than were allocated to permit for loss of some segments in nonagricultural areas. Locations of the sample segments by latitude and longitude coordinates can be found in the LARS technical report on this work [3].

1.7 Summary and Conclusions

A stratification was performed and sample segments were selected for an initial investigation of Multicrop problems. The effort was to support:

- Development and evaluation of procedures for using LACIE and other technologies for the classification of corn and soybeans.
- Identification of factors likely to affect classification performance.
- Evaluation of problems encountered and techniques which are applicable to the crop estimation problem in foreign countries as well.

The two types of samples, low density and high density, supporting these requirements were selected as a research data set for an initial evaluation of technical issues and should not be used in an aggregation scheme. In summary, looking at the geographic location of the strata, the system appears to be logical and the various strata seem to represent different conditions. This result is supportive not only of the variables and the methodology employed in the stratification, but also of the validity of the data sets employed.

2. RECOMMENDATIONS FOR DATA ACQUISITION

The new data set required to support the objectives of the major study was to be acquired by NASA/JSC. In order to insure that this data set would meet our research objectives, recommendations were made by LARS to NASA/JSC in the areas of crop inventory, periodic observations, and acquisition of aerial photography.

2.1 Recommendations for the Collection of Crop Information

The material included in the following pages was sent to NASA/JSC in early April, 1978. Recommendations are made for the sampling schemes to be followed and the information to be acquired for crop inventory and periodic observations. In addition to the materials reproduced here, three appendices were included which displayed sample data recording forms; discussed in detail how to identify the growth stages of corn, soybeans, and wheat; and gave guidelines for crop condition assessment.

COLLECTION OF CROP INFORMATION FOR MULTICROP EXPERIMENTS

Introduction

USDA and NASA are conducting experiments to evaluate new methods of estimating crop production using Landsat (satellite) data. An essential component of these experiments will be the collection of reliable "ground truth" or ground observations of crops in selected areas of the U.S. with which to develop procedures and evaluate results.

Some 160 test sites throughout the major corn and soybean production regions of the U.S. have been selected for study. Two kinds of ground truth data will be acquired for each segment: (1) "wall-to-wall" inventory of the crop identification of all fields in the 5 x 6 mile segment, and (2) periodic observations of the development and condition of a selected subset of fields. Specific instructions for each type of ground truth are given in the following paragraphs.

Ground Truth Sampling Methods

A. Crop Inventory

NASA will provide you with a recent aerial photograph of each 5 x 6-mile test site in your area. You should visit each field in the test site which is larger than approximately 5 acres and identify the crop or the current land use. Forms will be provided for recording this information (Form 1). Field numbers and boundaries should be marked on the aerial photo.

B. Periodic Observations of Crop Growth and Condition

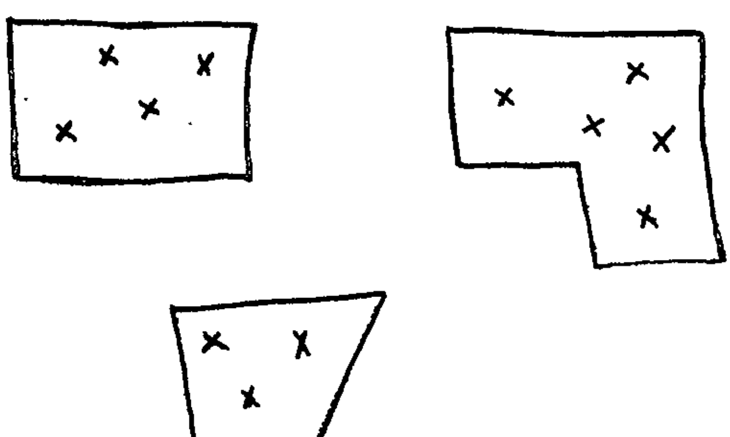
Within each test site designated for periodic observations, you should choose a subset of fields, larger than 20 acres in size, for evaluation of crop growth and condition. Ten fields of corn, 10 of soybeans, and 10 of wheat, other small grains, and pasture or hay crops should be selected.

If there are less than 10 fields of a particular crop within the test site, use all fields of that crop which are available. These fields should be sampled at 18 day intervals coincident with Landsat passes from May 1 to October 30 and information recorded on the forms provided (Form 2).

1. Sampling Within A Field.

Field sampling need not be highly complicated, but to be sure your sampling is reasonably accurate and unbiased, please observe the following guidelines:

- Do not sample field borders, fencerows, ditchbanks or other similar field areas. Sampling these areas may provide misleading information concerning the field as a whole. Therefore, go into the field <u>at least</u> 75 feet or 30 rows before beginning any type of sampling procedure.
- When sampling, try to make sure the sample represents the entire field. Field conditions may not be uniform, therefore, sampling from only a small area of the field may lead to erroneous conclusions concerning the whole field. Look at the following illustrations to see how to spread the sampling over the entire field. Each "x" indicates where a sample should be taken for different field shapes. Use your own imagination for field shapes not shown.



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- Take the samples randomly. When you get ready to start sampling, do <u>not</u> look at a plant and say to yourself, "Hey, this looks like a good plant to start with!" Instead, when you get into the general area of the field where you need to take a sample, look up at the sky or nearby tree, etc; look at anything but the crop. Walk forward five paces and start the sampling procedure with the plant nearest the toe of your right foot. Repeat this in each area of the field to be sampled.

2. Evaluating Crop Growth and Condition.

The following are instructions for completing Form 2 and evaluating crop growth and conditions.

1) <u>County and State</u> - name of county and state of the test site.
2) <u>Segment Number</u> - the number of the test site.
3) <u>Date</u> - date of this observation.
4) <u>Crop ID</u> - name of crop or cover type.
5) <u>Field No.</u>- number assigned to the field.
6) <u>Plant Height</u> - measure 5 representative plants in each of 5 locations in the field and record the average plant height for each location. Measure without extending or pulling leaves up.
7) <u>Percent Ground Cover</u> - estimate, to the nearest 10%, the percent of ground covered by the crop canopy.
8) <u>Growth Stage</u> - use the growth stage indices for corn, soybeans and wheat and evaluate the field as a whole.
9) <u>Green Leaves</u> - estimate, to the nearest 10%, the percentage of the leaves on the plants which are green.
10) <u>Crop Condition</u> - Evaluate the quality of the crop in each field in terms of each of these factors which may reduce crop yields. A rating of "0" indicates no effect of a particular factor and is the most desirable condition while a rating of "4" indicates that severe crop losses are expected. Because these ratings are somewhat subjective, the guidelines in Appendix 2 are recommended for this study. Additional comments about crop condition should be recorded in the "comments" section.

11) <u>Comments</u> - Describe other factors which will affect the production of each field (e.g., flooded areas, herbicide damage). Describe and give approximate dates of any major field operations (e.g., planting, cultivation, harvesting) which have occurred since your last visit to each field.

The following data should only be obtained once for only the corn, soybean, and wheat fields being observed periodically. These data should be recorded on Form 3.

1) <u>Hybrid or Variety</u> - For grain crops record the variety planted of corn (e.g., DeKalb XL 45), soybeans (Amsoy 71) or wheat (Arthur). For pastures and forages, record the species (e.g., bromegrass, alfalfa, or orchardgrass-alfalfa mixture).
2) <u>Date Planted</u> - applies to annual crops only.
3) <u>N Applied</u> - record the pounds per acre of <u>actual</u> nitrogen applied to this field. Two hundred pounds of 33-0-0 fertilizer equals 66 pounds of actual nitrogen.
4) <u>Row Width</u> - the distance of the center of plants in adjacent rows. Ignore for broadcast crops and forages.
5) <u>Plant Population</u> - applied to corn and soybeans only. Count the number of corn stalks in 50 feet of row or the number of soybean stems in 5 feet of row in 5 different areas of each field. These counts may be made anytime after all plants have emerged.
6) <u>Comments</u> - Additional descriptive information describing the field.

Note: We would also like to obtain an estimate of the grain yield of these fields. Separate instructions and forms for yield will be provided later.

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2.2 Recommendations for the Collection of Aerial Photography

The acquisition of aerial photography for the Multicrop high density segments is an important aspect of the Multicrop program. The aerial photography will permit objectives to be addressed concerning the location, number, and size of areas for training. These are questions which need to be answered for the optimal design of a crop inventory system.

The areas which are covered by aerial photography will be photointerpreted and the accuracy of the photointerpretation process will be checked with the wall-to-wall ground truth on those high density segments which are also covered by the flightlines. If aerial photography flightlines, ground truth over high density segments, and multitemporally registered Landsat full frames are available, a study of training procedures can draw upon these photointerpreted areas to look at dispersion of training areas throughout the area to be classified, the optimal total amount of training, and how this amount should be divided into size and number of segments.

To achieve these objectives, the aerial photography acquisition should follow these specifications:

Location. Four high density test areas have been located in eastern Indiana, west central Indiana/east central Illinois, north central Iowa, and west central Iowa. Three or four flightlines should be flown for each of the test sites totaling an average of about 400 miles per test area. The flightlines should be located such that the aircraft will cover exactly the same area each time.

Type of photography. Nine-inch color infrared photography with a 20 percent forward overlap should be acquired. It should be flown at an altitude and scale such that a strip of land four to five miles wide is covered.

<u>Times of acquisition</u>. The photography should optimally be acquired at three times during the growth season: May-June, July, and August. The early mission will provide coverage when corn and soybeans have a low percent soil cover to separate them from other cover types. The crops will also be sampled twice during their growth to permit separation of corn from soybeans. If only two missions can be acquired, these should be in the August and June-July time frame. If only a single mission can be flown, it should be in August.

3. EVALUATION OF PROCEDURE 1 FOR CORN AND SOYBEANS

3.1 Introduction

An analysis procedure known as Procedure 1 (P-1) was developed for use during the Large Area Crop Inventory Experiment (LACIE). The procedure encompasses the areas of training, classification, and area estimation and emphasizes the use of multitemporal information. In order to allow for extension of the LACIE procedures into foreign countries, ground reference data were not used for training, but analysts labeled training data by image interpretation. Procedure 1 utilizes a random grid selection technique to locate pixels (dots) on segment imagery. Analysts label dots which fall on grid intersections. These dots are of two types: Type 1 dots which are used for starting the clustering algorithm and labeling clusters and Type 2 dots which are used as bias correction dots. This approach reduced analyst time significantly, allowing the analyst to concentrate on just the labeling operation. In addition, this method of selecting training areas should be unbiased which is an advantage over analyst-selected training data.

Another aspect of Procedure 1 which is designed to reduce bias is in the use of designated other (DO) and designated unidentifiable (DU) areas. If an area is clearly not of interest (e.g., woods for a wheat inventory), that area is labeled DO to prohibit any of that area from being classified as the crop of interest. If an area is covered by clouds, it is labeled DU and proportion estimates made do not include this area.

A clustering algorithm is used to statistically define the training classes. Type 1 dots are used as starting vectors for the clustering algorithm and are also used to label the resulting clusters. The clustering algorithm which is used is the Iterative Self-Organizing Clustering System Processor (ISOCLS). Then a sum of densities classifier is used. The classification results are considered as a stratification of the segment into the various classes of interest. The stratified area estimate is then computed using the Type 2 dots to make proportion estimates in an unbiased way.

The objective of LACIE was to estimate wheat production in important wheat growing regions of the world. Recently, there has been increasing emphasis on making production estimates for crops other than wheat; in particular, corn and soybeans are the two crops of immediate interest. This preliminary study has been using currently available data to evaluate the LACIE procedures when applied to corn and soybeans and to recommend changes in the procedures for the new classification problem. In addressing these issues, this task supports the classification component of the corn and soybeans research effort.

3.2 Objectives

The overall objective of this investigation is to advance the development of large area crop inventory systems for multicrop regions by applying and evaluating recently developed techniques. This preliminary study addresses parts of this objective with currently available data. The specific objectives of the preliminary study are:

- Evaluate the LACIE Procedure 1 (P-1) for a corn, soybeans, and "other" crop identification problem.
- Investigate parameter changes which may improve the performance of P-1 on corn and soybeans.

3.3 Approach

The preliminary study used data on corn and soybeans which was acquired during the CITARS project. Assessment of the accuracy and variability of P-1 estimates was done with minimal changes to the procedure to work the three class problem. Each CITARS segment was divided into four 5 x 5 mile blocks for analysis because this is as close to the LACIE segment size as possible using only the segment data. The ratio of dots to total area to be classified was about the same as in LACIE. A key aspect of the approach was that ground truth or photointerpreted areas were used rather than analyst-labeled dots. This permitted evaluation of the analysis procedure itself rather than the image interpretation accuracy. Dot grids falling in areas with reference data (ground truth or photointerpreted crop types) were digitized and the pixels were associated with ground truth labels.

Both classification and area estimation accuracy were assessed and the variability resulting from different choices of Type 1 and Type 2 dots was estimated.

In an initial assessment of Procedure 1, analyses were conducted using parameters which had been used in LACIE. It was believed that these settings would not be optimal for the corn, soybeans, and "other" crop identification problem due to differences in the spectral distribution of the crops of interest from that of wheat, more confusion crops, differences in crop calendar, and other factors. Therefore, a parameter study was initiated to begin investigation of some of these issues.

3.4 Results of Initial Evaluation

A major accomplishment of this task is that personnel from LARS have become familiar with the philosophy and methodology of Procedure 1 and the P-1 software implemented on the Purdue/LARS IBM 370/148 computer system. Personnel from NASA/JSC, Lockheed, and LARS have worked cooperatively to standardize and improve the P-1 software. In support of this task, personnel attended the LACIE Symposium, held October 23-26, 1978, at the Johnson Space Center, to further their knowledge and understanding of the state of the art. A representative from this task attended the Advanced Seminar in Multicrop Labelling from Landsat Multitemporal Data, held November 1-8, 1978, at the University of California, Berkeley. Analysts have been participating in a series of workshops to learn how to apply all the clustering and classification routines which are implemented on the LARS computer. These experiences, coupled with data analysis utilizing the Procedure 1 software, have provided a well-rounded background in crop inventory procedures for the participants.

Identification of General Crop Inventory Issues

Early in the investigation, several general issues in crop inventory were identified. The general methodology for inventory of corn and soybeans needs to be of somewhat different design than for wheat. For example, in corn and soybean production areas, the practice of double cropping, particularly soybeans following winter wheat, is becoming increasingly important. A methodology for identification and classification of double cropped areas needs to be developed.

Cloud cover is a greater problem in the Corn Belt than in the U.S. Great Plains; this has potential impact on the handling of designated unidentifiable (DU) areas. If only the area which is cloud-free on all four acquisitions is used for area estimation, insufficient pixels may be available to give accurate and precise estimates for the segment proportions. If DU areas exceed a certain percentage of land area in a segment, perhaps three cloud-free acquisitions could be used to classify some additional areas to provide a broader base for area estimation.

Variability of Procedure 1 Estimates

An analysis was run to look at the variability of the stratified area estimates due to the location of the dot grids. In Procedure 1, two types of dots are selected. Type 1 dots are used to start the clusters and label them and Type 2 dots are used for bias correction. Both types are located on a systematic sample grid. Five grids were defined, two Type 1 grids and three Type 2 grids, giving a total of six grid combinations for analysis. Using these grid combinations, six analyses were run keeping all other parameters and procedures constant.

For an individual section, there was a significant amount of variability amoung the six estimates. Table B-4 gives an example of the variability encountered for one section. There appears to be more variability between grids of Type 1 dots than between grids of Type 2 dots. The interaction between grid types is also significant. This is best illustrated by the soybean estimates where there is a greater effect of Type 2 dot selection for the first selection of Type 1 dots than there is for the second selection.

The results in Table B-5 are more indicative of the amount of variability which might be noticed in practice since, in general, the

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Table B-4. Proportion estimates of corn and soybeans for section 61 in Livingston county.

	Corn		Soybeans	
Type 2 Grid	First Set of Type 1	Second Set of Type 1	First Set of Type 1	Second Set of Type 1
A	33.5	38.9	60.0	56.7
B	30.4	40.0	61.6	54.6
C	27.0	42.4	71.4	52.4

Table B-5. Averages of proportion estimates of corn and soybeans for eight sections in Livingston county.

	Corn		Soybeans	
Type 2 Grid	First Set of Type 1	Second Set of Type 1	First Set of Type 1	Second Set of Type 1
A	32.7	36.3	59.8	56.9
B	31.7	40.9	61.1	54.9
C	30.1	46.1	67.7	48.4

interest in estimation is for larger areas. In this case as well, the choice of dot grids does significantly affect the final stratified area estimates.

This study was conducted using 30 and 40 dots for Type 1 and Type 2, respectively. It is possible that using more dots could somewhat alleviate this problem, but insufficient ground truth was available for pursuit of this idea. This study does indicate, however, that final estimates can be significantly affected by selection of dots. It is necessary, therefore, to insure that: (1) the Type 1 dots represent the spectral subclasses present in the scene and (2) the proportions of Type 2 dots in each category are similar to the distribution of cover types in the area to be classified. Further study into these effects needs to be conducted to determine a methodology to remove this variability.

Effect of Distributions of Dots on Area Estimates

The LACIE procedure samples a random set of dots falling on a systematic grid over the segment. Type 1 and Type 2 dots are selected on different grids of the same type. The rationale of this sampling scheme is that the true distribution of crops present will be sampled in their respective proportions. When using the CITARS data, however, dots were sampled only from areas with reference data. The dots were not distributed throughout the segment, but a higher density of dots was sampled in a smaller portion of the segment which had available ground truth information. Since the areas sampled were either sections or quarter sections, the distribution of cover types present would probably not be as diverse as if the same number of dots were spread out over a larger geographic area. Table B-6 illustrates this problem.

By selecting this type of sample, it frequently occurred that one of the categories had very few pixels for starting clusters (maybe only three or four). These were insufficient to completely represent all the spectral subclasses which might be in a category. Theory indicates that the final estimates can be highly dependent upon the distribution of

Table B-6. Comparisons of proportions of pixels with ground truth available to county crop proportions.

County	Block	Proportion		
		Corn	Soybeans	Other
Fayette	1	7.8	49.7	42.4
	2	25.2	44.9	29.9
	3	24.5	68.3	7.2
	County*	14.2	23.8	62.0
Livingston	1	29.5	67.3	3.2
	2	41.3	54.1	4.6
	3	9.4	12.2	78.4
	County*	38.6	37.7	23.7

*USDA/SRS County Acreage Estimates for 1972 the Type 2 or bias correction dots. For these two reasons, a test was done to determine to what extent the dot distribution affects the final stratified area estimates.

Using the same set of parameters for clustering and classification, the first block of Livingston county was classified twice using two different distributions of dots. The first distribution, which will be referred to as the random distribution, was obtained by selecting dots as they fell on the grid. The second distribution, which will be referred to as the proportional distribution, was obtained by selecting dots from the grid with about the same proportion for each category as historical crop proportions for the county indicated. This approach counters the difficulties of having enough dots to represent the numerous spectral subclasses in each category and the bias which could be induced in the stratified area estimate.

Corn and soybean estimates made by each method were compared on several test areas for which true proportions were known using a paired t-test. The results of this comparison are presented in Table B-7. For both corn and soybeans, the proportion estimates derived by the two methods differed significantly at the one percent level. The estimates generated using proportional dot distributions did not differ significantly from the ground truth proportions. The random distribution estimates, however, differed significantly from the ground truth for soybeans (at the one percent level) and for corn (at the 15 percent level).

Based upon theory and these empirical results, it seems that a methodology should be developed to insure dot distributions which are representative of the distributions of cover types in the area to be classified. One possible solution to this problem is to sample from the spectral space rather than from the physical space.

Effect of Number of Dots on Area Estimates

Although this particular aspect of the procedure has not been

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Table B-7. Effect of distributions of Type 1 and Type 2 dots on proportion estimates for Livingston county.

Crop	Proportion		
	Random Distribution	Proportional Distribution	Ground Truth
Corn	26.2	34.7	30.4
Soybeans	71.2	38.0	39.5

extensively investigated in this task, it is believed that more dots should be used than were used in LACIE Phase III. The scene in the Corn Belt may be more complex than scenes of primarily wheat, indicating that with a one pass cluster routine more starting dots are needed to create a sufficient number of clusters to represent the scene. An increased number of Type 2 (bias correction) dots would result in a further variance reduction of the area estimates. The transition year (TY) analysis procedures at JSC call for a minimum of 40 Type 1 and 60 Type 2 dots rather than the 30 and 40 required in Phase III.

It is possible that even more dots might result in significantly more accurate and precise area estimates. It appears, however, that a judicious choice of dots and a good selection of clustering and classification parameters will provide a greater improvement in results than merely selecting more dots.

3.5 Summary and Future Plans

Progress has been made in identifying areas of difficulty in the classification of corn and soybeans. Dot distribution, number of dots, and parameters used in clustering and classification of the data seem to be significant factors. These analyses have been based on a small data set; analysis of additional data may confirm or contradict results obtained to date, possibly altering conclusions which may be drawn from the analyses. In many ways, this section should be viewed as a status or preliminary report of our results rather than a final report. Continuation and completion of the analyses described here, as well as additional analyses, are planned in the new SR&T contract to LARS.

This task is continuing into a second year which will address the objectives given in the introduction to this report, although the 1978 crop year data will not be available at the beginning of the contract. The work to be accomplished during the period before these data become available includes planning specific analyses to be conducted with the new data and a continuation of the P-1 study using CITARS data for a parameter investigation. Multitemporally registered Landsat data and digital ground truth tapes for 5 x 6 nm sample segments will be available for some high density segments in Indiana, Illinois, and Iowa. It is these data on which analyses will be conducted to investigate training, classification, and area estimation procedures.

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5. ACKNOWLEDGEMENTS

Many individuals have contributed to this task. The following personnel are acknowledged for their assistance: Donna Scholz, Nancy Fuhs, Marvin Bauer, Barbara Davis, Craig Daughtry, and Getulio Batista.

C2. Multisensor Multidate Spatial Feature Matching, Correlation, Registering, Resampling and Information Extraction*

1. INTRODUCTION

This subtask was formulated to seek answers to the problems of data merging and information extraction using multiple remote sensing and ancillary data types and to develop techniques for merging and analysis of certain data types using the results of this research. The specific remote sensing data types considered in this contract year are synthetic aperture radar (SAR) and Landsat data. Methods of merging map data and remote sensing data are also considered. Interest is growing in the remote sensing community in the utility of radar imagery as an addition to Landsat data. The tasks are oriented toward determining the spatial and spectral characteristics of SAR data and definition of merging system parameters.

2. DATA SET SURVEY AND ACQUISITION

The study was formulated on the assumption that three aircraft SAR data sets would be obtainable by at least the end of the second quarter. These were to be flights over the Salisbury, Maryland area, Gulf Coastal Zone area, and over the Phoenix, Arizona area. A Salisbury SAR flight is in house; however, it is of poor quality and a reprocessed data set is being prepared but has not yet been received as of November 15, 1978. Landsat data for Salisbury is on hand. The Gulf coast flight has not been flown due to SAR equipment problems on the NASA aircraft and may be flown and made available in the late fall of 1978 or spring of 1979. The radar data for the Phoenix site is on hand; however, the time

* This report is on the work under Task 2.2C Multisensor Radiometric Correction Correlation and Applications Analysis.

coincident Landsat data which was ordered in March 1978 has not been received as of November 15, 1978. Thus, none of the expected data sets is complete as planned.

In order to permit spatial distortion investigations to proceed the high noise level SAR from Salisbury, MD was used, and a second eastern Maryland shore SAR flight data set near Cambridge, Maryland was also used. These data sets were generated as part of NASA Contract NAS6-2816 from the Wallops Flight Center and are being used in this study to enable extension of the work on geometric characteristics of SAR/Landsat imagery. The characteristics of the registered data sets resulting from this previous study are listed in Table C-1.

The Phoenix, Arizona data set which was to be the primary one for the first year of the study could not be completed due to Landsat CCT data availability problems. Landsat scene #5 792-16152, June 19, 1977, was ordered in March 1978. On September 1, 1978 LARS was informed by EDC that the frame was "unavailable" even though LARS had on hand high quality imagery for the frame. The meaning of "unavailable" was explored and it was determined that ancillary data record problems existed but the imagery was readable. A request for the imagery only portion of the tape was made by late October 1978 and LARS is awaiting delivery of this data. Extensive ground truth was gathered in the Phoenix area in March 1978 and thus, it is of great interest to complete the data set so that analysis can be conducted.

In order to proceed with registration studies a fall 1972 Landsat frame was used to register with the SAR data. The analysis reported here was based on these time separated data sets.

3. AIRCRAFT/SAR SPATIAL/SPECTRAL MODELING

The spatial distortion characteristics of the three SAR data sets were investigated with respect to Landsat as a reference. Three distortion model sources were utilized. One consists of a systematic error

Table C-1. Merged SAR/Landsat Data Set Description.

Data Set No.	Site Identifier	Date of SAR FLIGHT	Landsat Frame/Date	LARS Data Set No.	Number of Lines	No. of Samples/Line	Pixel Size	No. of Channels	Tape No.	File No.
1	Salisbury, Maryland	August 22, 1976	2579-14535 August 23, 1976	76016404	2700	1906	25.4 x 25.4 M	5	3620	1
2	Cambridge, Maryland	August 22, 1976	2579-14535 August 23, 1976	76016413	681	598	25.4 x 25.4 M	7	3692	1
3	Phoenix, Arizona	June 17, 1977	1085-17330* October 16, 1972	72069110*	512	512	25x25M	7	160*	1*

* will change when 1977 Landsat data is received.

analysis program developed by Goodyear Aerospace for NASA. The second consists of affine and biquadratic models generated by LARS as part of the image registration system. The third source is the SPSS statistical analysis package included in the LARS system programs which utilizes first through fifth degree polynomial representation of distortion. The systematic model was shown to be equivalent to the affine model (see Appendix I) and is thus, not exercised in the cases discussed.

The geometric distortion of the SAR imagery relative to Landsat was analysed by visually selecting control points from imagery of both data types and processing the points with the various distortion analysis programs. The results of these analyses are described by site.

3.1 Salisbury Data

The results of the distortion model analysis for the Salisbury, Maryland, data set are shown in Table C-2. Since the SAR image is very noisy the residuals for the model are large. The errors are approximately the same in both reference frames because there is only a slight scale difference between the original images. The regression modeling improves with increasing degree in general. There are some anomalies in this trend shown between the biquartic and biquintic models. This effect is probably due to the addition of non-significant terms to the regression while decreasing the degrees of freedom in the data. Using the affine models, a parametric description of the SAR imagery relative to the Landsat image are obtained. They are as shown in Table C-3.

Table C-3. Parameters for Salisbury SAR-Landsat Distortion Model

Line Translation	=	4.13
Column Translation	=	-1031.51
Line Scale Factor	=	1.01
Column Scale Factor	=	1.05
Angle of Rotation	=	-16.16 Degrees
Shear	=	-0.04
or Shear Angle	=	-2.04 Degrees

Table C-2. Evaluation of Salisbury Overlay Models

Distortion Model	# of Terms	# of Points	SAR Line R.M.S.	SAR Column R.M.S.	Landsat Line R.M.S.	Landsat Column R.M.S.
			Residuals in Reference Frame			
Affine	3	34	11.15	3.54	10.87	3.74
Biquadratic	6	34	11.41	3.52	11.18	3.58
Bicubic	10	34	6.40	3.40	6.52	2.87
Biquartic	15	34	5.65	1.75	5.54	2.15
Biquintic	21	34	4.73	1.93	4.41	2.22

Landsat Grid Size - 25M. x 25M.

SAR Grid Size - 25M. x 25M.

Registered Grid Size - 25M. x 25M.

3.2 Cambridge Data Set

Using the Affine model, parameters for the distortion of the SAR image relative to the Landsat image were computed and are as shown in Table C-4.

Table C-4. Parameters for Cambridge SAR-Landsat Distortion Model

Line Translation	=	379.97
Column Translation	=	209.88
Line Scale Factor	=	0.35
Column Scale Factor	=	0.40
Angle of Rotation	=	12.91 Degrees
Shear	=	-0.01
or Shear Angle	=	-0.73 Degrees

The results for the regression modeling of the Cambridge distortion are given in Table C-5. Because of the large scale difference between reference frames, the residual errors differ greatly between reference frames. These differences can be accounted for by scaling the residuals. The circular error in the Landsat reference is approximately equal to the scaled circular error in SAR reference, i.e.,

$$(S_L \sigma_{LSAR})^2 + (S_C \sigma_{CSAR})^2 \doteq \sigma^2_{LLANDSAT} + \sigma^2_{CLANDSAT}$$

where L and C refer to line and column respectively.

Again the higher degree polynomial regressions model the misregistration more closely. To obtain the 47 point data set used, the points of the 51 point data set whose residuals were greater than twice the standard deviation of the residuals were regarded as bad data points and deleted. The residuals subsequently obtained are reduced significantly.

3.3 Phoenix Data Set

The data set of primary interest in the study is Phoenix since data quality is high and extensive ground truth is available. Figure C-1

Table C-5. Evaluation of Cambridge Overlay Models

			Residuals in Reference Frame			
			SAR		Landsat	
Distortion Model	# of Terms	# of Points	Line R.M.S.	Column R.M.S.	Line R.M.S.	Column R.M.S.
Affine	3	51	11.34	5.77	3.85	2.39
	3	47	7.04	4.36	2.41	1.81
Biquadratic	6	51	10.95	5.47	3.73	2.32
	6	47	6.51	4.04	2.24	1.67
Bicubic	10	51	11.13	5.23	3.78	2.24
	10	47	6.16	3.79	2.09	1.63
Biquartic	15	51	11.51	5.41	3.89	2.32
	15	47	6.16	3.79	2.09	1.63
Biquintic	21	51	11.62	5.45	3.88	2.45
	21	47	6.37	3.74	2.17	1.62

LANDSAT Grid Size - 25M. x 25M.

SAR Grid Size - 8.7M. x 10.0M.

Registered Grid Size - 25M. x 25M.

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Figure C-1. Goodyear SAR Data Set over Phoenix, Arizona used in the study. Flown on June 17, 1977 using an AN/APD-10 X band radar in an Air Force RF-4 aircraft. Area covered in approximately 12 by 38 miles at a resolution of approximately 10 feet.

shows the entire SAR data for the Phoenix area. Two agricultural areas exist at each end of the flight. The scene was scanned and digitized on an Optronics microdensitometer by NASA Wallops and reformatted at LARS into a LARSYS data set. Only an annotated film product was available at the time of processing, thus, the annotations appear in the data set. This should not cause degradation of data quality in areas not by the annotation. Figure C-2 contains Landsat frame 1085-17330 which was used as a reference in this study.

Checkpoints were manually determined in both data sets. The Pearson's product-moment correlation was used to obtain a measure of the dispersion of the checkpoints over the scene. If the correlation is small, then the dispersion is good. The Pearson's product moment for the chosen data points was -0.0957. The results of the regression distortion analysis is shown in Table C-6. The scale difference between the original Landsat and SAR imagery is much greater in the Phoenix data set than in the two previous. Using the affine distortion model, Table C-7 was constructed which specifies the distortion in the SAR imagery relative to the Landsat image.

Table C-7. Parameters for Phoenix SAR-Landsat Distortion Model

Line Translation	=	-5219.94
Column Translation	=	2658.08
Line Scale Factor	=	5.16
Column Scale Factor	=	4.28
Angle of Rotation	=	61.47 Degrees
Shear	=	0.03
or Shear Angle	=	2.01 Degrees

The circular error in the SAR reference frame is again related to the circular in the Landsat reference by the relation,

$$(S_L \sigma_{LSAR})^2 + (S_C \sigma_{CSAR})^2 = \sigma^2_{LLANDSAT} + \sigma^2_{CLANDSAT}$$

Also in Table C-6 the difference in results obtained using different algorithms and computers to implement the regression are illustrated.

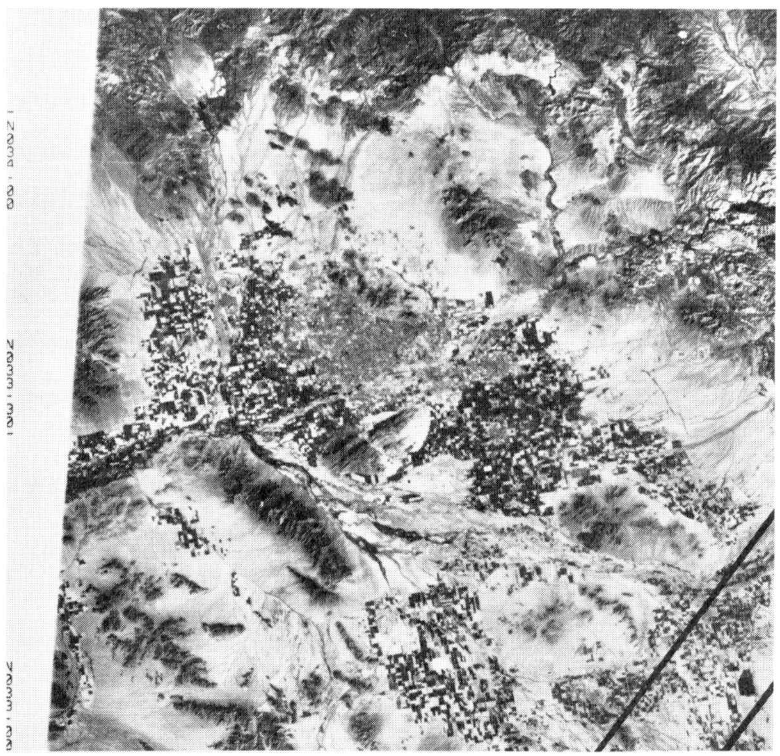

Figure C-2. Landsat frame 1085-17330 used as reference in the study. Imaged on October 16, 1972.

Table C-6. Evaluation of Phoenix Overlay Models

Distortion Model	# of Terms	# of Points	SAR Line R.M.S.	SAR Column R.M.S.	Landsat Line R.M.S.	Landsat Column R.M.S.
Affine						
SPSS/CDC	3	17	3.89	3.91	0.91	0.66
SPSS/IBM	3	17	3.89	3.91	0.91	0.66
LARS/IBM	3	17	3.53	3.58	0.90	0.81
Biquadratic						
SPSS/CDC	6	17	3.02	3.37	0.67	0.67
SPSS/IBM	6	17	3.02	3.37	0.67	0.67
LARS/IBM	6	17	2.72	2.92	0.54	0.66
Bicubic						
SPSS/CDC	10	17	2.53	1.54	0.21	0.65
SPSS/IBM	10	17	2.53	1.54	0.21	0.65
Biquintic						
SPSS/CDC	10	17	---	---	0.28	0.62
SPSS/IBM	10	17	3.15	0.07	0.28	0.62

(Residuals in Reference Frame)

LANDSAT Grid Size - 76.2M. x 61.10M.

SAR Grid Size - 14.8M. x 14.2M.

Registered Grid Size - 25M. x 25M.

The residuals shown for the SPSS packages (Statistics Package for the Social Sciences) are larger than those for the LARS Affine and Biquadratic programs. This is probably due to the loss of precision in computing the inverse matrix in the LARS program. The differences in the residual calculated between the SPSS program implementations are due to the precision of the machine used. The IBM/370 version uses a 32 bit word and the CDC 6500 a 60 bit word. These differences become evident first in the higher degree regressions.

The results indicate that for the small areas considered that the linear models do as well as higher degree models for representing distortion in the SAR imagery. The Salisbury data set was observed to have oscillatory scale errors and is probably not representative of typical flight data. The R.M.S. errors for the other two sites did not significantly decrease for the higher order cases.

The biquadratic error results are in the half reference pixel range, thus, the current LARS registration system can implement the SAR distortion representation. Thus, the SAR and Landsat data were registered using the biquadratic results. A block of data covering the agricultural area between Sun City and Phoenix was registered producing a 512 x 512 block of data. The Landsat data was interpolated using cubic convolution to 25 meter pixels. The results are shown in Figures C-3 and C-4. Figure C-3 is the interpolated Landsat data for band 5 and Figure C-4 is the SAR for the same area.

4. SATELLITE SAR SPATIAL/SPECTRAL MODELING

Data availability problems with aircraft cases resulted in the decision to include the satellite SAR case in future studies. Resources were placed on the aircraft SAR problem and other system aspects. Information on SEASAT SAR and other satellite SAR sensors was acquired and reviewed during the year, but no satellite data obtained. It is highly likely that the technology developed for the aircraft SAR cases will be useful in dealing with satellite SAR data, thus, the essence of this task is considered to be fulfilled by other results reported here.

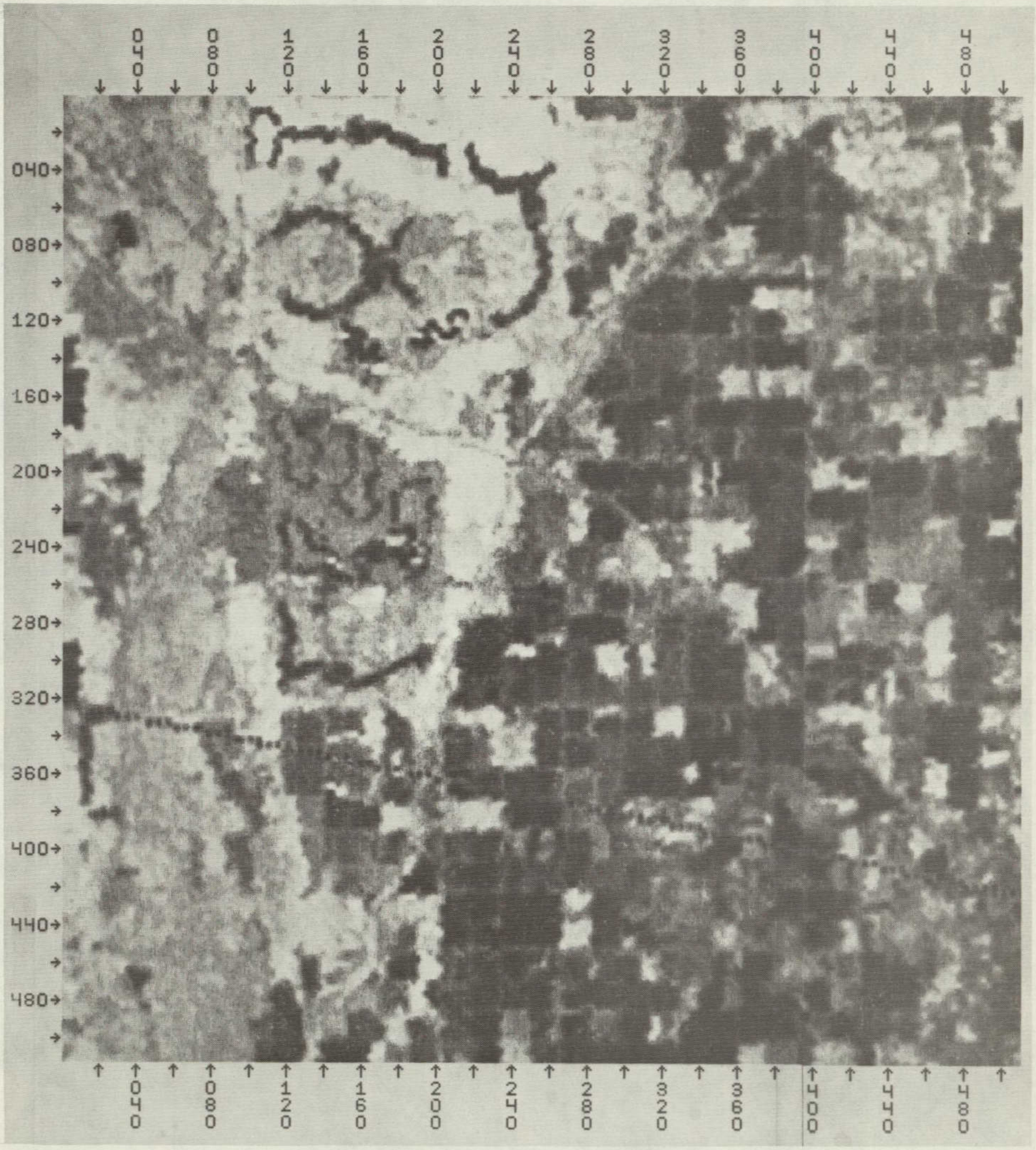

Figure C-3. Landsat Image, Channel 2 (0.6-0.7 μm), Cubic Resampling to a 25 x 25 Meter Resolution (Phoenix, AZ).

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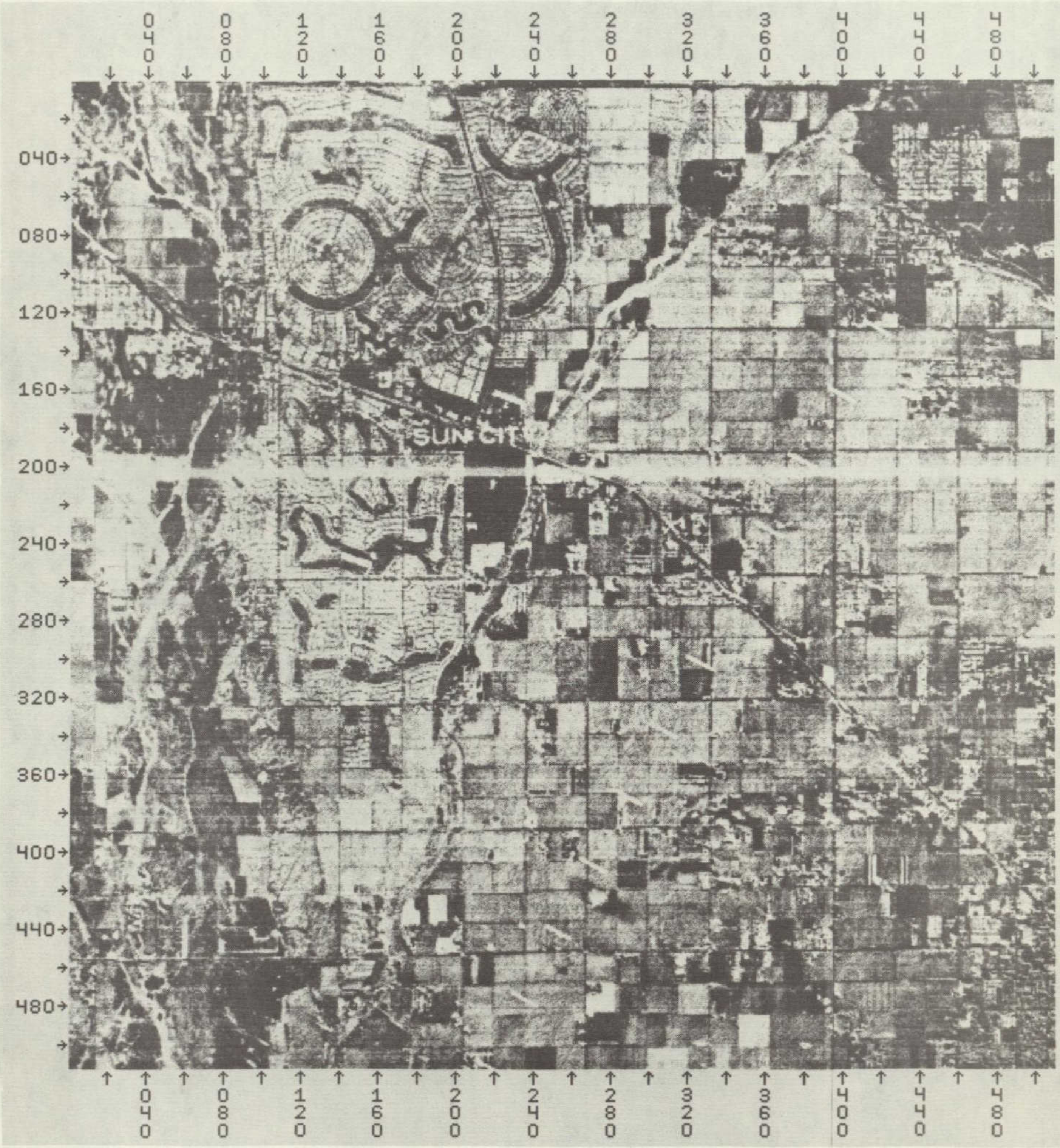

Figure C-4. Aircraft SAR (3 cm), Cubic Resampled and Registered to 25 x 25 Meter Landsat (Phoenix, AZ).

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Resources which would have been expended on the satellite SAR case were directed toward further studies of the aircraft data. Control point location is a difficult task and visual methods are time consuming and inaccurate. A correlation study was conducted to see if numerical control point finding methods would work on SAR/Landsat image pairs.

Figure C-5 contains correlation matrices for seven 101 by 101 pixel blocks from the registered Phoenix data set. The correlation of each of the four Landsat bands with the SAR is given in the fifth row of the matrix (the one labeled spectral band 3.0-3.0, refers to the nominal 3 cm wavelength of the SAR) the highest correlation in any of the blocks is -.43 for SAR versus band 5 (.6-.7 μm) in block four. There is a five year time difference in the Landsat and SAR; however, field structures are still very much the same and this correlation figure is typical of what has been observed for other sites with time coincident data. The purpose of this test was to see if gradient enhancement would increase the correlation.

Magnitude of gradient image transformation was made on band 6 of the Landsat and the SAR and added as channels 6 and 7 respectively as the registered data set. Block correlations were performed on the two gradient channels and the results presented in Figure C-6. In these tests the maximum correlation observed was .15. Correlations of either gradient with any of the unprocessed channels was not significantly higher. A gray scale image of the gradients for each data type are shown in Figures C-7 and C-8. These results are very unfavorable and indicate that numerical control point finding may not be possible. Observation of the gradient images indicates considerable agreement between roads and field edges and suggests some scheme may work for SAR correlation. Similar analysis was carried out for the Maryland data sets with equally poor results. The experiments will be repeated when time coincident data is obtained for Phoenix.

The primary intended purpose of the SAR registration is to enhance crop classification performance over that obtained with Landsat above, without time coincident Landsat data this could not be tested. However,

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FIELD 1
RUN NO. 72069109
OTHER INFORMATION

TYPE
NO. OF SAMPLES 10201

CORRELATION MATRIX

SPECTRAL BAND	0.50 - 0.60	0.60 - 0.70	0.70 - 0.80	0.80 - 1.10	3.00 - 3.00
0.50- 0.60	1.00				
0.60- 0.70	0.95	1.00			
0.70- 0.80	0.68	0.64	1.00		
0.80- 1.10	0.29	0.24	0.86	1.00	
3.00- 3.00	-0.20	-0.22	-0.07	0.03	1.00

LINES 20- 120 (BY 1)
COLUMNS 1- 101 (BY 1)

FIELD 2
RUN NO. 72069109
OTHER INFORMATION

TYPE
NO. OF SAMPLES 10201

CORRELATION MATRIX

SPECTRAL BAND	0.50 - 0.60	0.60 - 0.70	0.70 - 0.80	0.80 - 1.10	3.00 - 3.00
0.50- 0.60	1.00				
0.60- 0.70	0.95	1.00			
0.70- 0.80	0.81	0.86	1.00		
0.80- 1.10	0.50	0.54	0.86	1.00	
3.00- 3.00	-0.08	0.00	-0.05	-0.10	1.00

LINES 1- 101 (BY 1)
COLUMNS 220- 320 (BY 1)

Figure C-5a. Correlation Matrices for Sample Fields 1 and 2. (Phoenix, AZ; Channels 1-4, Landsat; Channel 5, Aircraft SAR).

FIELD 3
RUN NO. 72069109
OTHER INFORMATION

TYPE
NO. OF SAMPLES 10201

CORRELATION MATRIX

SPECTRAL BAND	0.50 - 0.60	0.60 - 0.70	0.70 - 0.80	0.80 - 1.10	3.00 - 3.00
0.50- 0.60	1.00				
0.60- 0.70	0.98	1.00			
0.70- 0.80	0.59	0.52	1.00		
0.80- 1.10	0.04	-0.06	0.79	1.00	
3.00- 3.00	-0.09	-0.09	0.07	0.15	1.00

LINES 70- 170 (BY 1)
COLUMNS 340- 440 (BY 1)

FIELD 4
RUN NO. 72069109
OTHER INFORMATION

TYPE
NO. OF SAMPLES 10201

CORRELATION MATRIX

SPECTRAL BAND	0.50 - 0.60	0.60 - 0.70	0.70 - 0.80	0.80 - 1.10	3.00 - 3.00
0.50- 0.60	1.00				
0.60- 0.70	0.86	1.00			
0.70- 0.80	0.78	0.81	1.00		
0.80- 1.10	-0.20	0.12	0.27	1.00	
3.00- 3.00	-0.37	-0.43	-0.29	0.03	1.00

LINES 180- 280 (BY 1)
COLUMNS 15- 115 (BY 1)

Figure C-5b. Correlation Matrices for Sample Fields 3 and 4 (Phoenix, AZ).

131.

FIELD 5
RUN NO. 72069109
OTHER INFORMATION

TYPE
NO. OF SAMPLES 10201

CORRELATION MATRIX

SPECTRAL BAND	0.50 - 0.60	0.60 - 0.70	0.70 - 0.80	0.80 - 1.10	3.00 - 3.00
0.50- 0.60	1.00				
0.60- 0.70	0.96	1.00			
0.70- 0.80	0.84	0.85	1.00		
0.80- 1.10	0.61	0.60	0.91	1.00	
3.00- 3.00	-0.16	-0.21	-0.24	-0.24	1.00

LINES 145- 245 (BY 1)
COLUMNS 180- 280 (BY 1)

FIELD 6
RUN NO. 72069109
OTHER INFORMATION

TYPE
NO. OF SAMPLES 10201

CORRELATION MATRIX

SPECTRAL BAND	0.50 - 0.60	0.60 - 0.70	0.70 - 0.80	0.80 - 1.10	3.00 - 3.00
0.50- 0.60	1.00				
0.60- 0.70	0.97	1.00			
0.70- 0.80	0.36	0.26	1.00		
0.80- 1.10	-0.25	-0.35	0.78	1.00	
3.00- 3.00	-0.23	-0.24	-0.06	0.08	1.00

LINES 160- 260 (BY 1)
COLUMNS 400- 500 (BY 1)

Figure C-5c. Correlation Matrices for Sample Fields 5 and 6 (Phoenix, AZ).

FIELD 7
RUN NO. 72069109
OTHER INFORMATION

TYPE
NO. OF SAMPLES 10201

CORRELATION MATRIX

SPECTRAL BAND	0.50 - 0.60	0.60 - 0.70	0.70 - 0.80	0.80 - 1.10	3.00 - 3.00
0.50-0.60	1.00				
0.60-0.70	0.96	1.00			
0.70-0.80	0.76	0.76	1.00		
0.80-1.10	0.03	-0.00	0.34	1.00	
3.00-3.00	-0.23	-0.24	-0.09	-0.03	1.00

LINES 345- 465 (BY 1)
COLUMNS 80- 180 (BY 1)

FIELD 8
RUN NO. 72069109
OTHER INFORMATION

TYPE
NO. OF SAMPLES 10201

CORRELATION MATRIX

SPECTRAL BAND	0.50 - 0.60	0.60 - 0.70	0.70 - 0.80	0.80 - 1.10	3.00 - 3.00
0.50-0.60	1.00				
0.60-0.70	0.92	1.00			
0.70-0.80	0.28	0.15	1.00		
0.80-1.10	-0.11	-0.26	0.63	1.00	
3.00-3.00	-0.07	-0.09	0.00	0.03	1.00

LINES 365- 465 (BY 1)
COLUMNS 245- 345 (BY 1)

Figure C-5d. Correlation Matrices for Sample Fields 7 and 8 (Phoenix, AZ).

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FIELD 9
RUN NO. 72069109
OTHER INFORMATION

TYPE
NO. OF SAMPLES 9999

CORRELATION MATRIX

SPECTRAL BAND	0.50 - 0.60	0.60 - 0.70	0.70 - 0.80	0.80 - 1.10	3.00 - 3.00
0.50- 0.60	1.00				
0.60- 0.70	0.91	1.00			
0.70- 0.80	0.14	0.12	1.00		
0.80- 1.10	-0.32	-0.38	0.51	1.00	
3.00- 3.00	0.11	0.06	-0.10	-0.13	1.00

LINES 340- 440 (BY 1)
COLUMNS 412- 510 (BY 1)

Figure C-5e. Correlation Matrix for Sample Field 9 (Phoenix, AZ).

FIELD 1
RUN NO. 72069110
OTHER INFORMATION

TYPE
NO. OF SAMPLES 10201

CORRELATION MATRIX

SPECTRAL BAND	0.50 - 0.60	0.60 - 0.70	0.70 - 0.80	0.80 - 1.10	3.00 - 3.00	0.0 - 0.0	0.0 - 0.0
0.50-0.60	1.00						
0.60-0.70	0.95	1.00					
0.70-0.80	0.68	0.64	1.00				
0.80-1.10	0.29	0.24	0.86	1.00			
3.00-3.00	-0.20	-0.22	-0.07	0.03	1.00		
0.0 - 0.0	0.06	0.07	0.09	0.05	-0.07	1.00	
0.0 - 0.0	-0.01	-0.02	-0.10	-0.12	0.21	0.06	1.00

FIELD 2
RUN NO. 72069110
OTHER INFORMATION

TYPE
NO. OF SAMPLES 10201

CORRELATION MATRIX

SPECTRAL BAND	0.50 - 0.60	0.60 - 0.70	0.70 - 0.80	0.80 - 1.10	3.00 - 3.00	0.0 - 0.0	0.0 - 0.0
0.50-0.60	1.00						
0.60-0.70	0.95	1.00					
0.70-0.80	0.81	0.86	1.00				
0.80-1.10	0.50	0.54	0.86	1.00			
3.00-3.00	-0.08	0.00	-0.05	-0.10	1.00		
0.0 - 0.0	-0.15	-0.13	-0.16	-0.17	0.00	1.00	
0.0 - 0.0	0.03	0.00	0.01	-0.02	-0.01	-0.02	1.00

Figure C-6a. Correlation Matrices for Gradient of Fields 1 and 2. (Phoenix, AZ; Channel 1-4, LANDSAT; Channel 5, SAR; Channel 6, LANDSAT; Channel 3, Gradient; Channel 7, SAR Gradient).

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FIELD 3
RUN NO. 72069110
OTHER INFORMATION

TYPE
NO. OF SAMPLES 10201

CORRELATION MATRIX

SPECTRAL BAND	0.50 - 0.60	0.60 - 0.70	0.70 - 0.80	0.80 - 1.10	3.00 - 3.00	0.0 - 0.0	0.0 - 0.0
0.50-0.60	1.00						
0.60-0.70	0.98	1.00					
0.70-0.80	0.59	0.52	1.00				
0.80-1.10	0.04	-0.06	0.79	1.00			
3.00-3.00	-0.09	-0.09	0.07	0.15	1.00		
0.0 - 0.0	0.14	0.16	-0.02	-0.12	-0.01	1.00	
0.0 - 0.0	0.18	0.18	0.05	-0.08	0.02	0.02	1.00

FIELD 4
RUN NO. 72069110
OTHER INFORMATION

TYPE
NO. OF SAMPLES 10201

CORRELATION MATRIX

SPECTRAL BAND	0.50 - 0.60	0.60 - 0.70	0.70 - 0.80	0.80 - 1.10	3.00 - 3.00	0.0 - 0.0	0.0 - 0.0
0.50-0.60	1.00						
0.60-0.70	0.86	1.00					
0.70-0.80	0.78	0.81	1.00				
0.80-1.10	-0.20	0.12	0.27	1.00			
3.00-3.00	-0.37	-0.43	-0.29	0.03	1.00		
0.0 - 0.0	-0.03	0.02	0.09	0.23	0.16	1.00	
0.0 - 0.0	0.00	-0.03	-0.00	0.00	0.14	0.14	1.0(

Figure C-6b. Correlation Matrices for Gradient of Fields 3 and 4. (Phoenix, AZ).

FIELD 5
RUN NO. 72069110
OTHER INFORMATION

TYPE
NO. OF SAMPLES 10201

CORRELATION MATRIX

SPECTRAL BAND	0.50 - 0.60	0.60 - 0.70	0.70 - 0.80	0.80 - 1.10	3.00 - 3.00	0.0 - 0.0	0.0 - 0.0
0.50- 0.60	1.00						
0.60- 0.70	0.96	1.00					
0.70- 0.80	0.84	0.85	1.00				
0.80- 1.10	0.61	0.60	0.91	1.00			
3.00- 3.00	-0.16	-0.21	-0.24	-0.24	1.00		
0.0 - 0.0	0.12	0.13	0.07	0.00	-0.04	1.00	
0.0 - 0.0	0.03	-0.01	-0.07	-0.10	0.35	0.10	1.00

FIELD 6
RUN NO. 72069110
OTHER INFORMATION

TYPE
NO. OF SAMPLES 10201

CORRELATION MATRIX

SPECTRAL BAND	0.50 - 0.60	0.60 - 0.70	0.70 - 0.80	0.80 - 1.10	3.00 - 3.00	0.0 - 0.0	0.0 - 0.0
0.50- 0.60	1.00						
0.60- 0.70	0.97	1.00					
0.70- 0.80	0.36	0.26	1.00				
0.80- 1.10	-0.25	-0.35	0.78	1.00			
3.00- 3.00	-0.23	-0.24	-0.06	0.08	1.00		
0.0 - 0.0	0.09	0.06	0.09	0.04	-0.04	1.00	
0.0 - 0.0	0.18	0.15	0.01	-0.09	-0.07	0.15	1.00

Figure C-6c. Correlation Matrices for Gradient of Fields 5 and 6 (Phoenix, AZ).

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FIELD 7
RUN NO. 72069110
OTHER INFORMATION

TYPE
NO. OF SAMPLES 10201

CORRELATION MATRIX

SPECTRAL BAND	0.50 - 0.60	0.60 - 0.70	0.70 - 0.80	0.80 - 1.10	3.00 - 3.00	0.0 - 0.0	0.0 - 0.0
0.50- 0.60	1.00						
0.60- 0.70	0.96	1.00					
0.70- 0.80	0.76	0.76	1.00				
0.80- 1.10	0.03	-0.00	0.34	1.00			
3.00- 3.00	-0.23	-0.24	-0.09	-0.03	1.00		
0.0 - 0.0	-0.05	-0.05	0.01	0.20	-0.05	1.00	
0.0 - 0.0	0.17	0.15	0.10	-0.03	0.06	0.02	1.00

FIELD 8
RUN NO. 72069110
OTHER INFORMATION

TYPE
NO. OF SAMPLES 10201

CORRELATION MATRIX

SPECTRAL BAND	0.50 - 0.60	0.60 - 0.70	0.70 - 0.80	0.80 - 1.10	3.00 - 3.00	0.0 - 0.0	0.0 - 0.0
0.50- 0.60	1.00						
0.60- 0.70	0.92	1.00					
0.70- 0.80	0.28	0.15	1.00				
0.80- 1.10	-0.11	-0.26	0.63	1.00			
3.00- 3.00	-0.07	-0.09	0.00	0.03	1.00		
0.0 - 0.0	0.13	0.11	-0.09	0.10	-0.03	1.00	
0.0 - 0.0	0.18	0.17	0.02	-0.03	0.16	0.08	1.00

Figure C-6d. Correlation Matrices for Gradient of Fields 7 and 8 (Phoenix, AZ).

FIELD 9
RUN NO. 72069110
OTHER INFORMATION

TYPE
NO. OF SAMPLES 9595

CORRELATION MATRIX

SPECTRAL BAND	0.50 - 0.60	0.60 - 0.70	0.70 - 0.80	0.80 - 1.10	3.00 - 3.00	0.0 - 0.0	0.0 - 0.0
0.50-0.60	1.00						
0.60-0.70	0.91	1.00					
0.70-0.80	0.12	0.10	1.00				
0.80-1.10	-0.33	-0.39	0.52	1.00			
3.00-3.00	0.11	0.06	-0.10	-0.13	1.00		
0.0 - 0.0	0.04	0.02	-0.07	0.09	-0.03	1.00	
0.0 - 0.0	0.15	0.10	-0.12	-0.14	0.33	0.02	1.00

Figure C-6e. Correlation Matrix for Gradient of Field 9 (Phoenix, AZ).

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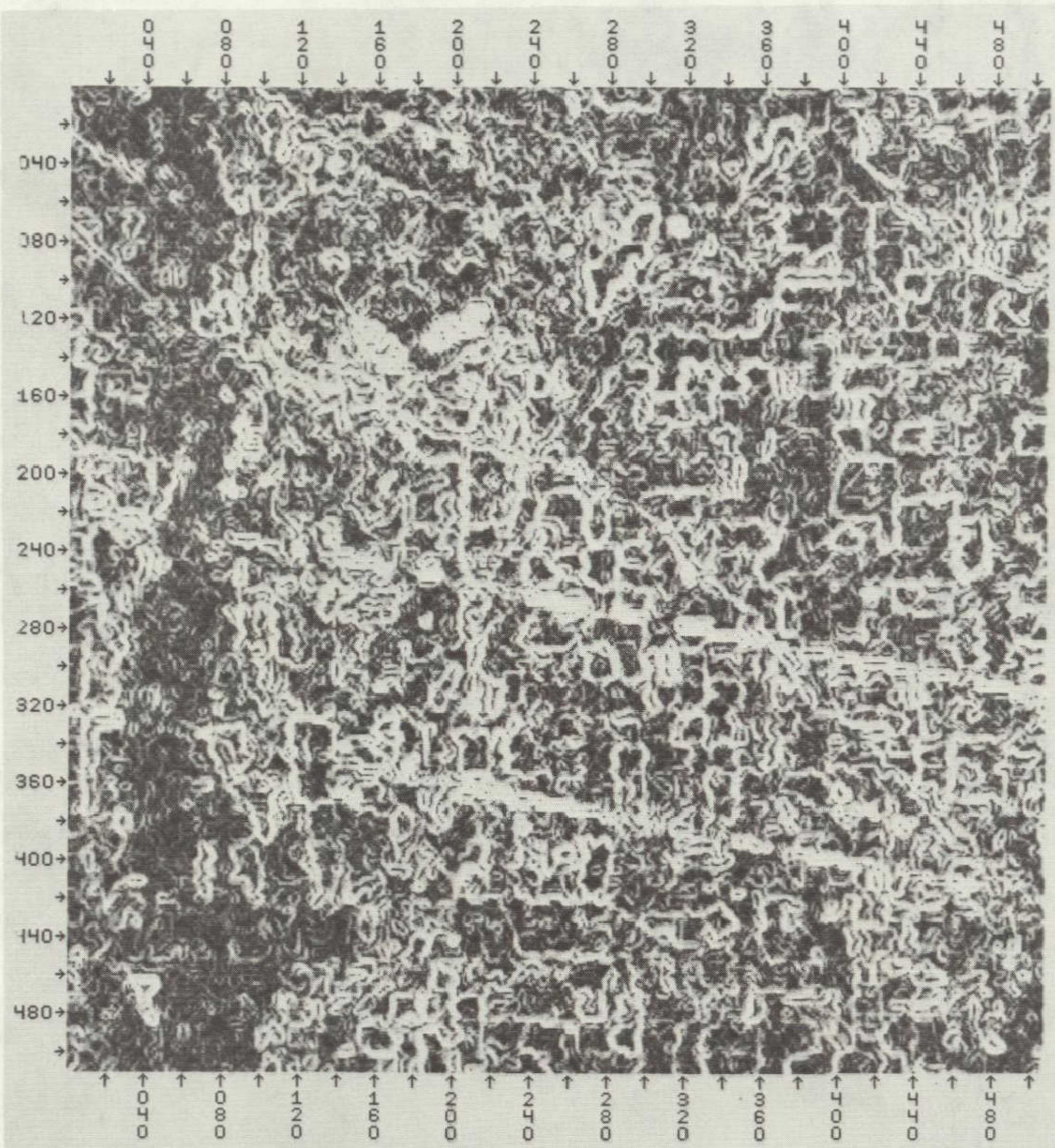

Figure C-7. Magnitude of Gradient for Landsat Channel 3 (0.7-0.8μm) (Phoenix, AZ).

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OF POOR QUALITY

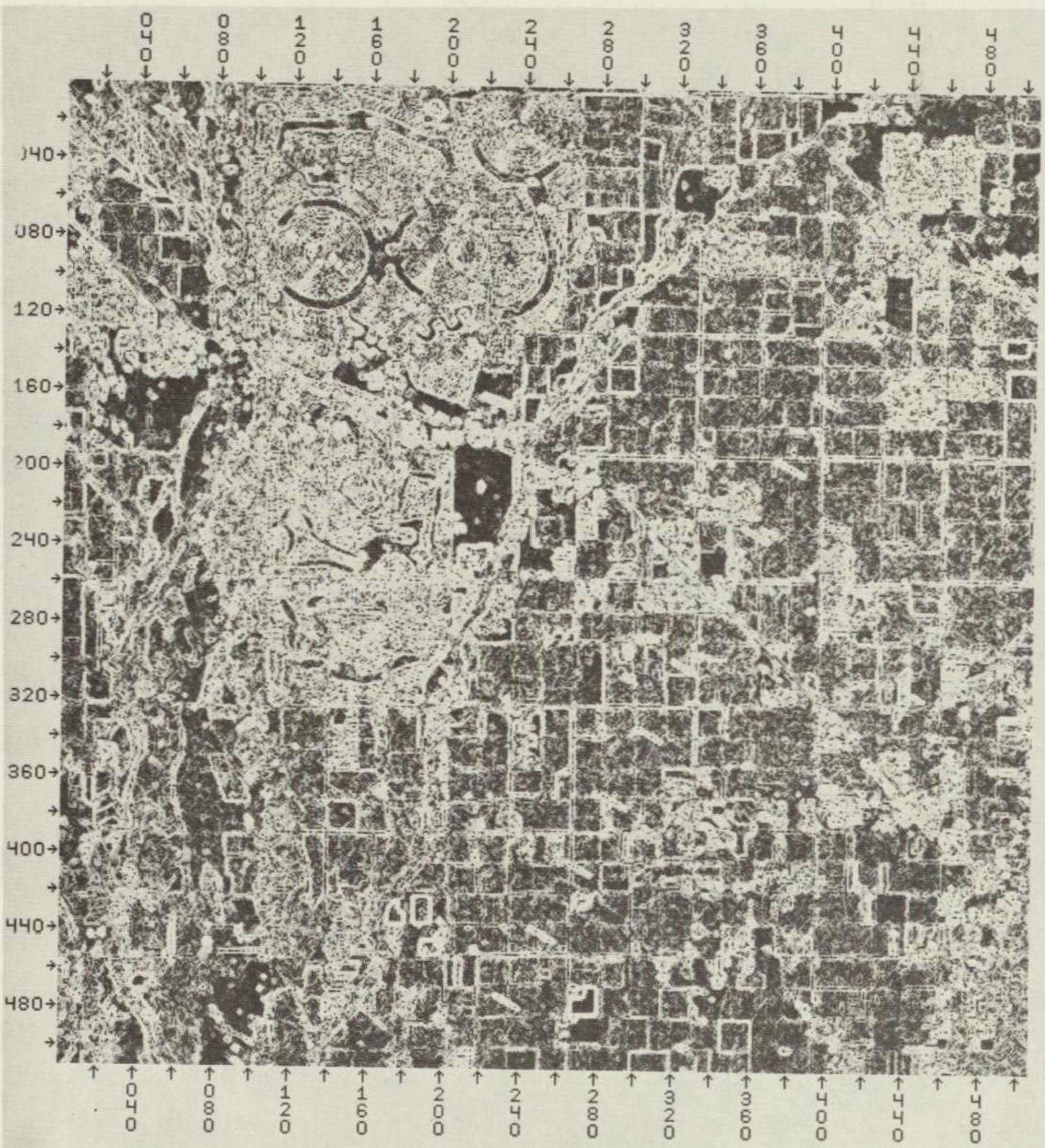

Figure C-8. Magnitude of the Gradient for Aircraft SAR (Phoenix, AZ).

since ground truth was available for Phoenix, data statistical analysis was performed to examine the separability of crops in the SAR channel (ch 5). Figure C-9 contains correlation matrices for the classes: alfalfa, barley, cotton, onions, sugar beets, urban and wheat. Figure C-10 contains histograms for these classes and C-11 contains their spectral plots. Only the last row (spectral band 3.0-3.0) is significant to the ground truth. The four Landsat bands are included to provide a typical crop vegetation comparison but the contents of the fields on October 16, 1972 are unknown. The SAR data shows some discrimination for cotton, barley and urban with alfalfa, wheat, sugar beets and onions having similar means and variances. These judgements are based only on histogram inspection and detailed analysis can only be done after the time coincident Landsat data is available.

5. GENERAL MULTIDATA MERGING SYSTEM STUDY AND MULTIDATA MERGING SOFTWARE AND DATA SET GENERATION

These two tasks were fulfilled within the scope of the aircraft SAR analysis performed and were not followed as separate task timelines except for the case of ancillary data. The project included consideration of ancillary data merging problems and this was not studied until the fourth quarter.

The process of manually digitizing a complex polygon map is slow, error prone and requires costly and often unreliable gridding of digitized arcs. An alternate method of map digitizing was described in the June 1976 LARS SR&T Final Report which was color scanning and digitizing of colored polygons on maps with computer classification to extract the polygons. This method showed promise and it was decided to test the method under controlled color conditions. In the previous test a pastel colored printed map was used which had color dot printing patterns rather than solid colors resulting in noise color signals.

The experiment carried out in the fourth quarter took as an example a complex forest operating area map which can not be successfully digitized by the manual method due to the complex shapes and small size of

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CLASS STATISTICS FOR GROUND TRUTH

CLASS....ALFALFA

TOTAL NUMBER OF SAMPLES... 465

CORRELATION MATRIX

SPECTRAL BAND	0.50 - 0.60	0.60 - 0.70	0.70 - 0.80	0.80 - 1.10	3.00 - 3.00
0.50- 0.60	1.00				
0.60- 0.70	0.70	1.00			
0.70- 0.80	-0.18	-0.73	1.00		
0.80- 1.10	-0.29	-0.81	0.98	1.00	
3.00- 3.00	-0.23	-0.32	0.29	0.33	1.00

CLASS....BARLEY

TOTAL NUMBER OF SAMPLES... 372

CORRELATION MATRIX

SPECTRAL BAND	0.50 - 0.60	0.60 - 0.70	0.70 - 0.80	0.80 - 1.10	3.00 - 3.00
0.50- 0.60	1.00				
0.60- 0.70	0.90	1.00			
0.70- 0.80	0.68	0.59	1.00		
0.80- 1.10	0.58	0.46	0.94	1.00	
3.00- 3.00	0.26	0.38	0.19	0.15	1.00

Figure C-9a. Correlation Matrices for Ground Truth Classes-Alfalfa and Barley (Phoenix, AZ).

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CLASS....COTTON

TOTAL NUMBER OF SAMPLES... 240

CORRELATION MATRIX

SPECTRAL BAND	0.50 - 0.60	0.60 - 0.70	0.70 - 0.80	0.80 - 1.10	3.00 - 3.00
0.50- 0.60	1.00				
0.60- 0.70	0.95	1.00			
0.70- 0.80	0.94	0.87	1.00		
0.80- 1.10	0.89	0.79	0.94	1.00	
3.00- 3.00	-0.10	-0.06	-0.13	-0.12	1.00

CLASS....ONIONS

TOTAL NUMBER OF SAMPLES... 396

CORRELATION MATRIX

SPECTRAL BAND	0.50 - 0.60	0.60 - 0.70	0.70 - 0.80	0.80 - 1.10	3.00 - 3.00
0.50- 0.60	1.00				
0.60- 0.70	0.69	1.00			
0.70- 0.80	0.20	-0.10	1.00		
0.80- 1.10	0.03	-0.28	0.84	1.00	
3.00- 3.00	-0.32	-0.41	-0.12	-0.09	1.00

Figure C-9b. Correlation Matrices for Ground Truth Classes-Cotton and Onions (Phoenix, AZ).

CLASS....SUGAR BE

TOTAL NUMBER OF SAMPLES... 420

CORRELATION MATRIX

SPECTRAL BAND	0.50 - 0.60	0.60 - 0.70	0.70 - 0.80	0.80 - 1.10	3.00 - 3.00
0.50-0.60	1.00				
0.60-0.70	0.96	1.00			
0.70-0.80	0.16	0.06	1.00		
0.80-1.10	-0.59	-0.68	0.60	1.00	
3.00-3.00	-0.00	-0.03	-0.06	-0.02	1.00

CLASS....URBAN

TOTAL NUMBER OF SAMPLES... 1066

CORRELATION MATRIX

SPECTRAL BAND	0.50 - 0.60	0.60 - 0.70	0.70 - 0.80	0.80 - 1.10	3.00 - 3.00
0.50-0.60	1.00				
0.60-0.70	0.96	1.00			
0.70-0.80	0.83	0.83	1.00		
0.80-1.10	0.69	0.68	0.94	1.00	
3.00-3.00	0.21	0.18	0.18	0.17	1.00

Figure C-9c. Correlation Matrices for Ground Truth Classes-Sugar Beets and Urban (Phoenix, AZ).

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CLASS....WHEAT

TOTAL NUMBER OF SAMPLES... 238

CORRELATION MATRIX

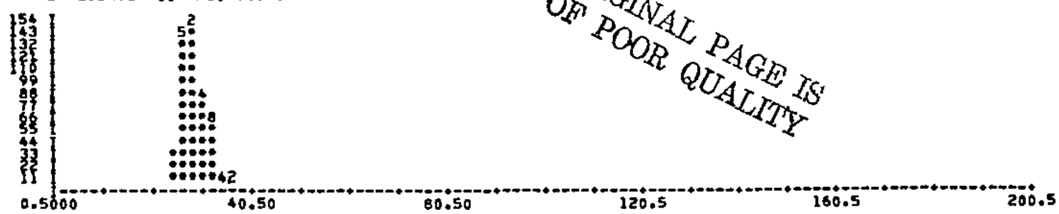
SPECTRAL BAND	0.50 - 0.60	0.60 - 0.70	0.70 - 0.80	0.80 - 1.10	3.00 - 3.00
0.50-0.60	1.00				
0.60-0.70	0.97	1.00			
0.70-0.80	0.73	0.71	1.00		
0.80-1.10	0.16	0.12	0.58	1.00	
3.00-3.00	0.02	-0.04	-0.16	-0.05	1.00

Figure C-9d. Correlation Matrices for Ground Truth Class-Wheat (Phoenix, AZ).

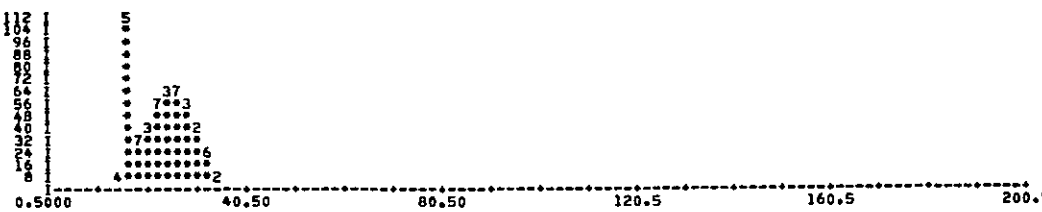
CLASS STATISTICS FOR GROUND TRUTH

CLASS....ALFALFA
HISTOGRAM(S)
TOTAL NUMBER OF SAMPLES... 465

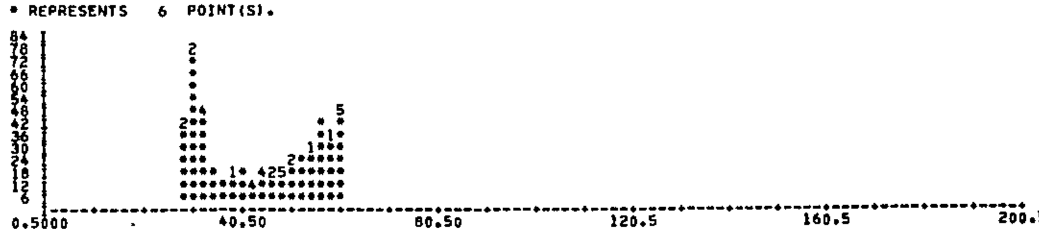
CHANNEL 1 0.50 - 0.60 MICROMETERS
EACH * REPRESENTS 11 POINT(S).



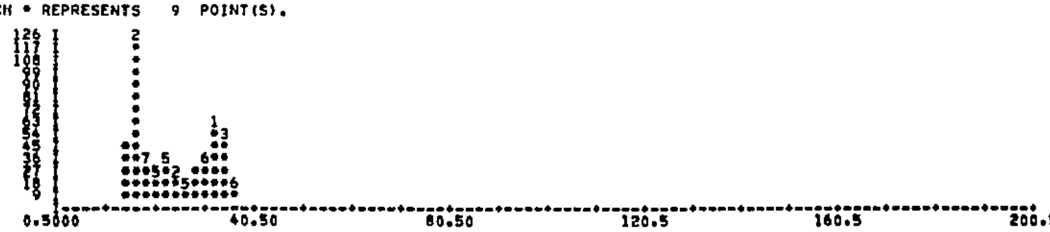
CHANNEL 2 0.60 - 0.70 MICROMETERS
EACH * REPRESENTS 8 POINT(S).



CHANNEL 3 0.70 - 0.80 MICROMETERS
EACH * REPRESENTS 6 POINT(S).



CHANNEL 4 0.80 - 1.10 MICROMETERS
EACH * REPRESENTS 9 POINT(S).



CHANNEL 5 3.00 - 3.00 MICROMETERS
EACH * REPRESENTS 4 POINT(S).

Figure C-10a. Histograms for Class-Alfalfa (Phoenix, AZ; Channels 1-4, Landsat; Channel 5, Aircraft SAR).

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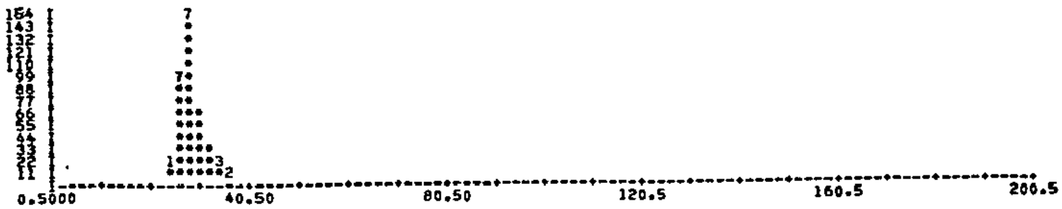
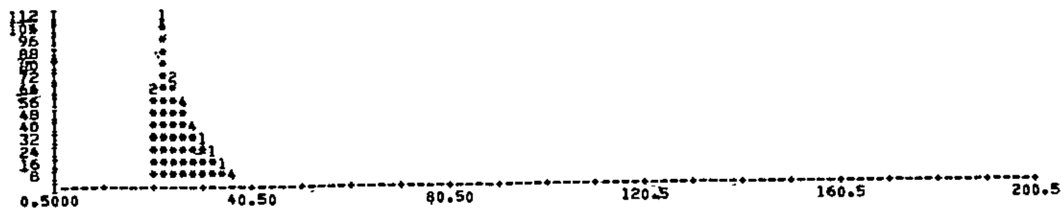
CLASS STATISTICS FOR GROUND TRUTH

CLASS....BARLEY
HISTOGRAM(S)
TOTAL NUMBER OF SAMPLES... 372

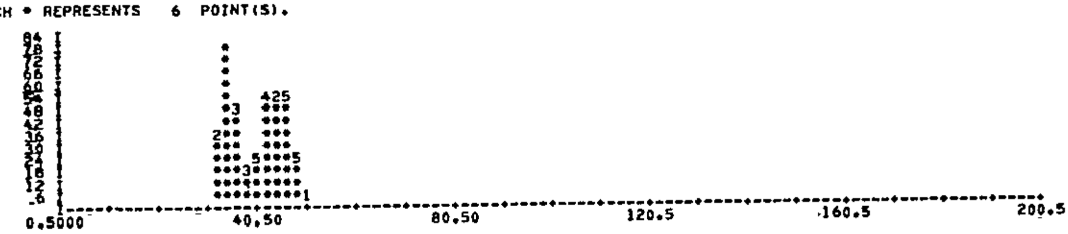
CHANNEL 1 0.50 - 0.60 MICROMETERS
EACH * REPRESENTS 11 POINT(S).



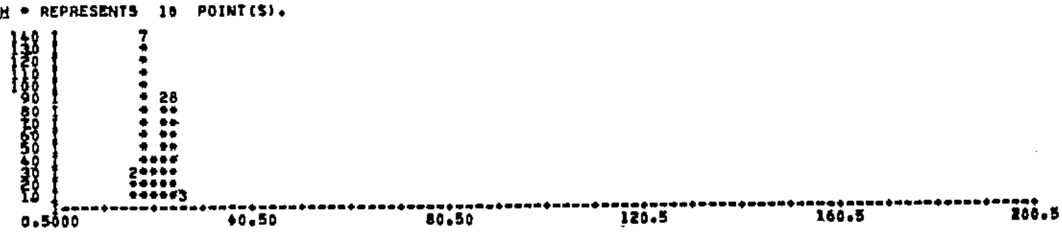
CHANNEL 2 0.60 - 0.70 MICROMETERS
EACH * REPRESENTS 8 POINT(S).



CHANNEL 3 0.70 - 0.80 MICROMETERS
EACH * REPRESENTS 6 POINT(S).



CHANNEL 4 0.80 - 1.10 MICROMETERS
EACH * REPRESENTS 10 POINT(S).



CHANNEL 5 3.00 - 3.00 MICROMETERS
EACH * REPRESENTS 4 POINT(S).

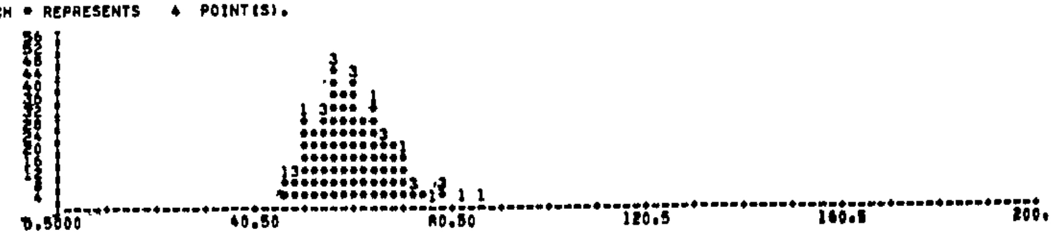


Figure C-10b. Histograms for Class-Barley (Phoenix, AZ).

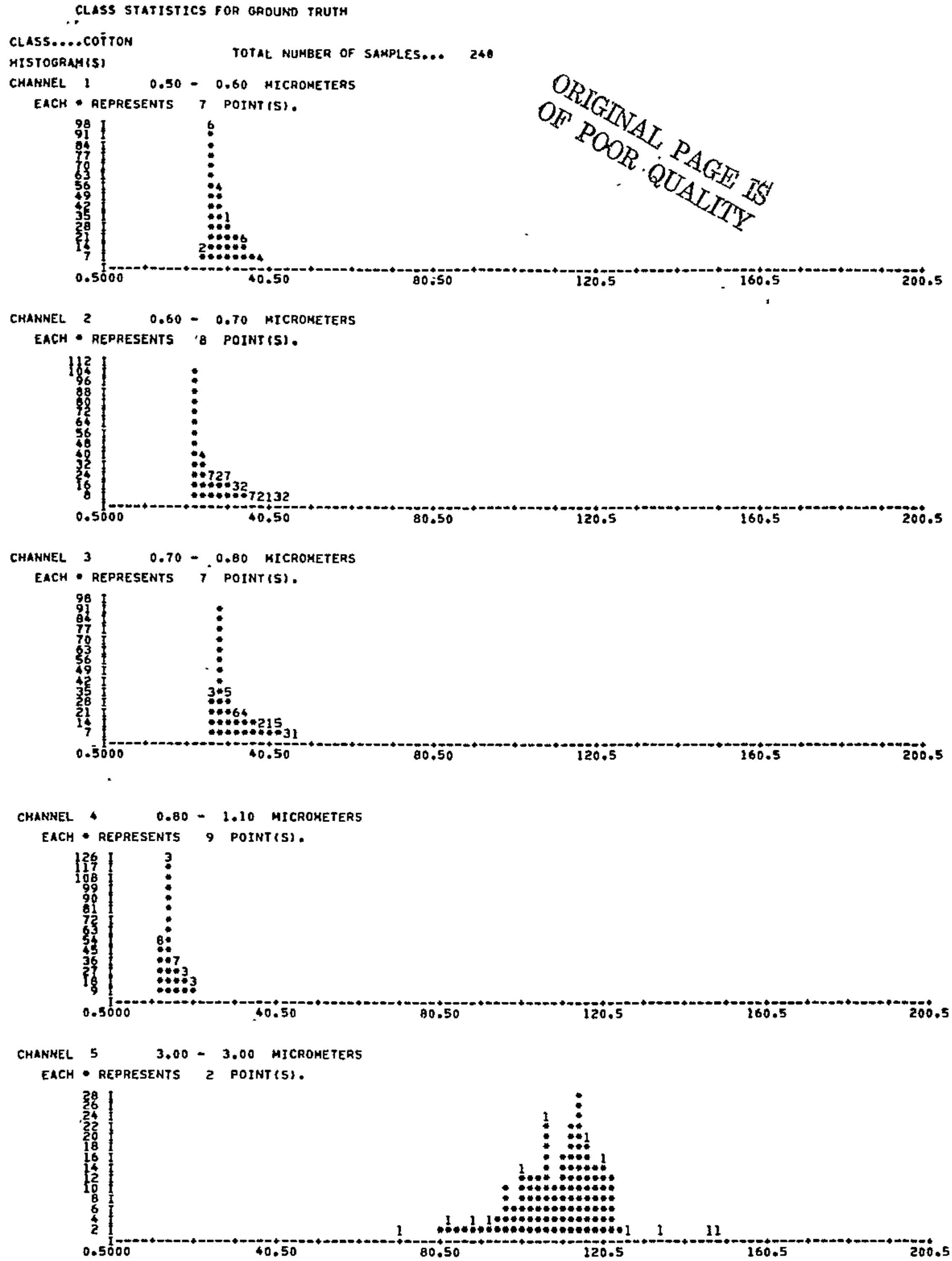
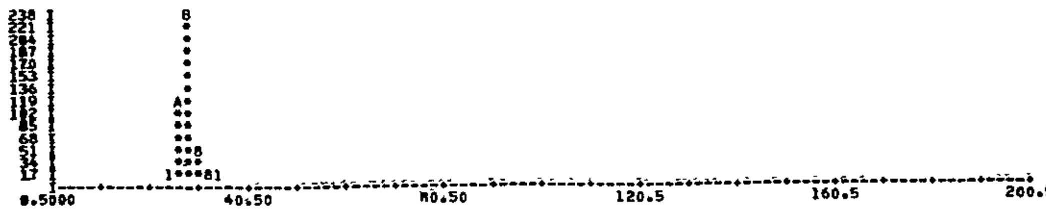


Figure C-10c. Histograms for Class-Cotton (Phoenix, AZ).

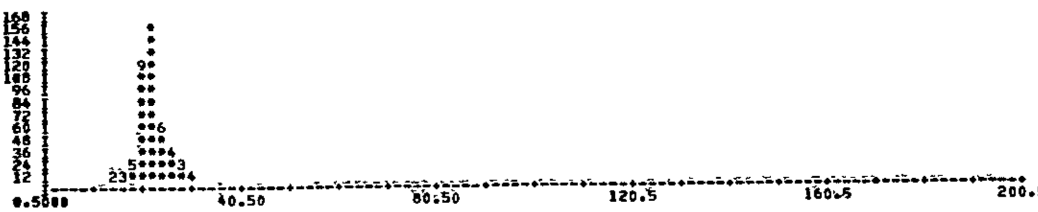
CLASS STATISTICS FOR GROUND TRUTH

CLASS....ONIONS
HISTOGRAM(S)
TOTAL NUMBER OF SAMPLES... 396

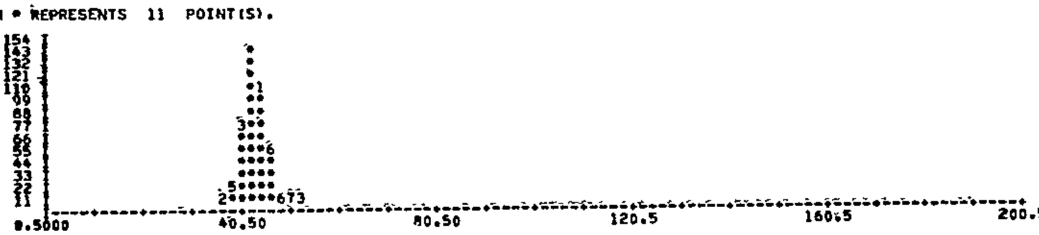
CHANNEL 1 0.50 - 0.60 MICROMETERS
EACH * REPRESENTS 17 POINT(S).



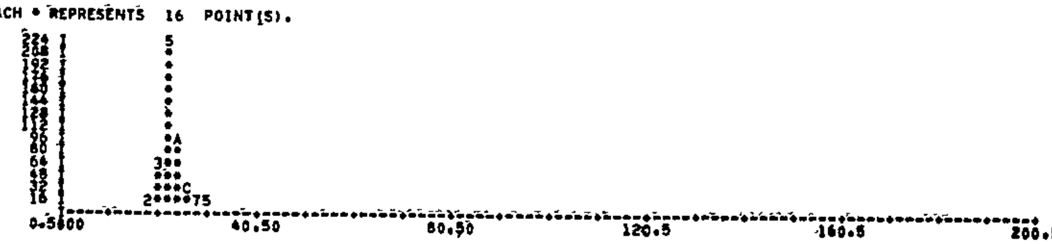
CHANNEL 2 0.60 - 0.70 MICROMETERS
EACH * REPRESENTS 12 POINT(S).



CHANNEL 3 0.70 - 0.80 MICROMETERS
EACH * REPRESENTS 11 POINT(S).



CHANNEL 4 0.80 - 1.10 MICROMETERS
EACH * REPRESENTS 16 POINT(S).



CHANNEL 5 3.00 - 3.00 MICROMETERS
EACH * REPRESENTS 3 POINT(S).

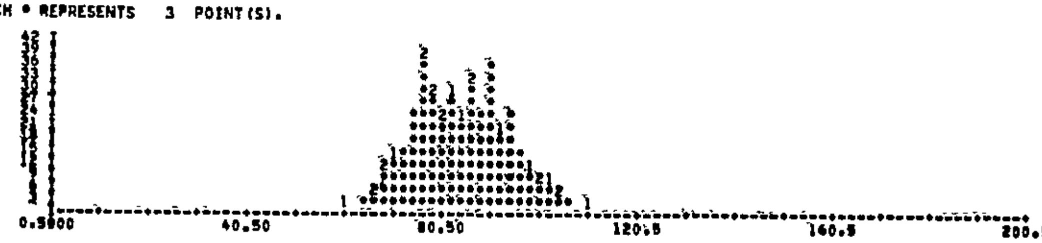


Figure C-10d. Histograms for Class-Onions (Phoenix, AZ).

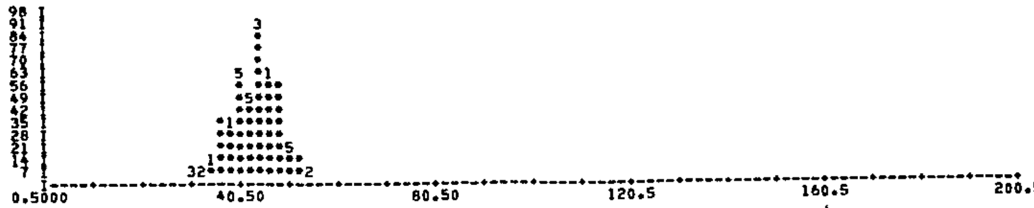
CLASS STATISTICS FOR GROUND TRUTH

CLASS....SUGAR BE   TOTAL NUMBER OF SAMPLES...   420

HISTOGRAM(S)

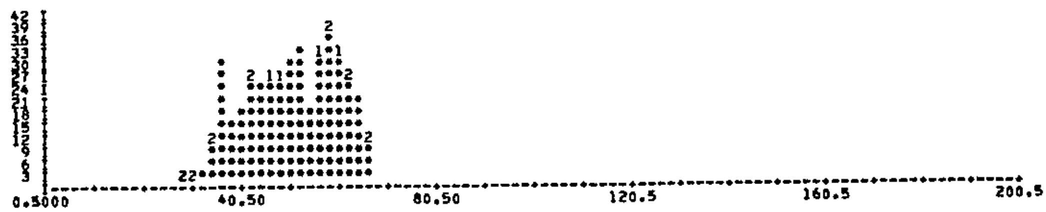
CHANNEL 1   0.50 - 0.60 MICROMETERS

EACH * REPRESENTS 7 POINT(S).



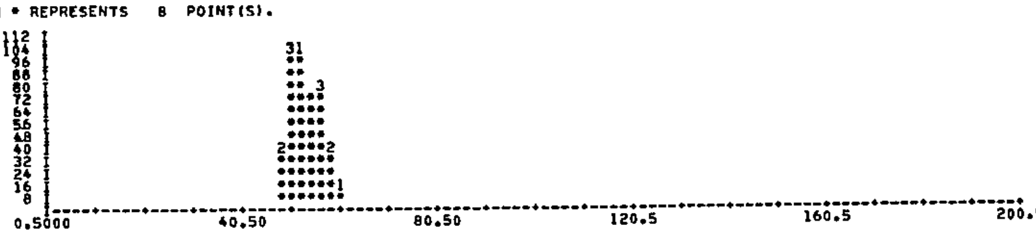
CHANNEL 2   0.60 - 0.70 MICROMETERS

EACH * REPRESENTS 3 POINT(S).



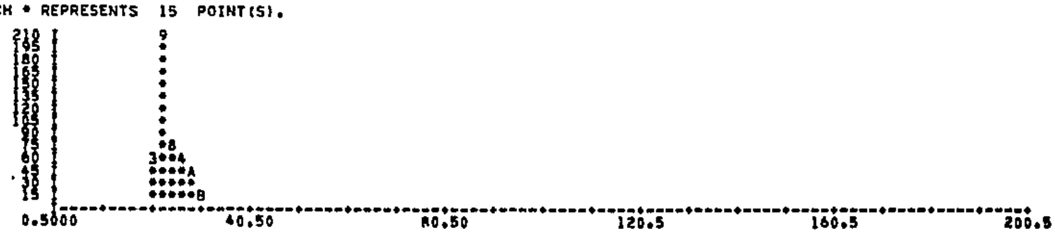
CHANNEL 3   0.70 - 0.80 MICROMETERS

EACH * REPRESENTS 8 POINT(S).



CHANNEL 4   0.80 - 1.10 MICROMETERS

EACH * REPRESENTS 15 POINT(S).



CHANNEL 5   3.00 - 3.00 MICROMETERS

EACH * REPRESENTS 2 POINT(S).

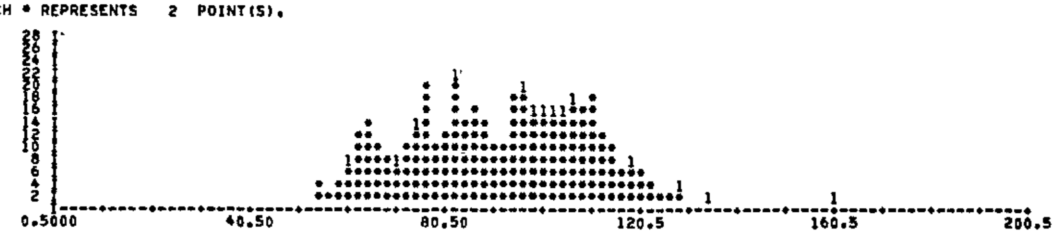


Figure C-10e. Histograms for Class-Sugar Beets (Phoenix, AZ).

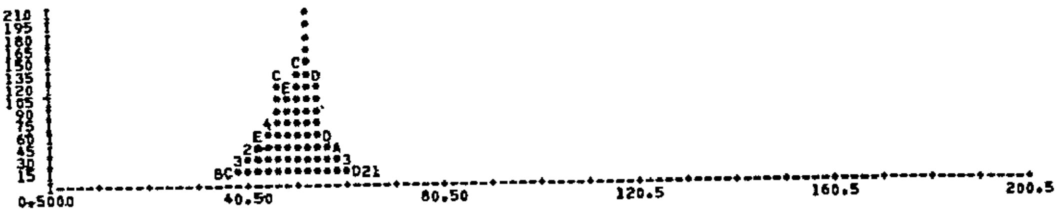
CLASS STATISTICS FOR GROUND TRUTH

CLASS....URBAN TOTAL NUMBER OF SAMPLES... 1066

HISTOGRAM(S)

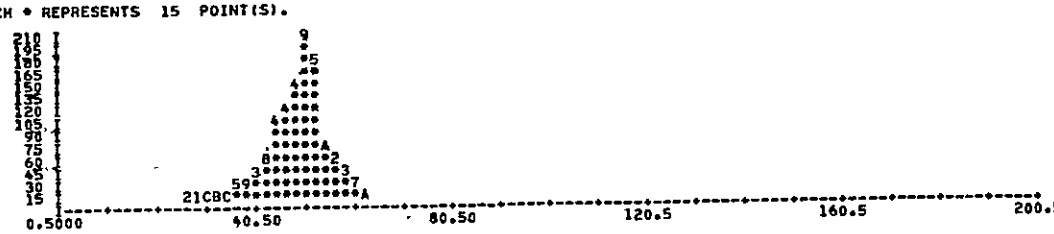
CHANNEL 1 0.50 - 0.60 MICROMETERS

EACH * REPRESENTS 15 POINT(S).



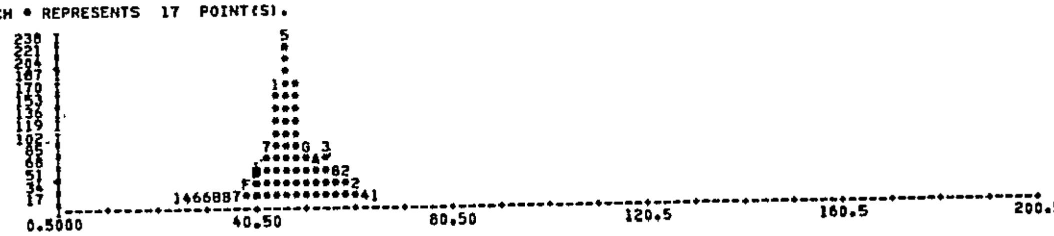
CHANNEL 2 0.60 - 0.70 MICROMETERS

EACH * REPRESENTS 15 POINT(S).



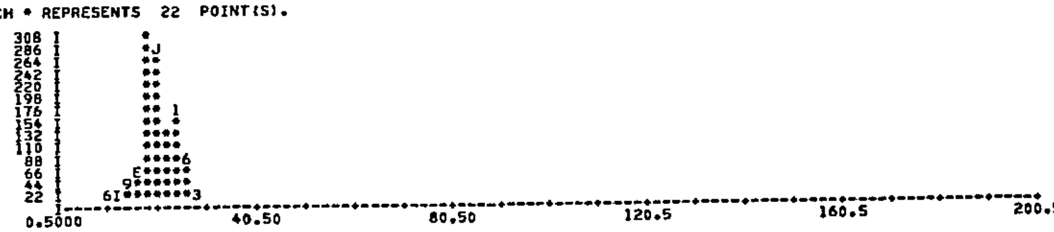
CHANNEL 3 0.70 - 0.80 MICROMETERS

EACH * REPRESENTS 17 POINT(S).



CHANNEL 4 0.80 - 1.10 MICROMETERS

EACH * REPRESENTS 22 POINT(S).



CHANNEL 5 3.00 - 3.00 MICROMETERS

EACH * REPRESENTS 3 POINT(S).

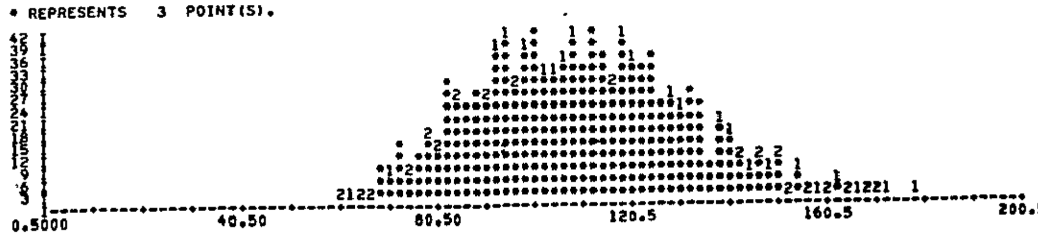


Figure C-10f. Histograms for Class-Urban (Phoenix, AZ).

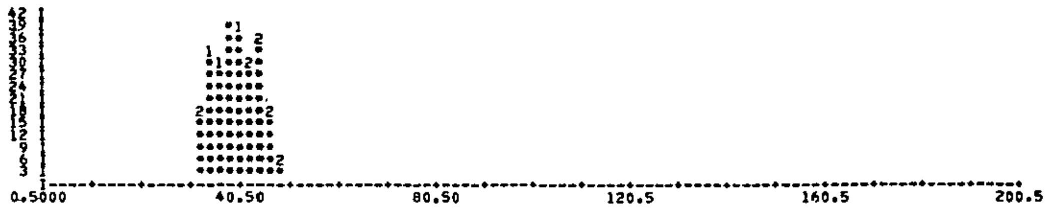
CLASS STATISTICS FOR GROUND TRUTH

CLASS....WHEAT TOTAL NUMBER OF SAMPLES... 238

HISTOGRAM(S)

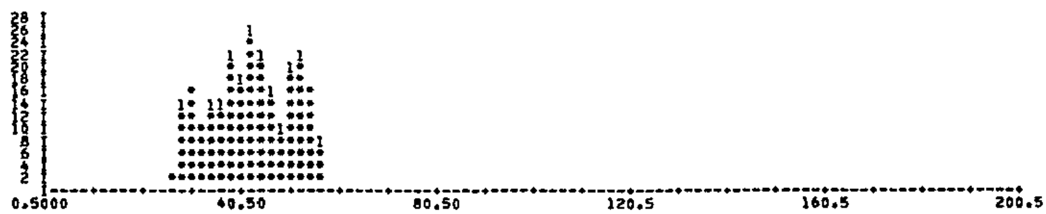
CHANNEL 1 0.50 - 0.60 MICROMETERS

EACH * REPRESENTS 3 POINT(S).



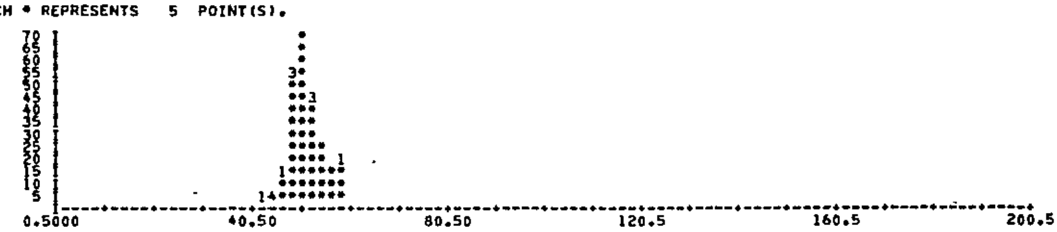
CHANNEL 2 0.60 - 0.70 MICROMETERS

EACH * REPRESENTS 2 POINT(S).



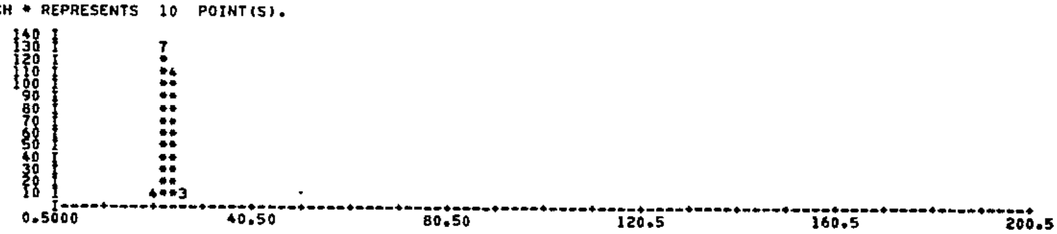
CHANNEL 3 0.70 - 0.80 MICROMETERS

EACH * REPRESENTS 5 POINT(S).



CHANNEL 4 0.80 - 1.10 MICROMETERS

EACH * REPRESENTS 10 POINT(S).



CHANNEL 5 3.00 - 3.00 MICROMETERS

EACH * REPRESENTS 2 POINT(S).

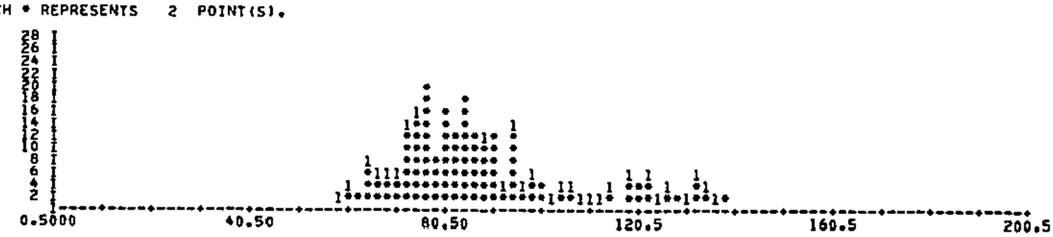


Figure C-10g. Histograms for Class-Wheat (Phoenix, AZ).

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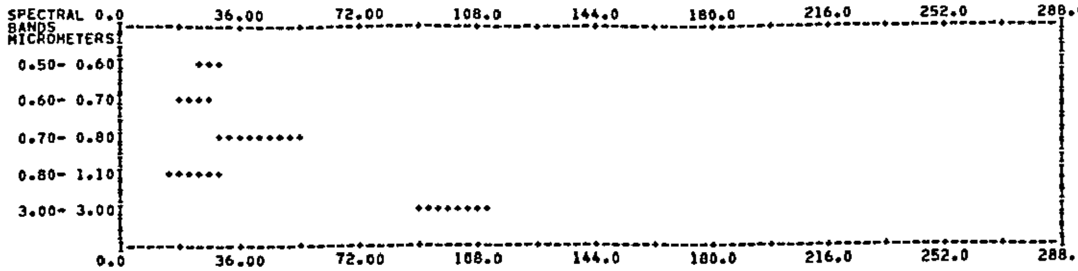
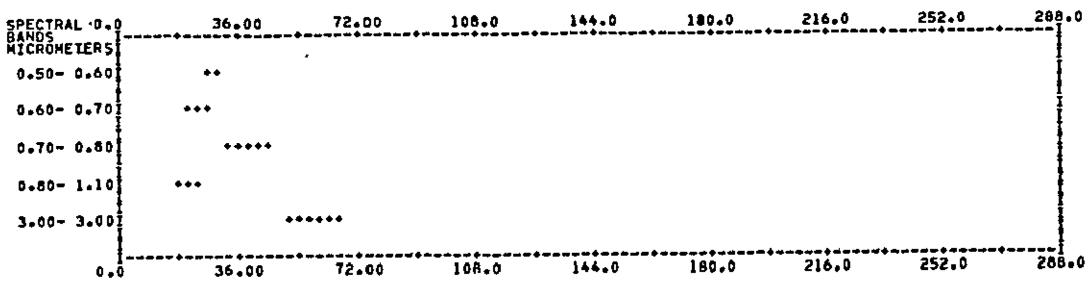
CLASS STATISTICS FOR GROUND TRUTH

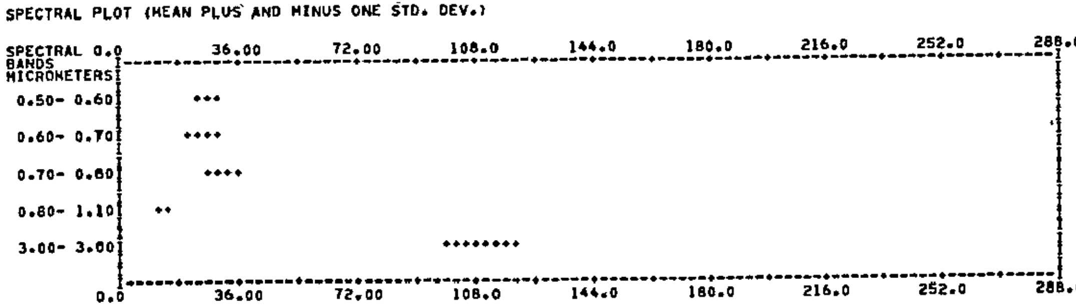
CLASS....ALFALFA
TOTAL NUMBER OF SAMPLES... 465
SPECTRAL PLOT (MEAN PLUS AND MINUS ONE STD. DEV.)



CLASS....BARLEY
TOTAL NUMBER OF SAMPLES... 372
SPECTRAL PLOT (MEAN PLUS AND MINUS ONE STD. DEV.)



CLASS....COTTON
TOTAL NUMBER OF SAMPLES... 240
SPECTRAL PLOT (MEAN PLUS AND MINUS ONE STD. DEV.)



CLASS....ONIONS
TOTAL NUMBER OF SAMPLES... 396
SPECTRAL PLOT (MEAN PLUS AND MINUS ONE STD. DEV.)

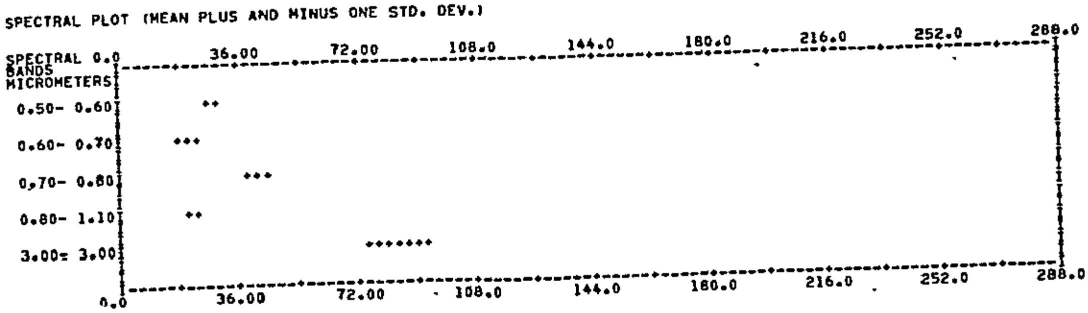
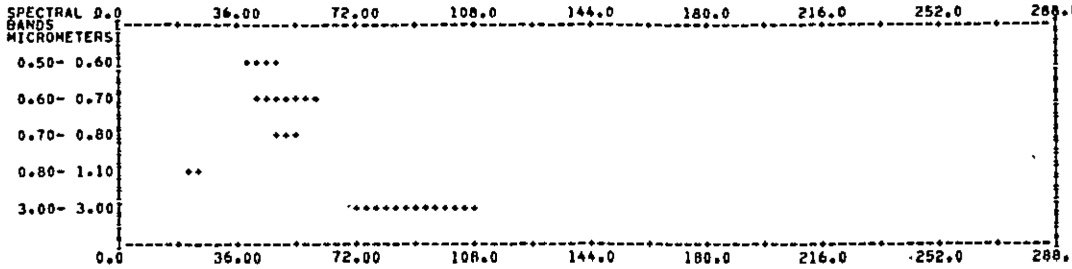


Figure C-11a. Spectral Plots for Classes (Phoenix, AZ).

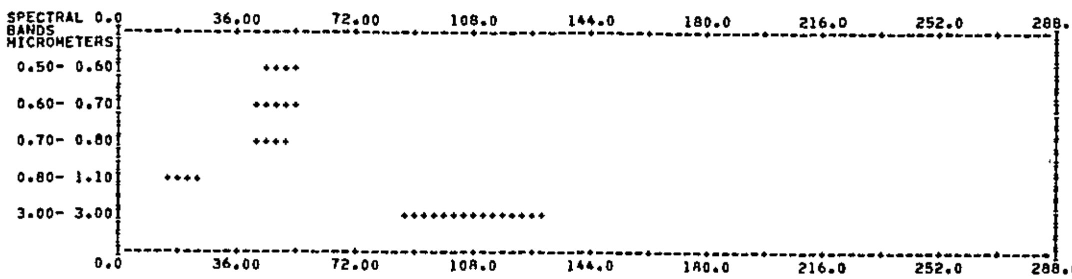
ORIGINAL PAGE IS
OF POOR QUALITY

CLASS STATISTICS FOR GROUND TRUTH

CLASS....SUGAR BE
TOTAL NUMBER OF SAMPLES... 420
SPECTRAL PLOT (MEAN PLUS AND MINUS ONE STD. DEV.)



CLASS....URBAN
TOTAL NUMBER OF SAMPLES... 1066
SPECTRAL PLOT (MEAN PLUS AND MINUS ONE STD. DEV.)



CLASS....WHEAT
TOTAL NUMBER OF SAMPLES... 238
SPECTRAL PLOT (MEAN PLUS AND MINUS ONE STD. DEV.)

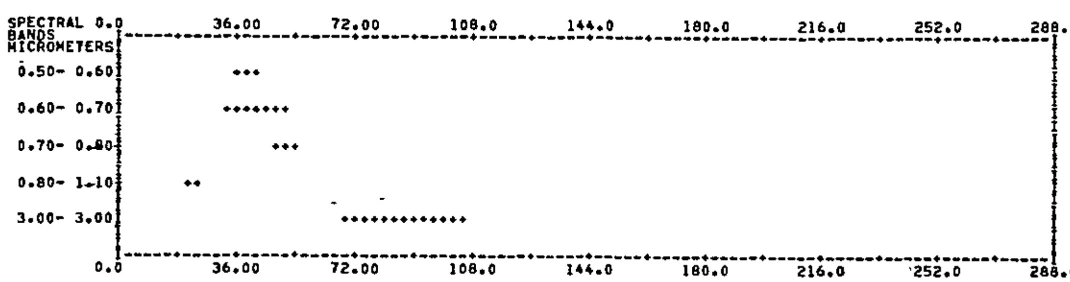


Figure C-11b. Spectral Plots for Classes (Phoenix, AZ).

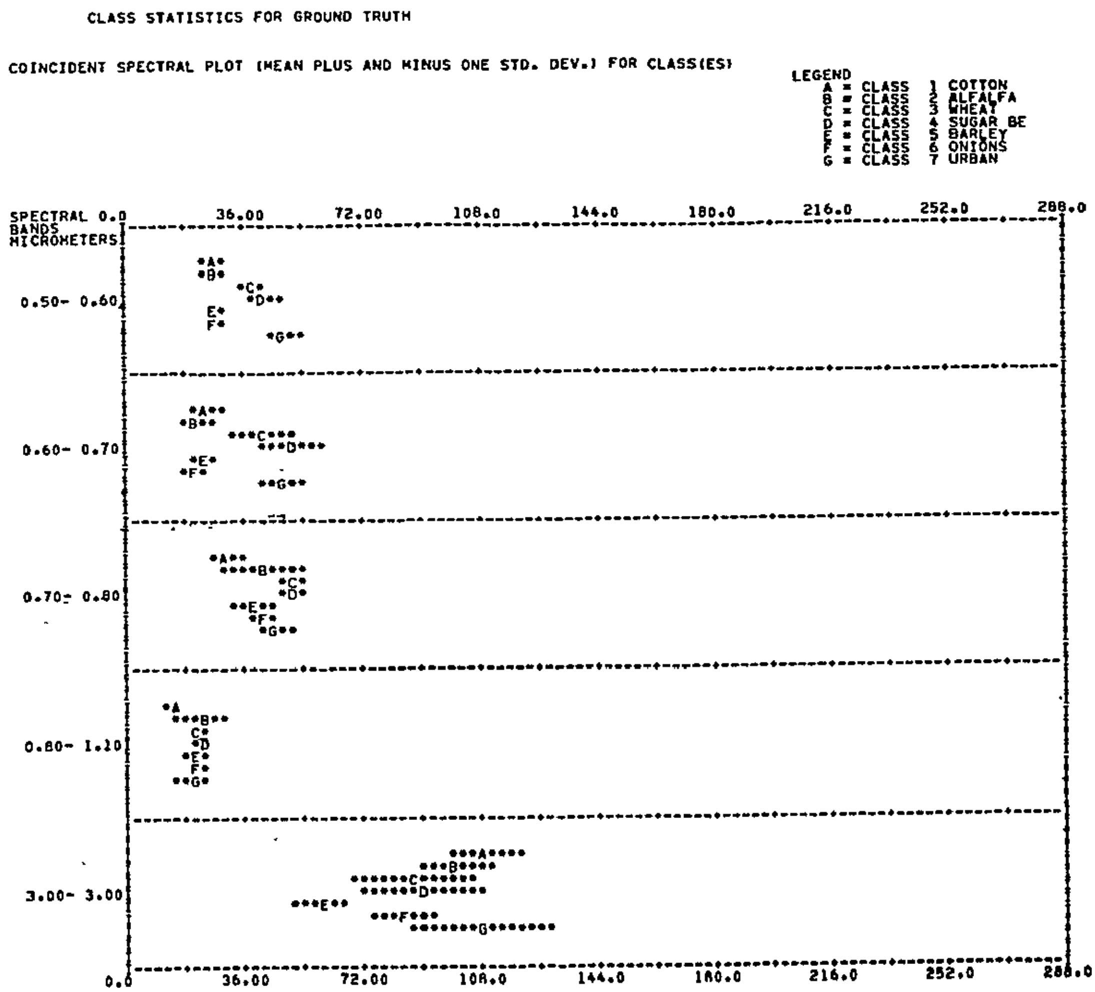


Figure C-11c. Spectral Plot for Classes (Phoenix, AZ).

areas relative to the grid size. One map segment was hand colored using acrylic polymer emulsion artists' paints which give bright solid colors. In the map segment chosen there were nineteen different areas requiring that many separable colors. Figure C-12 contains a black and white reproduction of the colored map. Separability of the darker colors is expected to be difficult. Three other sites are being colored and a brighter water based paint is being tested.

The colored maps will be digitized on a microdensitometer and three band (blue, green and red separations) LARS MIST tape will be generated. LARSYS classification analysis will then be performed to attempt to extract the 19 polygon types from the data. If the classification is highly accurate then a promising alternative is available for digitizing complex maps. In this case it may be the only way the map can be digitized and gridded.

6. SUMMARY AND CONCLUSIONS

Analysis of the geometric characteristics of the aircraft SAR relative to Landsat indicated that relatively low order polynomials would model the distortions to sub-pixel accuracy to bring SAR into registration for good quality imagery, e.g., Phoenix Goodyear data. Also, the area analysed was small, about 10 miles square, so this is an additional constraint. For the Air Force/ERIM data from Maryland none of the tested methods could achieve sub-pixel accuracy. The reasons for this is unknown; however, the noisy (high scintillation) nature of the data and attendent unrecognizability of features contribute to this error. Thus, the conclusion is that the quadratic model would adequately provide distortion modeling for small areas, i.e., 10 to 20 miles square. Note that in the Cambridge case going from quadratic to 5th order lowered the 47 point line error from 2.24 to only 2.17 pixels. Requirements for larger areas, e.g., SEASAT frame, were not determined.

The spectral nature of the SAR was investigated with respect to crop fields in the Phoenix area and some separability was noted in histograms. Further analysis must await receipt of time coincident Landsat data.

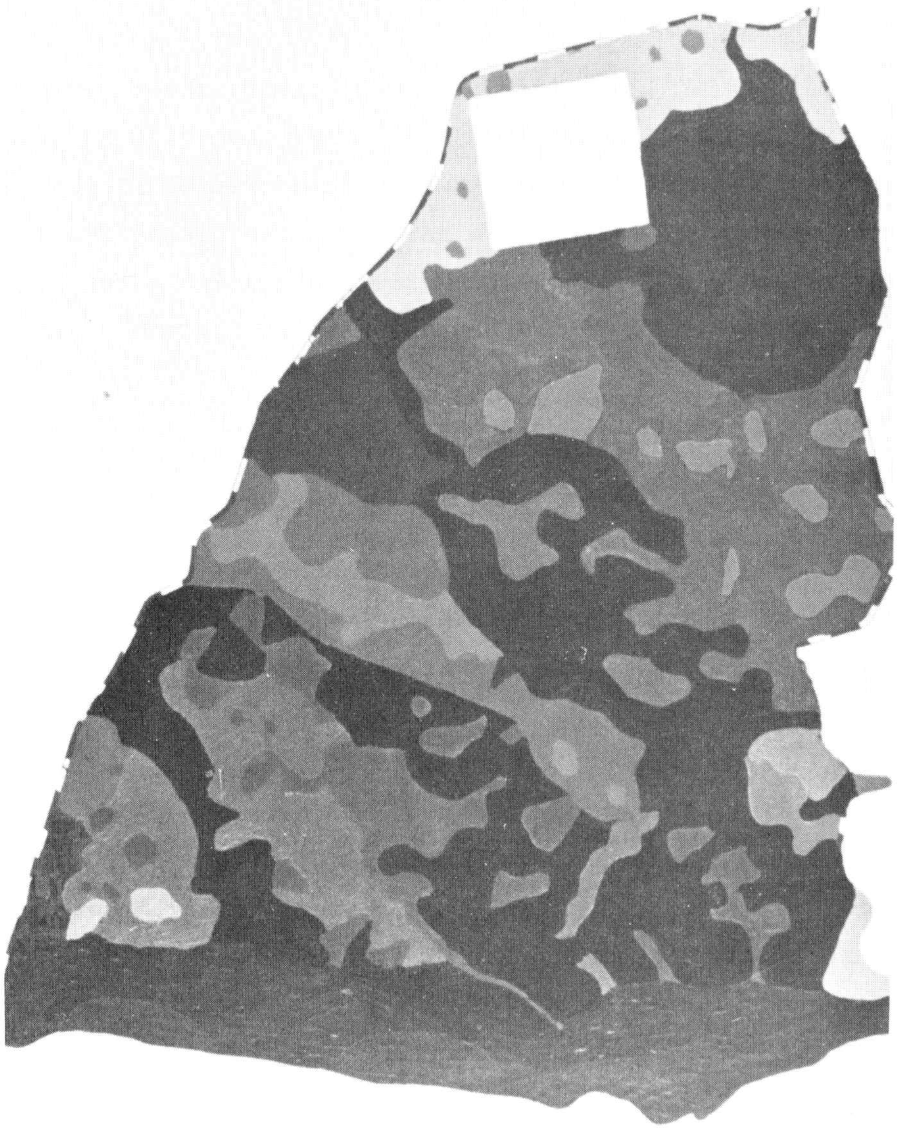


Figure C-12. Forest operating area map segment hand colored for scanning and digitizing. There are 19 different areas color coded with acrylic polymer paint.

A color map digitizing and classification scheme was studied for converting ancillary map data to gridded digital form. Map coloring and digitizing was completed by November 30, 1978 and analysis will be carried out in the first quarter of the follow-on year.

Appendix C-1

Comparison of LARS Affine and Wallops Systematic Error Model

The systematic error model and LARS Affine programs model geometric distortion in an image with respect to a reference image. The programs model rotation angle, range scale, track scale, and shear angle distortions. An outline of the systematic error model program operation is described in the NASA/WALLOPS SYNTHETIC APERTURE RADAR IMAGE PROCESSING, SYSTEM PLAN. So it will not be repeated here. A flowchart of the program operation and of the program mathematics are provided in Figure C-13 and C-14, respectively.

The systematic error model program can be shown to be essentially the same six parameter affine model used in the LARS AFFINE program. The following shows that the systematic error program is a six parameter affine model.

Let. $P \triangleq$ map track control point coordinates
$Q \triangleq$ map range control point coorindates
$X \triangleq$ distorted track control point coordinates
$Y \triangleq$ distorted range control point coordinates
$P' \triangleq$ rotated track control point coordinates
$Q' \triangleq$ rotated range control point coordinates

The mathematical description of the program provides the model:

$$P_i' = A_6(X_i + K(0.00005)Y_i) + \left(\sum_{j=1}^{N} (B_6 + r^x_{6j})\right)/N$$

$$Q_i' = A_3Y_i + \left(\sum_{j=1}^{N} (B_3 + r^Y_{3j})\right)/N ,$$

where $\sum_{j=1}^{N} (r^x_{6i})^2$ is a minimum and where $K \varepsilon I$ such that $\sum_{i=1}^{N} |r^x_{6i}|$ is a minimum; also $\sum_{i=1}^{N} (r^y_{3i})^2$ is a minimum.

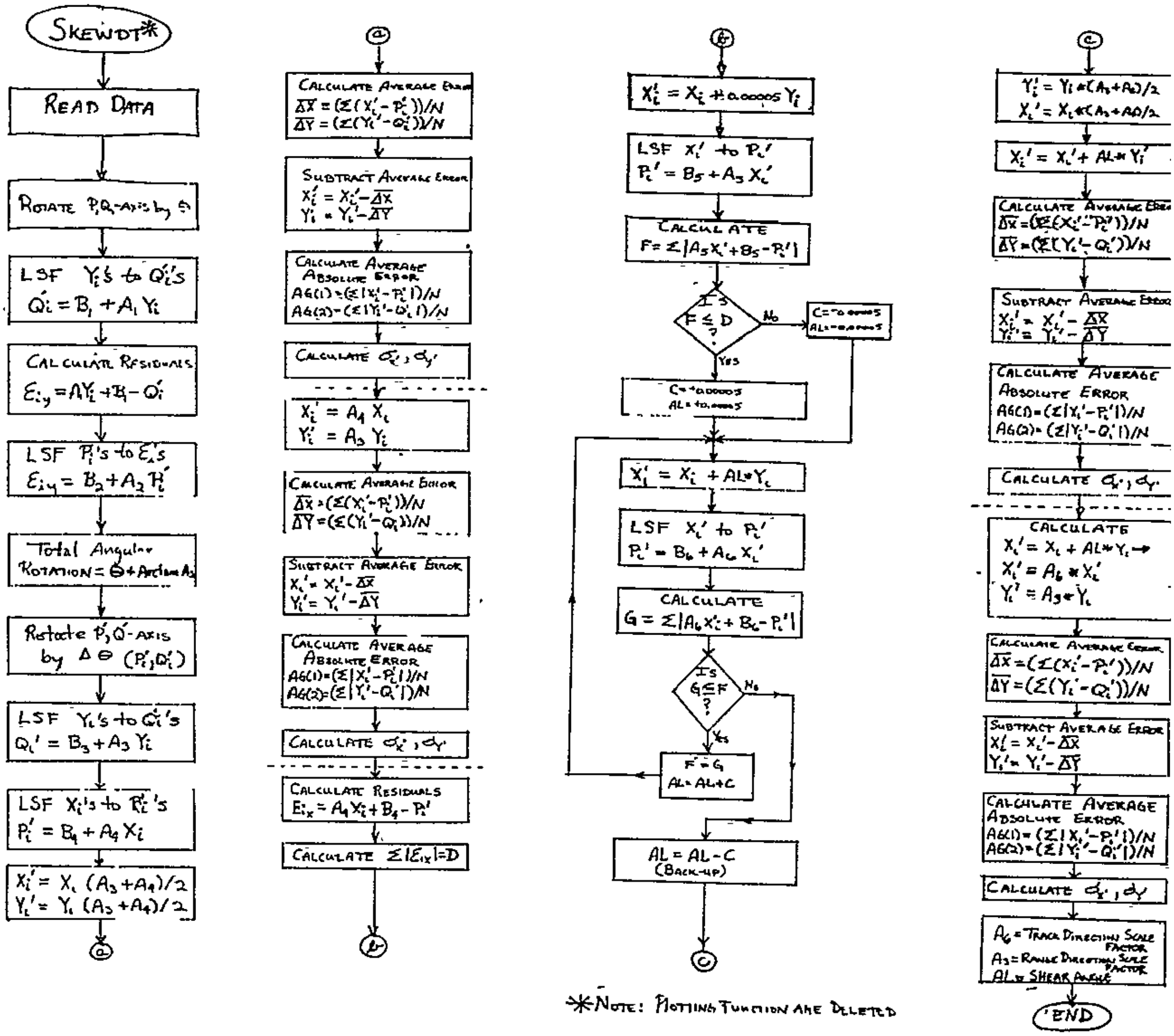


Figure C-13. Flowchart for NASA/Wallops Systematic Error Program (i.e., Subroutine SKEWDT).

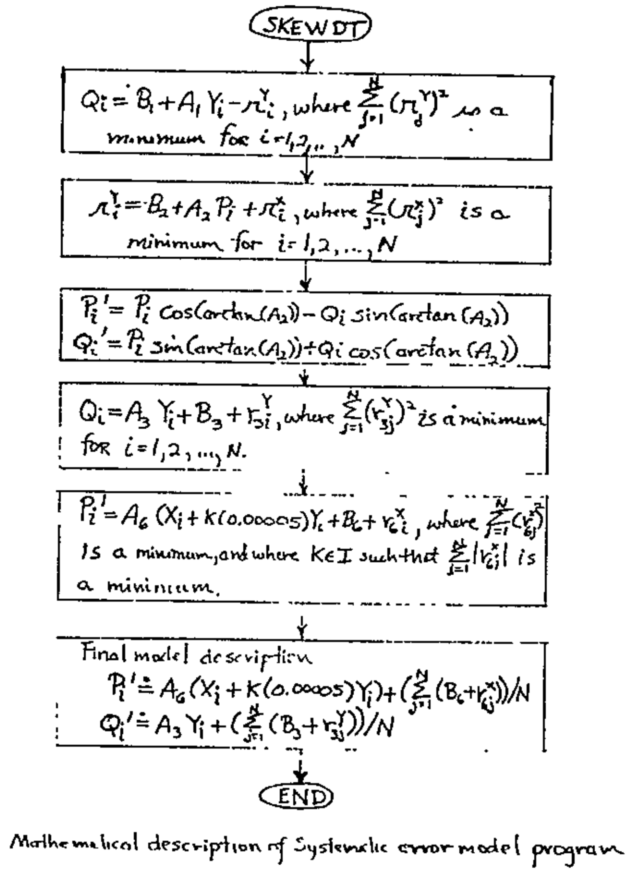


Figure C-14. Mathematical Model for Systematic Error Program.

This is a least-square approximation. First, in least-squares $\sum_{i=1}^{N} r_i = 0.$ So, the calculation of $\overline{\Delta(\cdot)} = B_{(\cdot)}$. The calculation of $\overline{\Delta x}$ and $\overline{\Delta Y}$ in the program is redundent in those cases where the scale and not the average scale is used in modeling. With this simplification and allowing $AL = K(0.00005)$, the model becomes

$$P_i' \cong A_6(X_i + AL\ Y_i) + B_6$$
$$Q_i' \cong A_3\ Y_i + B_3$$

where the approximation is in the least squares sense. Introducing now the model of the rotation

$$P_i' = P_i{*}\cos(ARAD) - Q_i{*}\sin(ARAD) = A_6{*}(X_i + AL{*}Y_i) + B_6$$
$$Q_i' = P_i{*}\sin(ARAD) + Q_i{*}\cos(ARAD) = A_3{*}Y_i + B_3$$

where $ARAD$ = angle of rotation A_6 = track scale factor
AL = shear A_3 = range scale factor
B_6 = translation in track B_3 = translation in range

Since ARAD is obtained by a least-squares approximation, the coordinates rotated and least-squares again applied, the model is overall a least-squares approximation.

Solving the above equations for P_i and Q_i,

$$P_i = A_6{*}\cos(ARAD){*}X_i + (A_3{*}\sin(ARAD) + A_6{*}AL{*}\cos(ARAD){*}Y_i$$
$$+ B_6{*}\cos(ARAD) + B_3{*}\sin(ARAD)$$

$$Q_i = (-A_6{*}\sin(ARAD)){*}X_i + (-A_6{*}AL{*}\sin(ARAD) + A_3{*}\cos(ARAD)){*}Y_i$$
$$-B_6{*}\sin(ARAD) + B_3{*}\cos(ARAD)$$

or more simply

$$P_i = AF*X_i + BF*Y_i + CF$$
$$Q_i = DF*X_i + EF*Y_i + FF \,,$$

which is a six parameter affine transformation.

The LARS AFFINE program performs a six parameter least-squares fit for the delta functions

$$\Delta_x \; (X^A, Y^A) = X^B - X^A = a_o + a_1{*}X_i{}^A + a_2{*}Y_i{}^A$$
$$\Delta_y \; (X^A, Y^A) = Y^B - Y^A = b_o + b_1{*}X_i{}^A + b_2{*}Y_i{}^A \,,$$

where superscripts A and B denote RUNA image and RUNB image, respectively. When the transformation is implemented, for each point in the area in the RUNA image to be registered the delta functions are computed. This transforms the RUNA image coordinate (LANDSAT) to the RUNB to the RUNB image coordinates (SAR). This determines the pixel (or interpolated pixel set) in the RUNB image to overlay at the corresponding RUNA coordinate position. This is the inverse operation of the systematic error model, if the P, Q (map coordinates) are regarded as the LANDSAT and the distorted image (S, Y coordinates), the SAR. Therefore, when residual errors were quoted in the Affine program, the errors are with respect to the RUNB or SAR image. When residual errors were quoted in the systematic error model program the errors are with respect to the X, Y or LANDSAT image. The resolution in the SAR image is usually much finer than that of the LANDSAT. So an error of 1 pixel in the LANDSAT image and quoted by the systematic error model program might map into an error of 3 pixels in the SAR image and so stated by the Affine program. This is due to the scaling differences between the images. The circular error in each reference frame are related by $(S_x\sigma_{xA})^2 + (S_y\sigma_{yA})^2 = (\sigma^2_{xB} + \sigma^2_{yB})$.

The following shows that if the checkpoint pairs are reversed in the systematic error model program, then the LARS Affine and the systematic error model program are identical.

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The systematic program model has been shown to be

$$P_i = AF{*}X_i + BF{*}Y_i + CF$$
$$Q_i = EF{*}X_i + CF{*}Y_i + FF$$

If the P, Q coordinate pair is allowed to represent the RUNB coordinates and X, Y coordinates the RUNA coordinates, then

$$X^B = AF{*}X^A + BF{*}Y^A + CF$$
$$Y^B = DF{*}X^A + EF{*}Y^A + FF.$$

The model used for the LARS Affine program is

$$\Delta_x\ (X^A,Y^A) = X^B - X^A = a_o + a_1{*}X^A + a_2{*}Y^A$$
$$\Delta_y\ (X^A,Y^A) = Y^B - Y^A = b_o + b_1{*}X^A + b_2{*}Y^A.$$

So,

$$X^B = a_o + (a_1{+}1){*}X^A + a_2{*}Y^A$$
$$Y_B = b_o + b_1{*}X^A + (b_2{+}1){*}Y^A.$$

Therefore, the models are equivalent where

$$a_o = CF \qquad a_1 = AF-1 \qquad a_2 = BF$$
$$b_o = FF \qquad b_1 = DF \qquad b_2 = EF-1.$$

The program for the systematic error model was edited so that the reversal was obtained. A subroutine, AFFPAR, was amended to the systematic program to calculate the affine and LARS "delta" Affine parameters. Another subroutine, RESID, was also added to the systematic program to calculate residual errors between the initial map coordinates and rotated coordinates using the model.

An example showing the equivalence of the two programs and an example showing corresponding changes in the r.m.s. error when the mapping is reversed are shown in Figure C-15 and Figure C-16. Here it

SKEW DETERMINATION

P(LINE)	Q(COL)	X(LINE)	Y(COL)
305.	701.	818.	917.
482.	406.	885.	918.
491.	780.	821.	963.
435.	636.	842.	935.
402.	544.	855.	917.
719.	509.	888.	978.
668.	688.	852.	988.
667.	845.	824.	1006.
820.	560.	888.	1005.
568.	1030.	783.	1004.
922.	610.	888.	1031.
919.	852.	845.	1058.
821.	318.	930.	978.
205.	840.	785.	910.
397.	871.	796.	952.
628.	207.	930.	926.
670.	1083.	783.	1032.
827.	69.	972.	951.

ANGULAR ROTATION = 113.2649 DEGREES

ERROR AFTER ROTATION, SCALE , TRANSLATION, & SHEAR

TABLE I - RESIDUAL ERRORS

POINT NUMBER	T ACK ERROR	RANGE ERROR
1	1.51	0.54
2	-0.00	-0.67
3	0.91	-0.10
4	0.97	-1.19
5	0.13	-1.55
6	0.10	-0.66
7	0.08	-0.01
8	0.26	0.92
9	0.70	-0.36
10	-2.32	0.20
11	0.19	-0.25
12	0.16	0.74
13	0.77	-0.43
14	-0.66	-0.16
15	-1.42	0.03
16	-0.27	1.59
17	-1.09	0.49
18	-0.01	0.91

AVERAGE ERROR MAGNITUDE
X = 0.6410
Y = 0.6005
X VARIANCE = 0.8930Y VARIANCE = 0.7615

THE TRACK DIRECTION SCALE FACTOR IS 1* -0.2219 , THE RANGE DIRECTION SCALE FACTOR IS 1* -0.2032, THE SHEAR IS -9.084 DEGREES

*************************** LARS RESID CALCULATION OF RESIDUALS **********************

RUNA LINE	RUNA COLUMN	RUNB LINE	RUNB COLUMN	COMPUTED LINE	COMPUTED COLUMN	LINE ERROR	COLUMN ERROR
305.	701.	818.	917.	817.90	915.40	0.104	1.600
482.	406.	885.	918.	884.38	918.27	0.620	-0.268
491.	780.	821.	963.	820.55	962.21	0.454	0.792
435.	636.	842.	935.	840.52	934.58	1.480	0.418
402.	544.	855.	917.	853.52	917.50	1.476	-0.498
719.	509.	888.	978.	887.35	978.17	0.646	-0.174
668.	688.	852.	988.	851.96	987.93	0.045	0.069
667.	845.	824.	1006.	824.74	1005.40	-0.740	0.598
820.	560.	888.	1005.	887.39	1004.50	0.607	0.496
568.	1030.	783.	1004.	784.10	1006.05	-1.098	-2.049
922.	610.	888.	1031.	887.69	1030.92	0.307	0.076
919.	852.	845.	1058.	845.62	1057.56	-0.615	0.442
821.	318.	930.	978.	929.30	977.46	0.705	0.537
205.	840.	785.	910.	785.11	910.67	-0.114	-0.665
397.	871.	796.	952.	796.58	953.29	-0.585	-1.292
628.	207.	930.	926.	931.56	925.63	-1.560	0.375
670.	1083.	783.	1032.	783.88	1032.81	-0.879	-0.808
827.	69.	972.	951.	972.85	950.65	-0.845	0.347

	LINE	COLUMN
AVERAGE ERROR	0.00	-0.00
ABSOLUTE AVG. ERROR	0.72	0.64
R.M.S. ERROR	0.847	0.818

AFFINE PARAMETERS
X1= 0.087639 *X + -0.172787 *Y + 912.289716
Y1= 0.203840 *X + 0.112581 *Y + 774.309689

AFFINE DELTA PARAMETERS
DELTA X= -0.912361 *XA + -0.172787 *YA + 912.289716
DELTA Y= 0.203840 *XA + -0.837419 *YA + 774.309689

Figure C-15. Systematic Error Model Program Example Results with Checkpoint Pairs Reversed.

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AFFINE TRANSFORM

RUN A77009000 - RUN 72069105
CHANNEL A 1 - CHANNEL 1
**** AT*A *** I= 1 II = 1

7415890.00000	6758377.00000	10946.00000
6758377.00000	8669887.00000	11549.00000
10946.00000	11549.00000	18.00000

ARA =			ARAB-C		LINEDELTA	COMPUTED DELTA	ERROR
305.00000	701.00000	1.00000	818.00000	917.00000	513.00000	513.15694	0.1569
482.00000	406.00000	1.00000	885.00000	918.00000	403.00000	402.68676	-0.3132
491.00000	780.00000	1.00000	821.00000	963.00000	330.00000	329.55993	-0.4401
435.00000	636.00000	1.00000	842.00000	935.00000	407.00000	405.69939	-1.3006
402.00000	544.00000	1.00000	855.00000	917.00000	453.00000	451.80690	-1.1931
719.00000	509.00000	1.00000	888.00000	978.00000	169.00000	168.34277	-0.6572
668.00000	688.00000	1.00000	852.00000	988.00000	184.00000	183.85976	-0.1402
667.00000	845.00000	1.00000	824.00000	1006.00000	157.00000	157.52626	0.5263
820.00000	560.00000	1.00000	888.00000	1005.00000	68.00000	67.24152	-0.7585
568.00000	1030.00000	1.00000	783.00000	1004.00000	215.00000	215.84375	0.8437
922.00000	610.00000	1.00000	888.00000	1031.00000	-34.00000	-34.59956	-0.5996
919.00000	852.00000	1.00000	845.00000	1058.00000	-74.00000	-73.85777	0.1422
821.00000	318.00000	1.00000	930.00000	978.00000	109.00000	108.32647	-0.6735
205.00000	840.00000	1.00000	795.00000	910.00000	590.00000	590.37093	0.3709
397.00000	871.00000	1.00000	796.00000	952.00000	399.00000	399.62395	0.6239
628.00000	207.00000	1.00000	930.00000	926.00000	302.00000	303.87056	1.8706
670.00000	1083.00000	1.00000	783.00000	1032.00000	113.00000	113.48203	0.4820
827.00000	69.00000	1.00000	972.00000	951.00000	145.00000	146.05940	1.0594

DETERMINANT =.15963D 14

INVERSE			COEFICIENT		RMS ERROR =	0.80469
0.00000	0.00000	-0.00106	LINE	-0.913370		
0.00000	0.00000	-0.00073	COL	-0.173547		
-0.00106	-0.00073	1.16638	CONS	913.391073		

ARA =			ARAB-C		COL DELTA	COMPUTED DELTA	ERROR
305.00000	701.00000	1.00000	818.00000	917.00000	216.00000	214.23906	-1.7609
482.00000	406.00000	1.00000	885.00000	918.00000	512.00000	512.51653	0.5165
491.00000	780.00000	1.00000	821.00000	963.00000	183.00000	182.00608	-0.9939
435.00000	636.00000	1.00000	842.00000	935.00000	299.00000	298.53735	-0.4627
402.00000	544.00000	1.00000	855.00000	917.00000	373.00000	373.55492	0.5549
719.00000	509.00000	1.00000	888.00000	978.00000	469.00000	469.36723	0.3672
668.00000	688.00000	1.00000	852.00000	988.00000	300.00000	299.89164	-0.1084
667.00000	845.00000	1.00000	824.00000	1006.00000	161.00000	160.17259	-0.8274
820.00000	560.00000	1.00000	888.00000	1005.00000	445.00000	444.66455	-0.3354
568.00000	1030.00000	1.00000	783.00000	1004.00000	-26.00000	-24.43317	1.5668
922.00000	610.00000	1.00000	888.00000	1031.00000	421.00000	421.05465	0.0546
919.00000	852.00000	1.00000	845.00000	1058.00000	206.00000	205.39377	-0.6062
821.00000	318.00000	1.00000	930.00000	978.00000	660.00000	659.91717	-0.0828
205.00000	840.00000	1.00000	795.00000	910.00000	70.00000	70.30615	0.3062
397.00000	871.00000	1.00000	796.00000	952.00000	81.00000	81.95221	0.9522
628.00000	207.00000	1.00000	930.00000	926.00000	719.00000	719.15738	0.1574
670.00000	1083.00000	1.00000	783.00000	1032.00000	-51.00000	-50.70897	0.2910
827.00000	69.00000	1.00000	972.00000	951.00000	882.00000	882.41086	0.4109

DETERMINANT =.15963D 14

INVERSE			COEFICIENT		RMS ERROR =	0.77234
0.00000	0.00000	-0.00106	LINE	0.204133		
0.00000	0.00000	-0.00073	COL	-0.886630		
-0.00106	-0.00073	1.16638	CONS	774.908094		

AFFINE COEFFICIENTS TO SYSTEMATIC PARAMETERS

LINE COEFFICIENT NO.1=	913.39086914
LINE COEFFICIENT NO.2=	-0.91336995
LINE COEFFICIENT NO.3=	-0.17354697
COLUMN COEFFICIENT NO.1=	774.90795898
COLUMN COEFFICIENT NO.2=	0.20413297
COLUMN COEFFICIENT NO.3=	-0.88862997

LINE TRANSLATION = 913.390869
COLUMN TRANSLATION = 774.907959
LINE SCALE FACTOR = 0.221754
COLUMN SCALE FACTOR = 0.203264
ANGLE OF ROTATION = -67.004776 DEGREES
SHEAR = 0.170825 OR SHEAR ANGLE = 9.6940 DEGREES

Figure C-16. LARS AFFINE Model Program Example Results with Checkpoint Pairs Reversed.

should be noted that the "Variance" shown in the WALLOPS program description outline and in the labeling of the printed results is actually the standard deviation not the variance.

By comparing the results of the two programs, they are essentially the same model (allowing for small computational errors). The differences noticed between the r.m.s. errors calculated by the systematic program and by RESID are due to the fact that errors computed in the program are with P&Q rotated with respect to X&Y. In RESID errors are computed with X, Y rotated with respect to P&Q. Therefore, a small error is interchanged between the line and column errors between the two calculations.

The LARS Affine program obtains the model in total with only one least-squares fit, while the systematic program requires at least six to obtain the same result. The additional insight the systematic error program provides in printing rotation angle, scaling, and shear angle can be obtained in the LARS program with the addition of a simple subroutine calculation. The following is a derivation of the necessary subroutine calculations.

$$\begin{bmatrix} X^B \\ Y^B \end{bmatrix} = \underbrace{\begin{bmatrix} +\cos\Theta & +\sin\Theta \\ -\sin & +\cos \end{bmatrix}}_{\text{Rotation}} \underbrace{\begin{bmatrix} 1 & \alpha \\ 0 & 1 \end{bmatrix}}_{\text{Shear}} \underbrace{\begin{bmatrix} S_x & 0 \\ 0 & S_y \end{bmatrix}}_{\text{Scale}} \begin{bmatrix} X^A \\ Y^A \end{bmatrix} + \underbrace{\begin{bmatrix} a_o \\ b_o \end{bmatrix}}_{\text{Translation}}$$

$$\begin{bmatrix} X^B \\ Y_B \end{bmatrix} = \begin{bmatrix} X_x\cos\Theta & \alpha S_y\cos\Theta - s_y\sin\Theta \\ -S_x\sin\Theta & (-\alpha S_y\sin\Theta) + S_y\cos\Theta \end{bmatrix} \begin{bmatrix} X^A \\ Y^A \end{bmatrix} + \begin{bmatrix} a_o \\ b_o \end{bmatrix}$$

The AFFINE delta function

$$\begin{bmatrix} X^B \\ Y^B \end{bmatrix} - \begin{bmatrix} X^A \\ Y^A \end{bmatrix} = \begin{bmatrix} a_1 \\ b_1 \end{bmatrix} \cdot \begin{bmatrix} a_2 \\ b_2 \end{bmatrix} \begin{bmatrix} X^A \\ Y^A \end{bmatrix} + \begin{bmatrix} a_o \\ b_o \end{bmatrix}$$

or

$$\begin{bmatrix} X^B \\ Y^B \end{bmatrix} = \begin{bmatrix} a_1+1 & a_2 \\ b_1 & b_2+1 \end{bmatrix} \cdot \begin{bmatrix} X^A \\ Y^A \end{bmatrix} + \begin{bmatrix} a_o \\ b_o \end{bmatrix}$$

Solving these for Θ, S_y, S_x, and α,

$$\Theta = \arctan \left(\frac{-b_1}{a_1+1}\right) \qquad S_x = \frac{a_1+1}{\cos\Theta}$$

$$S_y = (b_2+1)\cos\Theta + a_2\sin\Theta \qquad \alpha = \frac{[a_2\cos\Theta] - [(b_2+1)\sin\Theta]}{S_y}$$

In implementing these relations the single least-squares fit operation of the LARS Affine program will also provide a parametric description of the distortion. Table C-8 provides comparison of the systematic error model and the LARS affine model. The direction of the scaling and the angular rotations apparently differ. They are actually the same. The LARS affine calculation of the parameter chooses the rotation and scale directions such that the line scale factor is always positive. The small errors between the LARS affine and systematic calculated residuals are a result of the systematic error model which rotates the reference and then scales and screws, where the LARS model rotates the distorted image.

Table C-8. Comparison of WALLOPS Systematic Error Model and LARS Affine Model.

	FORWARD		REVERSED	
	LARS AFFINE	WALLOPS SYSTEMATIC	LARS AFFINE	WALLOPS SYSTEMATIC
LINE R.M.S. ERROR	3.82530	4.1923 (3.829)*	0.80489	0.8930 (0.842)*
COLUMN R.M.S. ERROR	3.63939	3.1940 (3.622)*	0.77234	0.7615 (0.818)*
LINE TRANSLATION	-5238.323913	-5242.444701	913.391072	912.289716
COLUMN TRANSLATION	2646.570270	2653.129237	774.8094	774.309689
TRACK SCALE	5.157719	-5.1582	0.221754	-0.2219
RANGE SCALE	4.299145	-4.2992	0.203264	-0.2032
ROTATION ANGLE	61.387711°	-118.6180°	-67.004776°	113.2649°
SHEAR ANGLE	2.0788°	-1.822°	9.6940°	-9.084°

* LARS calculation of residual in systematic error program

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