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DEVELOPMENT AND EVALUATION OF AN AUTOMATIC LABELING TECHNIQUE FOR SPRING SMALL GRAINS

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16. Abstract

A labeling technique is described which seeks to associate a sampling entity with a particular crop or crop group based on similarity of growing season and temporal-spectral patterns of development. Human analysts provide contextual information, after which labeling decisions are made automatically. Results of a test of the technique on a large, multi-year data set are reported. Grain labeling accuracies are similar to those achieved by human analysis techniques, while non-grain accuracies are lower. Recommendations for improvements and implications of the test results are discussed. This research was carried out within the Supporting Research Project of the AgRISTARS program.

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TECHNICAL REPORT

DEVELOPMENT AND EVALUATION OF AN AUTOMATIC LABELING TECHNIQUE FOR SPRING SMALL GRAINS

BY

Eric P. Crist and William A. Malila

This report describes results of research carried out in support of the Area Estimation Design Element of the Supporting Research Project.

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PREFACE

The Agriculture and Resources Inventory Surveys Through Aerospace Remote Sensing program, AgRISTARS, is a six-year program of research, development, evaluation, and application of aerospace remote sensing for agricultural resources, which began in Fiscal Year 1980. This program is a cooperative effort of the National Aeronautics and Space Administration, the U.S. Agency for International Development, and the U.S. Departments of Agriculture, Commerce, and the Interior. AgRISTARS consists of eight individual projects.

The work reported herein was sponsored by the Supporting Research (SR) Project under the auspices of the National Aeronautics and Space Administration, NASA. Dr. Jon D. Erickson, NASA Johnson Space Center, succeeded by Robert B. MacDonald, was the NASA Manager of the SR Project and Thomas Pendleton was the Technical Coordinator for the reported effort.

The Environmental Research Institute of Michigan and the Space Sciences Laboratory of the University of California at Berkeley comprise a consortium having responsibility for development of corn/soybeans area estimation procedures applicable to South America within both the Supporting Research and Foreign Commodity Production Forecasting Projects of AgRISTARS.

This reported research, directed at the labeling of small grains in multi-date Landsat data, was performed within the Environmental Research Institute of Michigan's Infrared and Optics Division, headed by Richard R. Legault, a Vice-President of ERIM, under the technical direction of Robert Horvath, Program Manager, and Dr. William A. Malila, Task Leader.

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1.0
INTRODUCTION

Crop acreage estimates made using Landsat (or indeed any remotely sensed data) invariably require, at some point, association of a crop label or labels with some sampling entity (e.g., pixel, field, cluster, etc.). The accuracy with which this association is made clearly has a substantial impact on the accuracy of the acreage estimates produced. In the Large Area Crop Inventory Experiment (LACIE), the labeling step, which was carried out through manual analysis of imagery and associated information, was found to be both time-consuming and a source of considerable error.

To the degree that sensor limitations or imperfect spectral separability of crops are the causes of labeling errors, new techniques can offer little hope of substantial improvements in accuracy. However, that portion of the labeling error associated with the labeling techniques themselves, or with human limitations, might be reduced through new approaches to labeling. An obvious candidate for improving both the objectivity and the timeliness of labeling decisions is automation of much of the labeling process.

The technique described herein is a response to the need for a faster, more accurate, and more objective labeling procedure. Human analysts are utilized only to set up the system and provide contextual information which can be used to adjust the labeling procedure to local conditions; the labeling decisions themselves are left to the machine.

In addition, this procedure is intended to provide a demonstration of some of the applications of what we have called profile technology, that is, the use of features derived directly or indirectly from characterizations of the continuous patterns of temporal-spectral crop development [1].

We do not, however, put this technique forward as the final and best use of profile technology, but rather as a first generation technique, a demonstration of concepts, that can be used to more fully understand profiles and their uses, and thereby to develop improved labeling techniques.

Similarly, while fully automatic labeling procedures may be desirable in terms of efficiency, the complexity of some of the decisions which must be made, particularly those made on a more general level, probably precludes replacing human analysis entirely at this time. Again, the technique presented here is intended to provide some starting point for the development of later procedures which can more fully utilize the particular contributions both the human and the machine can bring to the labeling process.

Finally, the procedure as described and tested is focussed on the identification of spring small grains (principally spring wheat, barley, and oats). The underlying concepts, however, are more generally applicable and could be used in techniques to label other agricultural crops.

2.0
DESCRIPTION OF PROCEDURE

2.1 GENERAL CONCEPTS

Basic to most labeling techniques which operate on Landsat data are the presuppositions that at least some crop groups or cover types exhibit distinct and characteristic temporal patterns of spectral development, and that at least some of these pattern differences are detectable at the resolution of the Landsat multispectral scanners. Manual techniques have depended on human analysts to detect these patterns and pattern differences from the available Landsat acquisitions [2]. However, at least two factors hinder the ability of humans to accurately carry out this process. First, the Landsat observations are fairly widely spaced discrete samples from what are for the most part continuous spectral development patterns. As a result, much of the necessary information must be inferred from the available data. Second, samples of a particular crop may vary considerably, over a small region, in terms of stage of development and, therefore, spectral appearance on any given day. The combination of sparse observations and variation in development stage can result in samples of a single crop type showing little apparent spectral similarity.

By characterizing the continuous patterns of which the Landsat observations are samples, one can address these problems, particularly though not exclusively in automated procedures. Techniques of this general type have achieved promising results [3]. The labeling technique presented here is another of this class of approaches. Specifically, it uses the characterizations of spectral development, termed profiles, both to adjust for planting date differences within a crop and to assign crop labels to unknown samples.

The central element in the procedure is a group of profile sets representing spectral development of a number of crops in the domain described by Tasseled-Cap Greenness and Brightness (physically interpretable linear combinations of Landsat MSS band values - see Reference 4). These profile sets were developed using spectral data from fields of known crop type, sampled from the U.S. Northern Great Plains over three growing seasons. The actual profile sets are shown in Figures 1 and 2.

The profile sets serve as reference standards to which each unknown sampling entity is compared. For each profile set, a series of comparisons is carried out. First, a temporal shift is determined which maximizes the cross-correlation of the data points to the Greenness profile [5]. This provides an estimate of the date of spectral emergence, and indirectly of the start of the growing season of the target field. The temporal shift estimate also provides a means of normalizing the planting dates of fields of a single crop type, and thereby minimizes one major source of spectral confusion.

After estimating and applying the temporal shift, a multiplicative scale factor is computed, again using the Greenness profile. This scale factor is applied to normalize the magnitude of the Greenness development profile which is strongly influenced, within a single crop type, by the percentage of ground covered by green vegetation (which is itself influenced by such factors as planting density, fertilization, and moisture availability).

With both adjustments made, a goodness-of-fit of the data to the Greenness profile is computed, and similarly, using the Greenness profile temporal shift, a fit or correlation of the Brightness data to the Brightness profile is computed.

The shift, Greenness fit, and Brightness correlation are used to compute a probability associated with the crop represented by the profile set and the sampling entity, and this combined probability serves

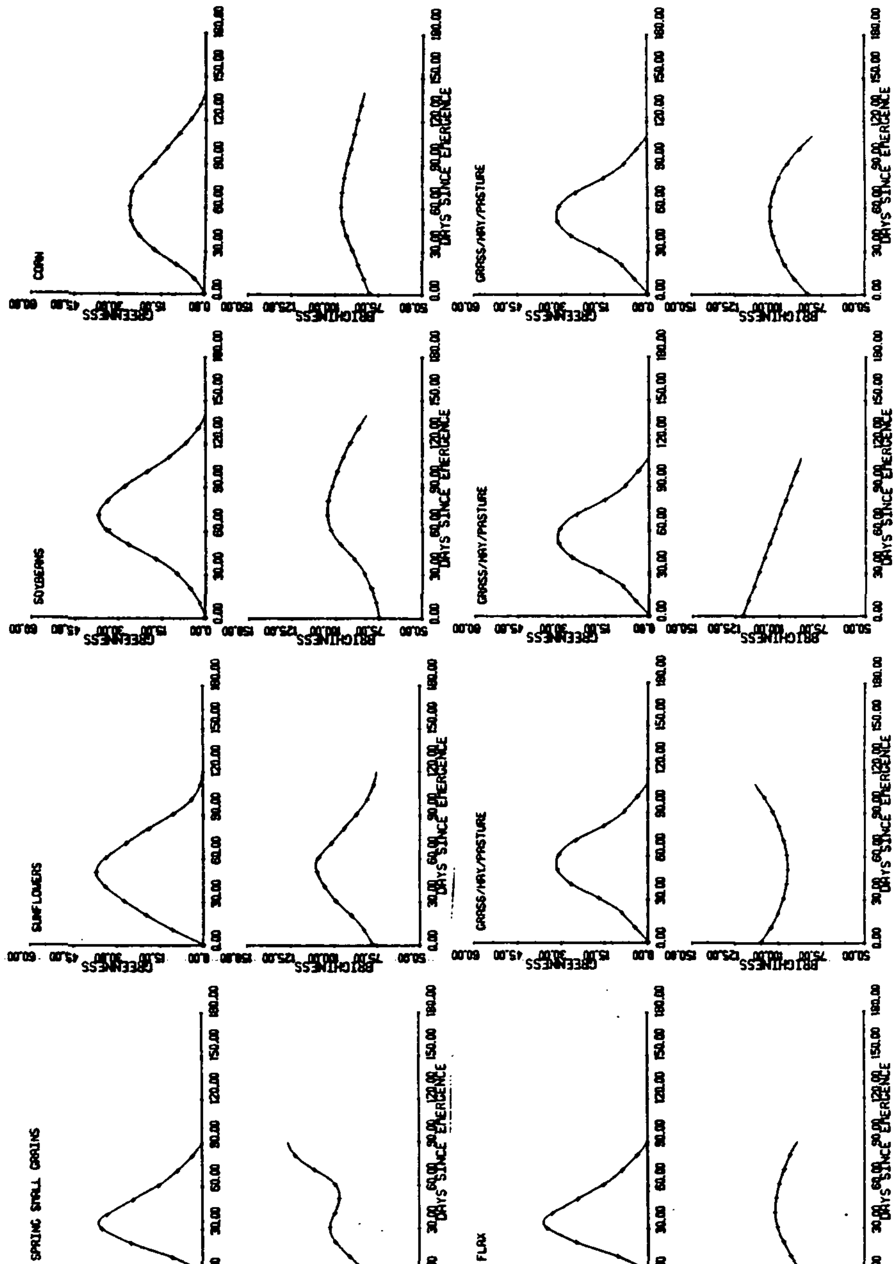


FIGURE 1. PROFILE SETS USED IN LABELER

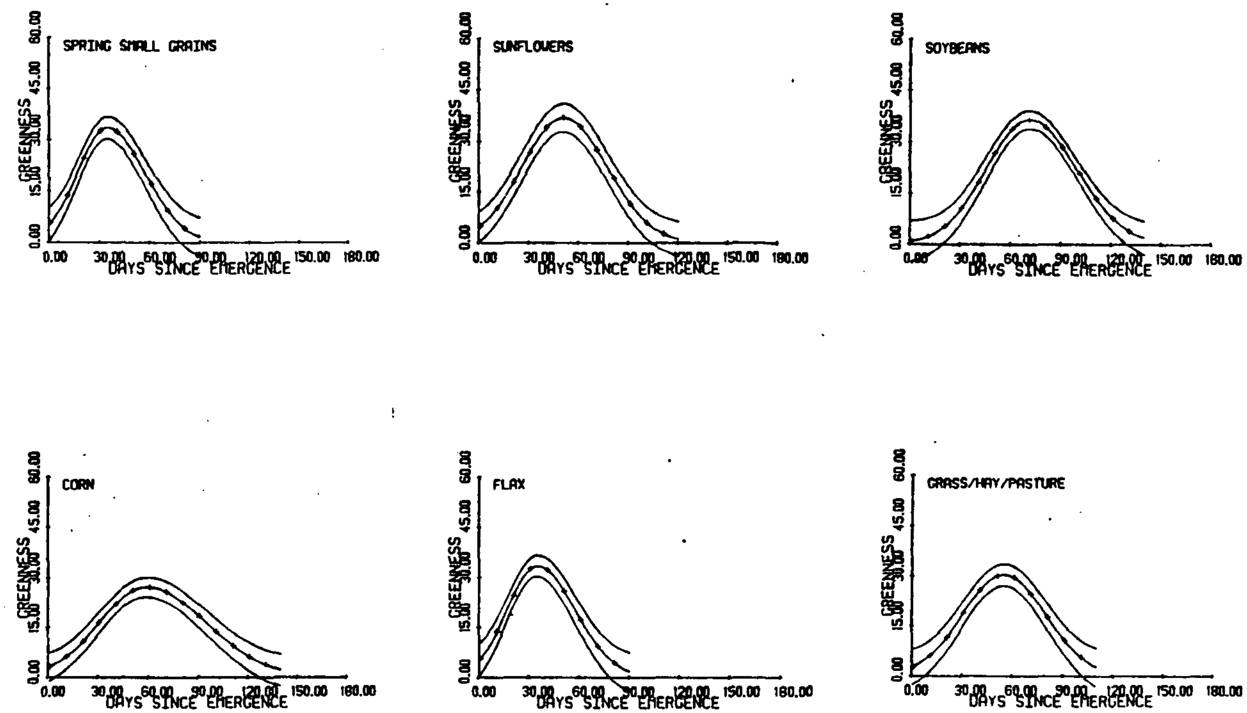


FIGURE 2. GREENNESS PROFILES WITH VARIANCES USED IN LABELER

as the basis for labeling decisions. More detailed description of the steps of the procedure is provided in Section 2.3. In a different application of this procedure, one might use different or additional features to compute the requisite probabilities.

2.2 RECOMMENDED ENVIRONMENT

The concept of comparing unknown samples to static representations of crop spectral development necessarily requires that all sources of spectral variation other than crop type be eliminated or minimized. As a result, this procedure was developed and tested using data normalized with respect to haze, sun angle, and sensor calibration, and screened for clouds, cloud shadows, etc., using algorithms developed at ERIM [4].

By the same reasoning, pixels that are a mixture of more than one crop type will not be as readily labelable as those which are pure with respect to crop type. In an effort to remove mixture pixels from consideration, and also to smooth some of the extraneous variability among pixels in a single field, an ERIM-developed spectral-spatial clustering algorithm, SUPERB, was used to provide sampling entities (quasi-fields or blobs) for labeling [6].

It should be expected that the performance of this or any similar technique would degrade if such normalization and clustering steps were omitted.

2.3 SPECIFIC STEPS

Appendix A presents a flow diagram of the major elements in the labeling procedure.

2.3.1 ANALYST FUNCTIONS

The focus of the labeler development reported here was on the machine aspects of the procedure. As a result, the functions assigned to a human analyst are only defined in general terms.

Acquisition Selection

A human must decide which acquisitions to process. This selection is based on considerations such as apparent growing season, presence of clouds or haze, view angle similarity, spacing, etc. No specific process has been laid out for this procedure.

Crop Calendar Adjustment

Beginning with either historical or model-derived crop calendars, the human must develop estimates of the time of spectral emergence of the crops represented by profile sets. This is a combination of image interpretation, computer data analysis, and use of historic or expected crop calendar relationships between crops. While no technique has been defined for the specific application described in this report, a similar procedure has been developed for use in U.S. 1981 corn/soybeans pilot experiment [7]. Eventually one might utilize outputs from meteorologically based crop calendar models.

The expected output of this step is estimated mean days of spectral emergence for all crops or crop groups represented by profile sets.

2.3.2 PRELIMINARY PROCESSING STEPS

Data Transformation

All spectral data are transformed using the Tasseled-Cap transformation [4]. Only Brightness and Greenness values are retained.

Acquisition Check

Both mathematics and common sense require that some minimum number of vegetated acquisitions be available for a sampling entity before it can be labeled using this technique. That minimum number is set at three. The determination of whether or not a particular acquisition is vegetated is based on a simple thresholding in Greenness. "Bare soil" data typically range between 25 and 35 counts of Greenness (with 32-count offset applied); the lower end of the range was used as the threshold value. If a sampling entity has less than three acquisitions with Greenness greater than 25, it is labeled "unknown".

Maximum Greenness Check

Those targets which have at least three vegetated acquisitions are also required to have one acquisition with Greenness greater than 35. This requirement accomplishes two purposes. First, it screens out fields with abnormally low green vegetation development. Such fields are unlikely to exhibit the same spectral characteristics as healthy fields of the same crop. Second, it eliminates fields which, although they have passed the acquisition number requirement, lack acquisitions in the time period during which the crop is well-developed. Again, targets failing to meet the requirement are labeled "unknown".

2.3.3 CROP CALENDAR EVALUATION

(Steps described in Sections 2.3.3 through 2.3.5 are carried out for each of the profile sets used in the procedure.)

Shift Estimation

The day of maximum green development is estimated through a technique called crop calendar shift estimation [5]. The Greenness values of the target are compared to the Greenness profile being considered, and a temporal shift is selected which maximizes a cross-correlation-like factor. The shift algorithm also makes additional checks on acquisition number and spacing. After a temporal shift based on an initial rough estimate of the day of peak Greenness, it checks to see that there are at least three acquisitions spaced more than ten days apart.

This constraint is the result of observations that pairs of data obtained from consecutive passes of different satellites do not carry the weight of more widely-spaced acquisitions and, in fact, tend to behave in the procedure as one acquisition. If a target passes this test and a shift is estimated, the test is applied again using the final shift estimate. If there are too few sufficiently-spaced acquisitions available, an "unknown" label is assigned.

It should be noted that for this and all subsequent steps, Greenness values are reduced by 25 counts. This brings the "bare soil" Greenness to near zero, and both downweights the importance of fitting at low signal values and allows for application of the multiplicative scaling previously mentioned.

Probability Computation

The shift estimate is compared to an expected shift for the crop, which is derived from the expected mean day of spectral emergence, as provided by the analyst. The difference between these two values is used to assign a probability, based on an empirically-defined probability distribution. The distribution is a modified normal with mean zero and standard deviation 14 days, but with an equal probability of .99 assigned to all values within one standard deviation (+ or - 14 days) to reflect the range of planting dates which are typically observed for a single crop in a sample segment.

2.3.4 COMPARISON TO GREENNESS PROFILE

Computation of Scale Factor

As previously described, a multiplicative scale factor is computed to maximize the fit of the shifted data values to the Greenness profile. The scale factor is computed by

$$\text{Scale} = \frac{\Sigma F_i^2}{\Sigma F_i * G_i} \tag{1}$$

where

F_i = profile value at time T_i

G_i = data value at time T_i

Since planting and harvesting methods and field conditions can cause more variations in Greenness values at the tails of the profile, a better scaling can be computed if those values are excluded. Therefore the scale factor is based only on those acquisitions which fall at least 20 days from either end of the profile. If one or no acquisitions meet this criterion, an "unknown" label is assigned.

Greenness Profile Fit

A chi-squared fit is computed for the scaled data and the profile, as

$$\text{Fit} = \Sigma \frac{(F_i - sG_i)^2}{\sigma_i^2} \tag{2}$$

where

F_i = profile value at time T_i

G_i = data value at time T_i

s = scale factor

σ_i^2 = expected variance about profile at time T_i

The variances used were determined using data of known crop type from the 26 segments comprising the developmental data set.

A probability is then determined for the computed fit, with degrees of freedom equal to one less than the number of acquisitions used.

2.3.5 COMPARISON TO BRIGHTNESS PROFILE

While the characteristics of Greenness profiles and crop Greenness development allow for relatively simple scaling and fitting, the same tasks using Brightness profiles are not so straightforward. Since Brightness is (as was intended) strongly influenced by soil characteristics, the early and late season portions of Brightness profiles, where soil is the dominant scene component, vary considerably. In addition, at least some of the Brightness profiles exhibit more complex shapes than the Greenness profiles. Finally, variations in the amount of vegetative cover, which result in a simple reduction in amplitude of the Greenness profile, have widely varying effects on Brightness profiles, since they primarily affect the amount of soil viewed.

Since adjustment for within-crop variations in Brightness spectral development cannot be readily accomplished, the assumptions necessary for use of a chi-squared test, particularly that of a normal distribution of data about the mean on any given day, are not justified, and use of the chi-squared test is inappropriate.

For this labeling technique, the simplifying assumption is made (based on empirical evidence) that the characteristic shape of the Brightness profiles for the various crops will be detectable most of the time even with the described variations in actual Brightness values. In order to compare overall profile shapes rather than actual values, a cross-correlation calculation is made as follows:

$$R = \frac{\Sigma\ f_i * g_i}{\sqrt{(\Sigma g_i^2) * (\Sigma f_i^2)}} \qquad (3)$$

where

$$f_i = (\text{profile value at time } t_i) - \text{profile mean}$$

$$g_i = (\text{data value at time } t_i) - \text{data mean}$$

and

$$\text{Profile mean} = \frac{\sum_{i=1}^{n} (\text{profile value at } t_i)}{n}$$

where

$$n = \text{number of data values used}$$

The probability associated with the calculated cross-correlation is determined using empirically derived cumulative distributions of cross-correlation of known grain data (from the developmental data set) to the grain profile.

2.3.6 CALCULATION OF COMBINED PROBABILITY

The three probabilities associated with each profile set are combined into one probability using Fisher's omnibus procedure [8]*. This test, which assumes independence of the individual statistics, has the advantage of retaining the same level of significance in the combined statistic as that of the individual statistics. The combined test statistic is of the form

$$T = -2 \sum_{i=1}^{3} w_i \ln P_i \tag{4}$$

where

w_i = weight assigned to the i^{th} test

P_i = probability associated with the i^{th} test

---

*Suggested by Dr. Jack Tubbs, University of Arkansas.

Using a chi-squared test, the combined probability of T is determined, with degrees of freedom

$$DF = 2 \sum_{i=1}^{3} w_i \qquad (5)$$

The individual statistics are weighted by their importance as discriminants. There are no inherent constraints on the values of the weights and they need not sum to one.

If the combined probability exceeds a threshold value, the crop represented by the profile set used is considered probable enough to be retained as a candidate. Otherwise, the crop is rejected.

2.3.7 LABEL ASSIGNMENT

When all profile sets have been evaluated, a labeling decision can be made. This may be either a single label based on the most probable profile set, or a set of probabilities associated with the ensemble of profile sets whose probabilities exceeded the defined acceptance threshold. The selection of one or the other of these alternatives is a function of the proportion estimation procedure which utilizes the labels.

3.0
DESCRIPTION OF TEST

A test of the labeling technique was carried out on an independent data set in order to evaluate and understand its performance.

3.1 DATA SET

A total of 38 5x6-mile sample segments were used, spanning the same three years as the developmental data set. The segment locations are shown in Figure 3.

The SUPERB clustering algorithm was applied in its supervised mode, such that only pixels of the same crop type could be placed in the same blob. This was done to isolate the labeling performance from the effect of mixed blobs. However, a test of the performance on such mixed blobs would be a useful exercise in the future.

3.2 ANALYSES TO BE CARRIED OUT

3.2.1 LABELING ACCURACY

The accuracy with which the technique identified grain and non-grains was determined using a number of different procedure configurations (see Section 3.3). For the most part, determination of accuracy was based on the most probable crop rather than on the set of probabilities. Non-grain accuracy was based on failure to choose the grain profile, rather than selection of the correct non-grain crop profile.

In addition to an overall accuracy evaluation, the significance of effects related to growing year, agrophysical stratum unit, and number of available acquisitions was assessed. Year and agrophysical unit should affect crop spectral characteristics, relative spectral differences between crops, and relative crop calendar differences, all of which

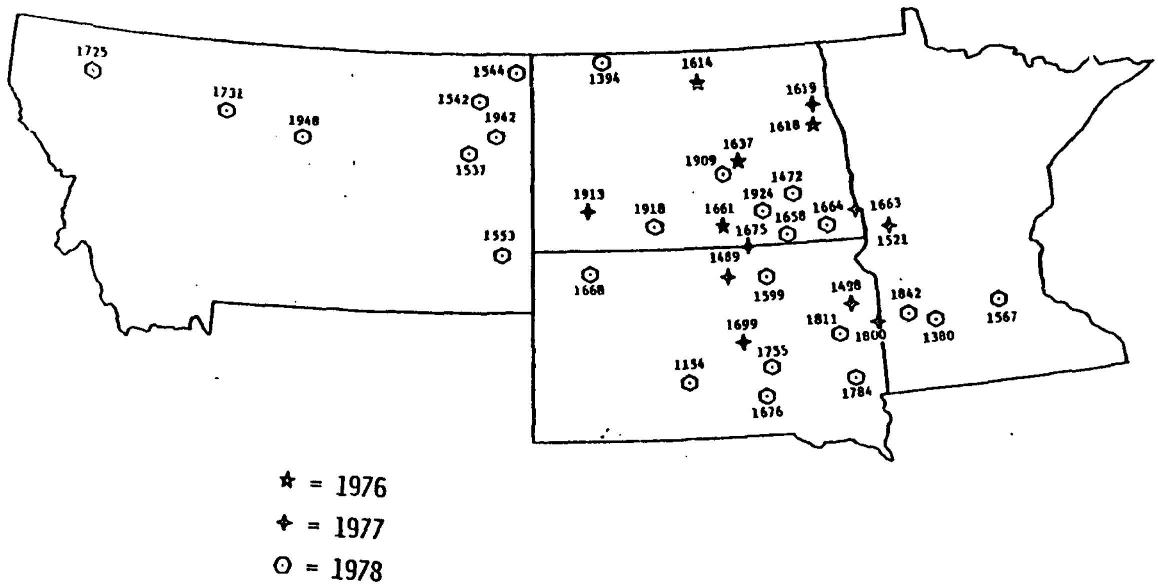


FIGURE 3. LOCATIONS OF TEST AND EVALUATION SEGMENTS

should affect labeling accuracies. The number of acquisitions available should be directly related to accuracy, since more acquisitions should provide a better characterization of the temporal-spectral development of the target field.

3.2.2 LABELING ERROR CHARACTERIZATION

A related area of analysis involved determining the nature of the errors made. Of interest were the relative probabilities of grains being called one of the non-grains, and vice versa.

3.2.3 QUALITATIVE COMPONENT EVALUATION

In addition to the more quantitative evaluations described above, a qualitative evaluation was included in the test to answer less easily defined questions related to the underlying concepts and techniques. These were primarily focused on the use of profiles as features, use of profiles as the basis for labeling procedures, and use of crop calendar shift.

3.3 PROCEDURE CONFIGURATIONS

Some elements of the labeling techniques were either modified in order to isolate effects of errors in various parts of the procedure or applied with several different parameter sets to determine optimum configurations.

3.3.1 CROP CALENDAR ADJUSTMENT

While the impact of errors in estimating mean days of spectral emergence is of great importance, it is first important to understand the behavior of the technique given good estimates of spectral emergence days. Thus ground truth information was used rather than analyst interpretation in this test.

Expected mean days of spectral emergence were determined for each segment by applying the crop calendar shift technique to all data of each crop type. The results of this process were histogrammed and, where enough data were available for a particular crop in a particular segment, an estimate of the central tendency of the distribution was made. Where too few data were available, historical relationships, results from similar segments, or average results for several segments were used to fill in the expected spectral emergence days.

3.3.2 PROFILE SETS

As shown in Figure 1, the entire set of profiles developed for the labeling procedure represents six crops or crop groups. Similarities among certain of the crops, however, suggest that they could be more frequent sources of error than others. Specifically, grasses and flax have spectral characteristics and development patterns that are most similar to the spring small grains, and are thus most likely to be confused with grain. As a result, the procedure was applied with all six profiles (listed in Table 1), all profiles except grass, all except flax, and all except grass and flax.

Even crop profiles that are substantially different from the grain profile set will tend to draw some blobs away from the grain profile. It is therefore likely that elimination of any profile set would result in some increase in grain labeling accuracy. It might be possible, based on historical information, to omit profile sets representing crops unlikely to occur in the segment of interest. The results of such a procedure were simulated by re-running the labeling procedure with the four profile combinations described above, but also omitting any crop (except grain and grass) which had five or fewer blobs in the segment (using ground truth information). Grain and grass were never excluded in this mode since grain is the crop of interest, and grass could never be ruled out as a possibility.

TABLE 1. CROPS REPRESENTED BY PROFILE SETS

Spring Small Grains

Grasses

Sunflowers

Corn

Soybeans

Flax

TABLE 2. TEST STATISTIC WEIGHTINGS EVALUATED

(first value applies to Greenness Fit, second to Brightness Correlation, third to Crop Calendar Shift)

1-0-0	1-1-0	1-1-1
0-1-0	1-0-1	1-1-2
0-0-1	0-1-1	1-2-3

3.3.3 TEST STATISTIC WEIGHTINGS

As previously described, the three pieces of information used in making labeling decisions (crop calendar shift, Greenness Fit, and Brightness correlation) can be weighted to reflect confidence or importance. Nine weightings, placing different emphasizes on the three factors, were used (see list in Table 2). Each factor was used alone, all pairs were used, and a selected group of weightings using all three factors was used. This last group was selected based on results obtained in the developmental data set, which suggested that the shift estimate was of greatest importance, followed by Brightness and then Greenness.

3.3.4 PROBABILITY THRESHOLDS

The minimum combined probability used to select candidate profiles as described earlier, was set at a number of different levels: 0.0, .25, .33, .50, .667, and .75. One would expect higher thresholds to reduce errors of commission relative to the grain profile, but increase errors of omission. The range of thresholds was included to evaluate the best mix between these two error rates.

4.0
TEST RESULTS AND EVALUATION

4.1 ABILITY TO ASSIGN LABELS

As previously described, there is a required minimum number of acquisitions for any particular sampling entity to be labeled. If a blob fails this criterion for any of the profile sets, it can only be labeled based on partial information. Since the grain profile spans the shortest amount of time of all the profiles used, it is most likely to be rejected from consideration due to the acquisition availability constraint. If labels were assigned in cases where blobs could not be compared to every profile, many grains with poor acquisitions would be labeled non-grains. Instead, such blobs were called "unlabelable".

Since the developmental data set tended to have more acquisitions available per segment, determination of the percentage of "labelable" blobs was based on the combined development and test data set (64 segments). For this data set, 57% of the blobs could be labeled. However, considered individually, most segments were either "labelable" or not. Sixteen of the segments had less than 20% of their blobs labeled, while 31 of the 64 had more than 80% of their blobs labeled.

4.2 LABELING ACCURACY

Table 3 shows the grain/non-grain accuracies for the various configurations used. Grain labeling accuracies reached 86%, but errors of commission were also high with the same configuration. In general, errors of commission and omission were inversely related.

Overall accuracies (grain and non-grain) reached 74% (Table 4), while the best mix of accuracies occurred at about 69% correct for grain and 72% correct for non-grain. Similar results were observed in Phase 3 and Transition Year 1978 in the LACIE [9,10] with analyst-intensive procedures.

TABLE 3. GRAIN/NON-GRAIN ACCURACIES

Using All Profiles	Threshold					
	0.0		0.5		0.667	
Weighting	Grain	Other	Grain	Other	Grain	Other
1-0-0	.22	.87	.15	.94	.12	.95
0-1-0	.43	.72	.41	.74	.38	.77
0-0-1	.35	.75	.35	.76	.35	.76
1-1-0	.36	.81	.30	.88	.26	.91
1-0-1	.37	.83	.32	.90	.29	.91
0-1-1	.48	.72	.47	.73	.46	.74
1-1-1	.47	.79	.41	.85	.39	.87
1-1-2	.47	.78	.44	.83	.42	.84
1-2-3	.48	.76	.47	.79	.46	.80

Excluding Grass and Flax Profiles	Threshold					
	0.0		0.5		0.667	
Weighting	Grain	Other	Grain	Other	Grain	Other
1-0-0	.53	.66	.36	.85	.30	.89
0-1-0	.59	.54	.52	.65	.45	.72
0-0-1	.83	.33	.79	.48	.79	.48
1-1-0	.64	.62	.50	.80	.43	.86
1-0-1	.84	.40	.65	.73	.58	.80
0-1-1	.86	.33	.79	.52	.73	.59
1-1-1	.85	.41	.68	.73	.62	.79
1-1-2	.86	.35	.74	.66	.69	.72
1-2-3	.86	.34	.77	.60	.74	.66

Note: "Grain" includes all blobs with Ground Truth of Spring Wheat, Durum Wheat, Barley, and Oats.
"Other" includes all blobs with other Ground Truth classes except "Problem Field", "No Ground Truth", and "Mixture".

TABLE 4. LABELING RESULTS FOR ALL PIXELS COMBINED

	All Profiles Used			No Grass or Flax Profiles		
	Thresholds			Thresholds		
Weighting	0.0	0.5	0.667	0.0	0.5	0.667
1-0-0	.68	.71	.71	.62	.71	.71
0-1-0	.63	.65	.66	.56	.61	.64
0-0-1	.63	.64	.64	.48	.57	.57
1-1-0	.68	.71	.72	.62	.71	.73
1-0-1	.70	.73	.73	.53	.71	.73
0-1-1	.65	.66	.66	.48	.60	.63
1-1-1	.69	.72	.73	.54	.72	.74
1-1-2	.69	.71	.72	.50	.69	.71
1-2-3	.68	.70	.70	.49	.65	.68

On a segment-by-segment basis, however, accuracies varied considerably. Tables 5 and 6 and Figure 4 present these results. Neither year, agrophysical stratum unit, or the number of available acquisitions were shown to be significant with respect to grain labeling accuracy. This result is surprising, since logical connections exist between these factors and the labeling technique (see Section 3.2.1). One explanation for the lack of significance may be that the acquisition placement is critically important (see Section 4.4.2), and overshadowed the influence of the factors tested.

4.3 LABELING ERROR CHARACTERIZATION

4.3.1 ERRORS OF OMISSION

Accuracy by Type of Grain Crop

Only three of the spring small grains had enough data to support analysis: Spring Wheat, Barley, and Oats. Durum Wheat was only represented by a few blobs in two segments, and therefore could not be evaluated. Of the three crops, Oats showed the worst labeling results, usually several percentage points below Wheat. When the test-statistic included all three features (Greenness, Brightness, and shift) Barley was most often correctly labeled, though again by only a few percentage points. Those Spring Wheat blobs that were correctly labeled, however, seemed to fit the grain profile better than did the other grain crops. When the probability threshold was increased from 0.0 to 0.5, the percentage of Spring Wheat blobs still called grain decreased less than did the percentage for Barley or Oats. There were too few strip fallow grain blobs to allow separate evaluation of this category.

TABLE 5. SELECTED LABELING RESULTS BY SEGMENT

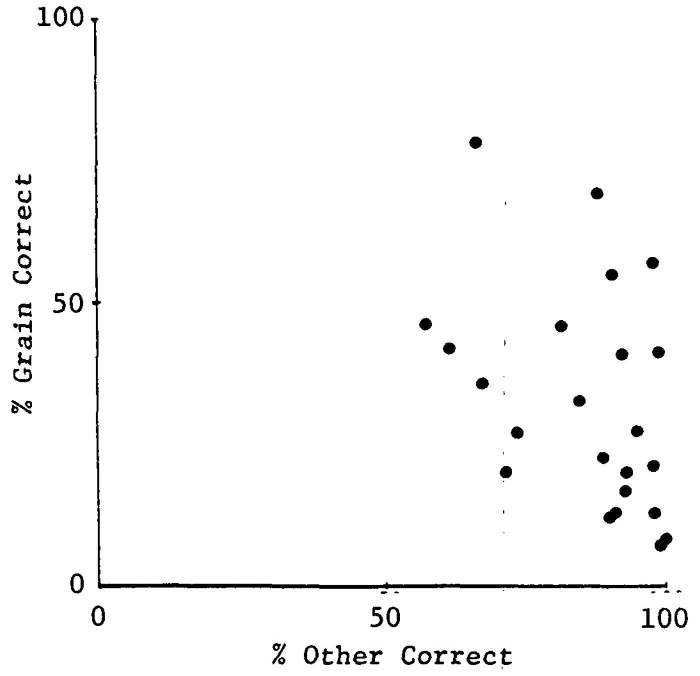
All Profiles
Weighting: 1-1-1
(Only segments with 10 or more Grain Blobs Labeled)

	Threshold					
	0.0		0.5		0.667	
Segment	Grain	Other	Grain	Other	Grain	Other
1380	.56	.99	.47	.99	.41	.99
1394	.56	.84	.55	.91	.55	.91
1498	.44	.83	.33	.89	.17	.93
1521	.86	.63	.81	.67	.78	.67
1542	.28	.89	.20	.93	.20	.93
1567	.11	.97	.07	.99	.07	.99
1614	.28	.75	.24	.89	.23	.89
1618	.42	.91	.41	.92	.41	.92
1619	.23	.94	.22	.98	.21	.98
1637	.75	.75	.71	.85	.69	.88
1661	.52	.59	.49	.78	.46	.82
1663	.71	.95	.60	.98	.57	.98
1675	.51	.52	.49	.56	.46	.58
1676	.50	.83	.42	.85	.33	.85
1725	.57	.60	.28	.70	.20	.72
1731	.13	.91	.13	.91	.13	.91
1755	.12	.89	.12	.90	.12	.90
1800	.52	.51	.47	.57	.42	.62
1811	.52	.54	.37	.63	.36	.68
1842	.08	.99	.08	1.00	.08	1.00
1913	.44	.55	.31	.69	.27	.74
1942	.27	.94	.27	.95	.27	.95
1948	.50	.87	.19	.97	.13	.98

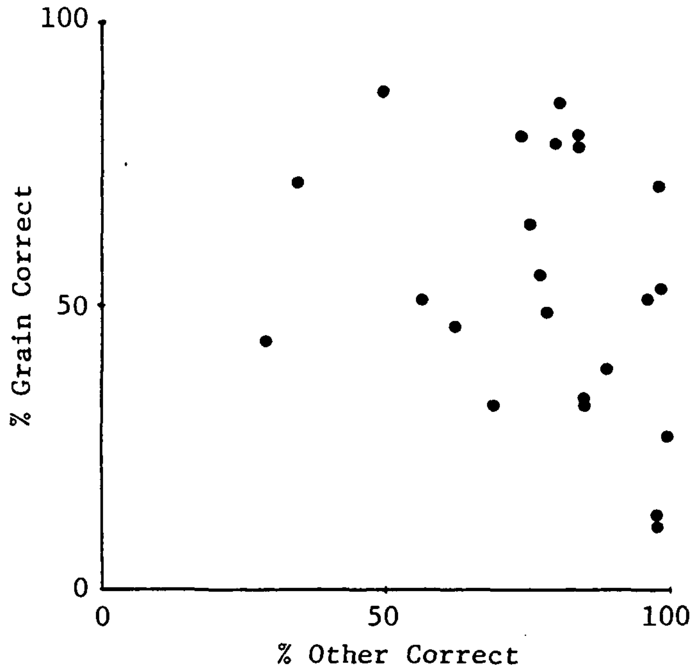
TABLE 6. SELECTED LABELING RESULTS BY SEGMENT

No Grass or Flax Profiles
Weighting: 1-1-1
(Only segments with 10 or more Grain Blobs Labeled)

	Threshold					
	0.0		0.5		0.667	
Segment	Grain	Other	Grain	Other	Grain	Other
1380	.75	.97	.59	.99	.53	.99
1394	.88	.39	.82	.79	.78	.84
1498	1.00	.08	.61	.79	.39	.89
1521	.97	.25	.91	.42	.88	.50
1542	.79	.42	.64	.82	.44	.85
1567	.21	.92	.14	.97	.11	.98
1614	.99	.03	.76	.72	.65	.75
1618	.92	.55	.87	.79	.86	.81
1619	.57	.66	.53	.92	.51	.96
1637	.98	.11	.87	.75	.80	.84
1661	.96	.07	.57	.73	.49	.78
1663	.95	.87	.78	.98	.71	.98
1675	.92	.06	.82	.22	.72	.34
1676	.50	.83	.42	.85	.33	.85
1725	.96	.05	.57	.22	.44	.29
1731	1.00	.39	.93	.59	.80	.74
1755	.82	.25	.60	.73	.56	.77
1800	.86	.16	.58	.48	.51	.56
1811	.71	.34	.51	.56	.47	.62
1842	.30	.99	.27	1.00	.27	1.00
1913	.78	.24	.39	.61	.32	.69
1942	.98	.59	.85	.77	.79	.80
1948	.88	.45	.22	.96	.13	.98



(a) Results Using All Profiles



(b) Results Excluding Grass and Flax Profiles

Weighting: 1-1-1
Threshold: 0.667

FIGURE 4. ACCURACIES BY SEGMENT

Major Error Sources

By far the most common confusion profile set for grains was that representing grass. In every configuration grass was the second most frequently chosen profile after grain. With no probability threshold, as much as 44% of the grain sample was assigned to the grass class (depending on test-statistic weighting). Flax was the second most commonly chosen confusion profile, attracting as much as 25% of the grain sample. Both of these results were expected, since the profile shapes for the three crops were very similar (see Figure 1).

When the grass profile was omitted, grain labeling accuracies increased by about 15 percentage points, while omission of the flax profile resulted in an increase of 10 percentage points. When both profiles were omitted, grain labeling accuracy increased approximately 30 percentage points. While these figures varied somewhat with thresholds and test-statistic weightings, the trends were very stable.

The other crop profiles were much less likely to draw away grain samples. Even when the grass and flax profiles were omitted from the procedure the corn, sunflower, and soybean profiles each drew only 2-6% of the grain sample.

4.3.2 ERRORS OF COMMISSION

The primary sources of error related to non-grains called grain were the same crops that captured most of the grain samples: grasses and flax.

The grasses class, which was comprised of all blobs assigned ground truth labels of grass, hay, pasture, and idle fallow, had around 25% of its members labeled grain, or 50-75% if the grass profile was omitted. Broken down further, the four major elements of the class had approximately the same accuracies. It should be noted, however, that the pasture class comprised 65% of the total grass blobs, and 80% of the total interior pixels of this class. Thus in terms of absolute numbers, pasture was the most important source of erroneous grain labels. A technique to detect pasture prior to the labeling process, perhaps based on the irregular field shapes typical of the class, could increase accuracy considerably. Table 7 shows the results obtained when Pasture blobs are designated Other. The results can be compared to those presented in Tables 3 and 4.

Flax was called grain 40-50% of the time, while 15-20% of the corn and soybeans blobs were labeled grain. Although 30-60% of the sunflower blobs were called grain, this may not accurately indicate the spectral confusion between these crops. Even sunflower data were not called sunflowers very frequently, suggesting that the sunflower profile set was not in fact a good representation of sunflower spectral development; the confusion, given a good sunflower profile, would probably have been less.

Labeling accuracy for two other important crops was also evaluated: winter wheat and alfalfa. Although it is planted in the fall, the development of winter wheat in the spring is very similar to that of spring wheat, so one might expect that winter wheat would frequently be called a spring grain in this procedure. However, on the average, only about 20% of the winter wheat blobs were called spring grains. The majority of winter wheat blobs best fit the corn profile, and thus were labeled other.

The cutting cycles of alfalfa can produce a wide range of spectral patterns for alfalfa blobs, some of which could easily be mistaken for grain. Nonetheless, two to three times as many alfalfa blobs were labeled grass as were labeled grain. Only about 20% of the alfalfa blobs received grain labels. However, this number increased substantially, to about 60%, when grass and flax profiles were omitted.

TABLE 7. LABELING ACCURACIES WITH PASTURE DESIGNATED OTHER

No Grass or Flax Profiles
(% Other Correct Includes all Pasture Pixels)

	Threshold								
	0.0			0.5			0.667		
Weighting	Grain	Other	Combined	Grain	Other	Combined	Grain	Other	Combined
1-0-0	.53	.72	.66	.36	.88	.73	.30	.91	.73
0-1-0	.59	.67	.64	.52	.74	.68	.45	.79	.69
0-0-1	.83	.52	.61	.79	.63	.68	.79	.63	.68
1-1-0	.64	.71	.69	.50	.85	.75	.43	.89	.75
1-0-1	.84	.57	.65	.65	.80	.76	.58	.84	.77
0-1-1	.86	.52	.62	.79	.65	.70	.73	.70	.71
1-1-1	.85	.58	.66	.68	.80	.76	.62	.83	.77
1-1-2	.86	.54	.63	.74	.75	.75	.69	.79	.76
1-2-3	.86	.53	.62	.77	.72	.74	.74	.75	.75

4.4 QUALITATIVE COMPONENT EVALUATION

4.4.1 CROP CALENDAR SHIFT

The concept of crop calendar shift estimation relies on the assumption that the span of the growing season can be determined from the few scattered acquisitions available. In particular, it depends on the ability to detect a peak Greenness. Examination of histograms of the shift estimates by ground-truth class suggests that for the most part the technique performed as intended. Figure 5 provides illustrations of "good" results, and the normal-like distributions one would expect for planting dates in a given region.

In other segments, however, shift estimates for a given crop type varied considerably (Figure 6). Such results tended to occur when there were few acquisitions available in the growing season, when the acquisitions were spaced such that large gaps in coverage were apparent, or when the crop of interest showed unusually little green development. All of these conditions affect the spectral features used to estimate crop calendar shift. While it could be the case that planting occurred in an unusual pattern in the particular segment, it is most likely that the algorithm was fooled by noise, too little information, or information of low quality.

This conclusion can be confirmed by looking at the fit to the Brightness profile. While the shift estimate maximizes Greenness correlation, and thus should provide a somewhat reasonable Greenness fit, the fit to the Brightness profile, with a shape that differs substantially from that of the Greenness profile (at least for spring grains), would be expected to be worse with inaccurate shift estimates. Figure 7 illustrates that for the spring small grains, that is indeed what happens. One sees a reduced incidence of high probability fits to Brightness as the deviation from the mean or expected shift increases.

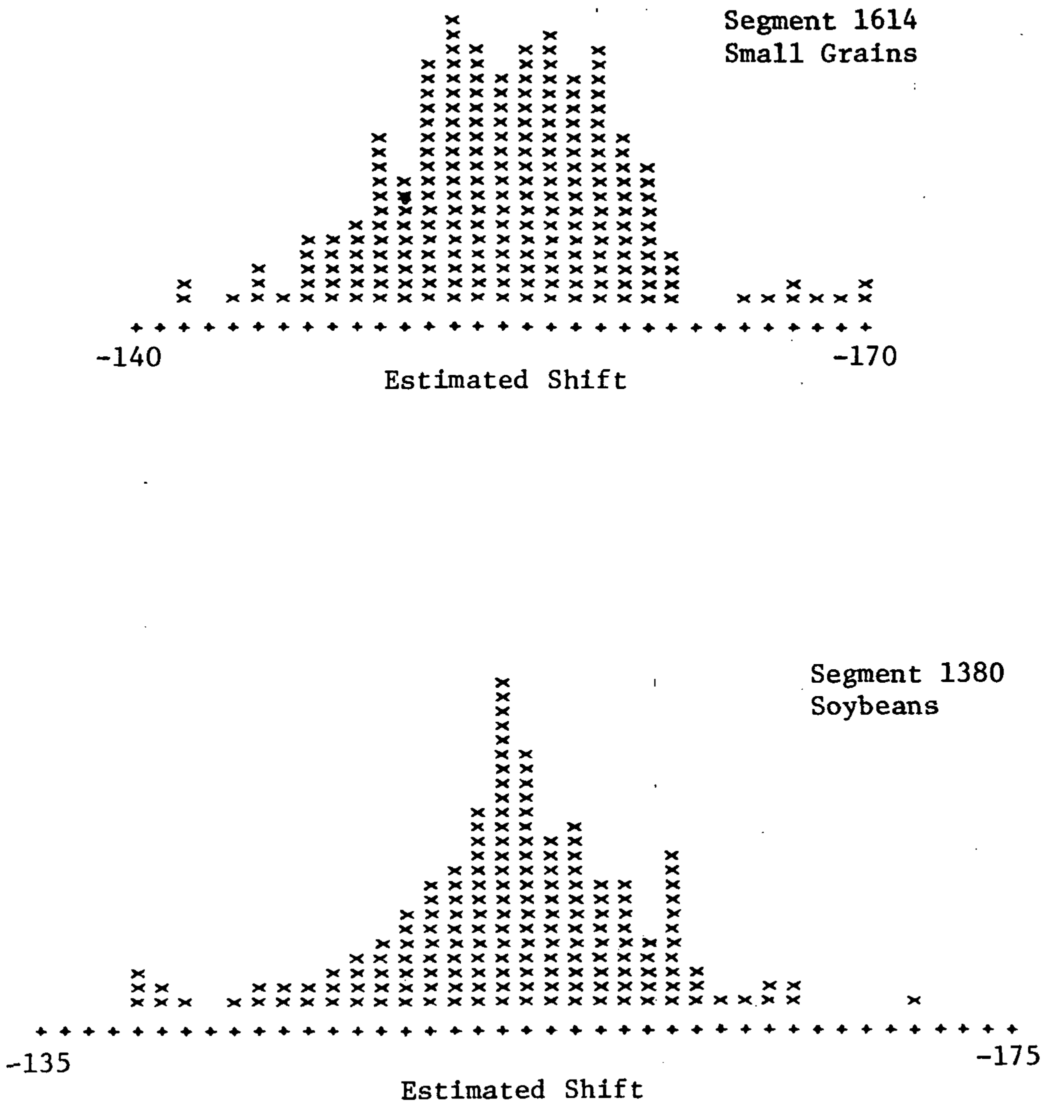


FIGURE 5. CROP CALENDAR SHIFT HISTOGRAMS - GOOD RESULTS

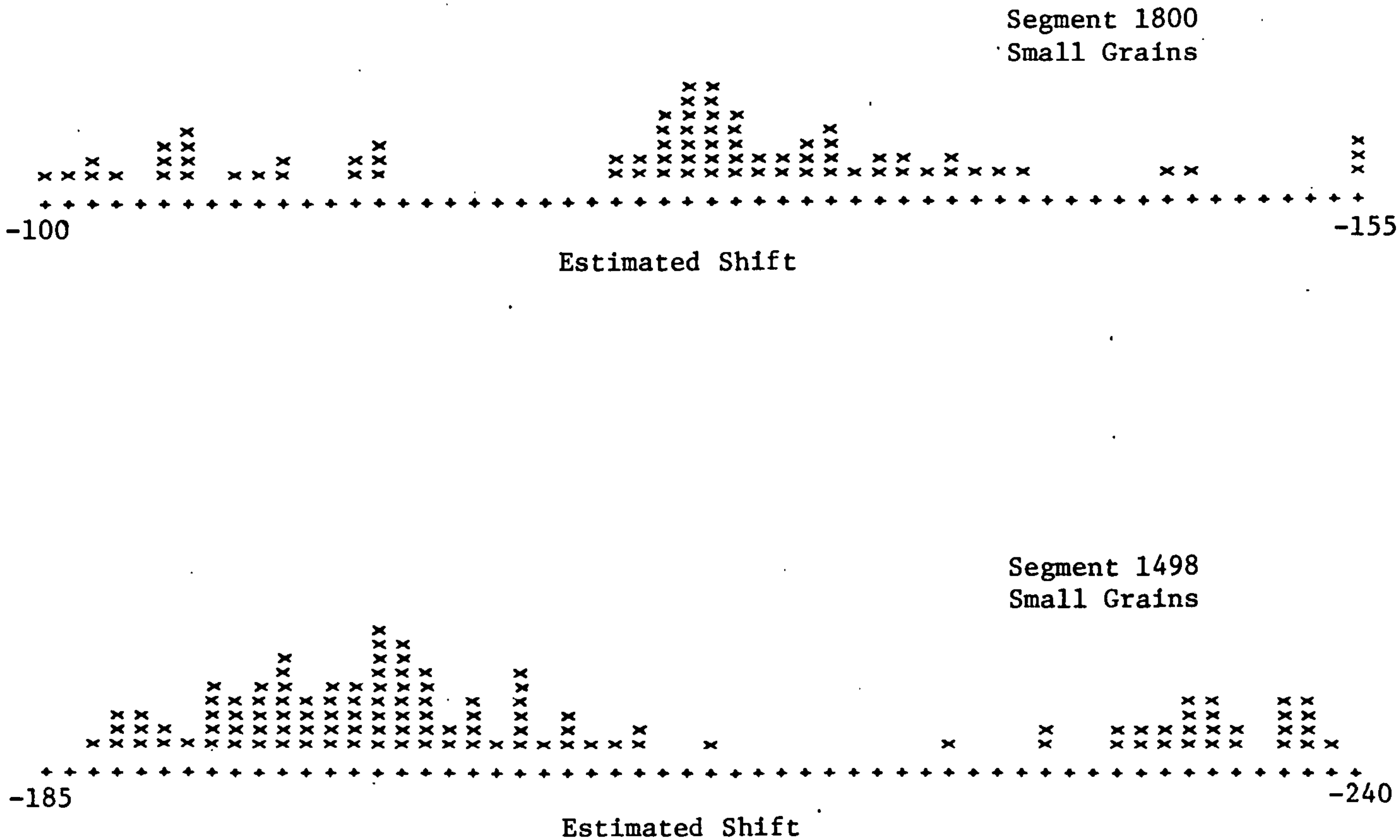


FIGURE 6. CROP CALENDAR SHIFT HISTOGRAMS - POOR RESULTS

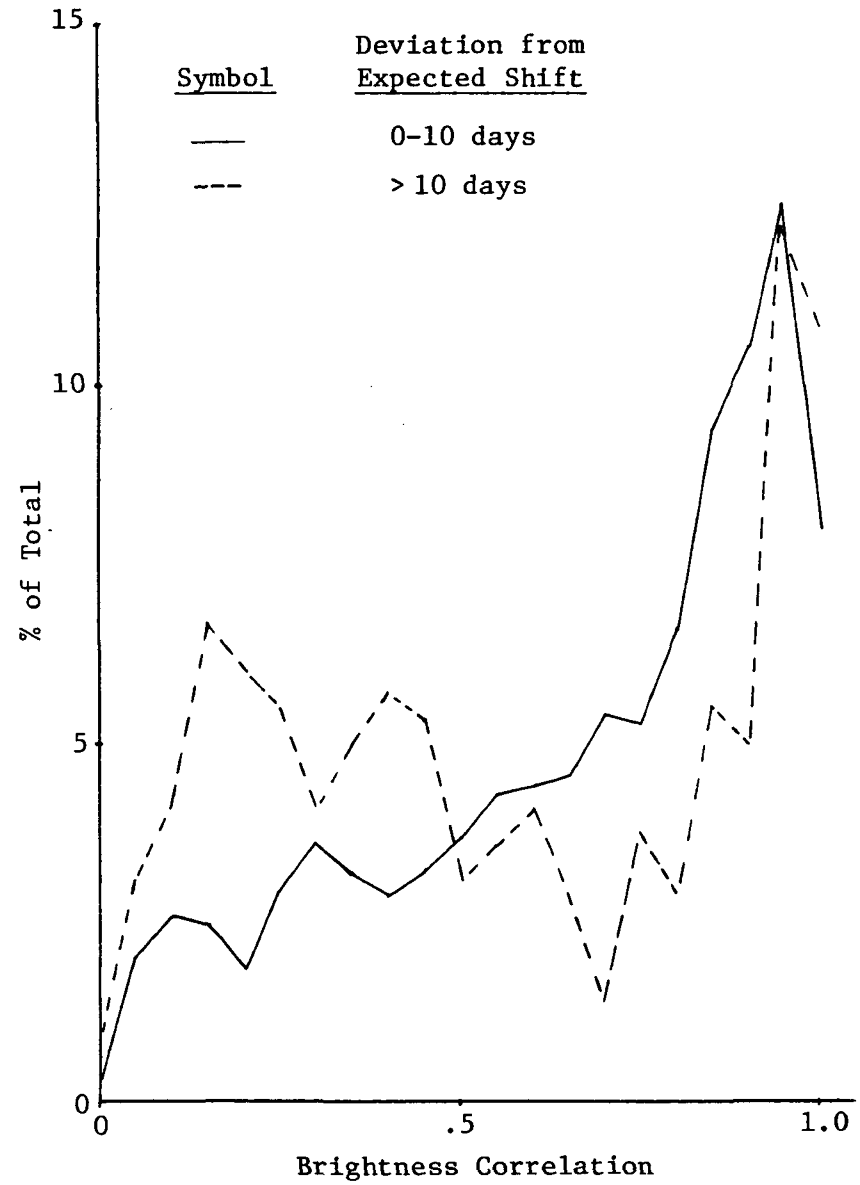


FIGURE 7. BRIGHTNESS CORRELATION AS RELATED TO DEVIATION FROM EXPECTED SHIFT. (Grain Data Fit to Grain Profile)

While the crop calendar shift procedure seems for the most part to be providing adequate information, it is limited by the spectral data available to it, and as a result is itself limited to segments which provide a good set of acquisitions. The problem of little or no green development will be addressed in the next section.

4.4.2 PROFILES AND PROFILE FITTING

Greenness

The most basic assumption of the labeling technique presented in this report is that data of a particular crop type do follow a characteristic pattern of spectral development. In terms of Greenness, this assumption is clearly supportable. Figures 8 and 9 show shifted data for two crops from all the test segments combined. While individual trajectories are not traced in the figure, it is clear that the data as a whole do follow a general pattern, and indeed follow a different pattern based on crop type. Such results have been observed before [6,11]. Nevertheless not all blobs said to be of a given crop type in the ground truth information follow the expected pattern of Greenness development. Figures 10 and 11 illustrate this fact. Whether the cause of these spectral patterns is misregistration, ground truth errors, cultural factors such as abandonment and early cutting, or environmental factors such as drought and hail damage, the patterns deviate enough from a "normal" profile that the fields probably would not be detectable as grains in any procedure based on multitemporal spectral analysis.

An additional issue raised by these data relates to their treatment in tests such as this, or in operational systems. Some odd profiles are the result of ground truth errors, and clearly "errors" in labeling such data may not be errors at all. Where misregistration is the cause of deviant spectral development patterns, the "true" label of a blob

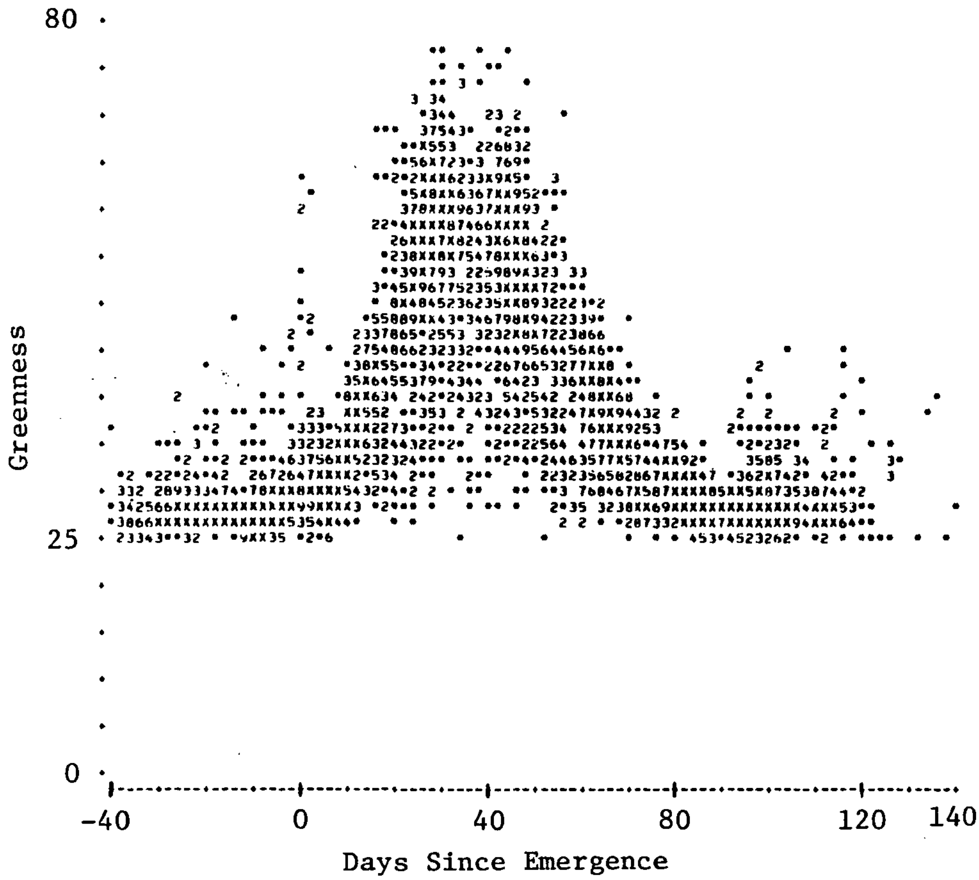


FIGURE 8. COMPOSITE OF ALL SHIFTED GRAIN DATA - GREENNESS

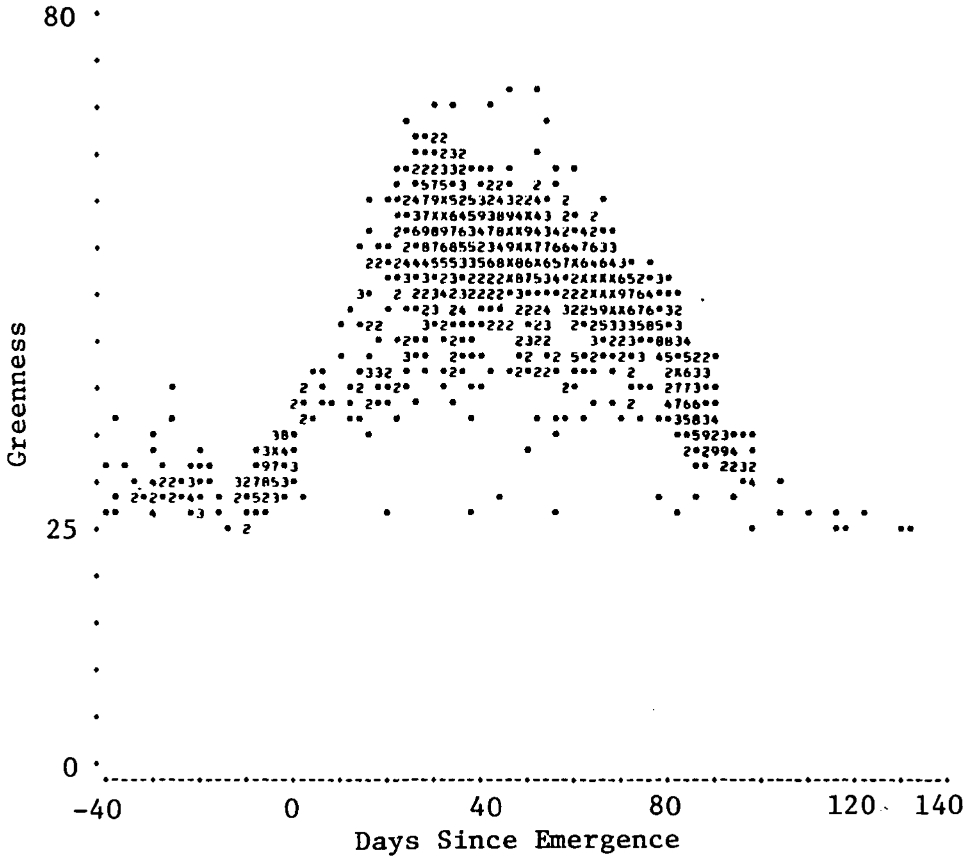


FIGURE 9. COMPOSITE OF ALL SHIFTED CORN DATA - GREENNESS

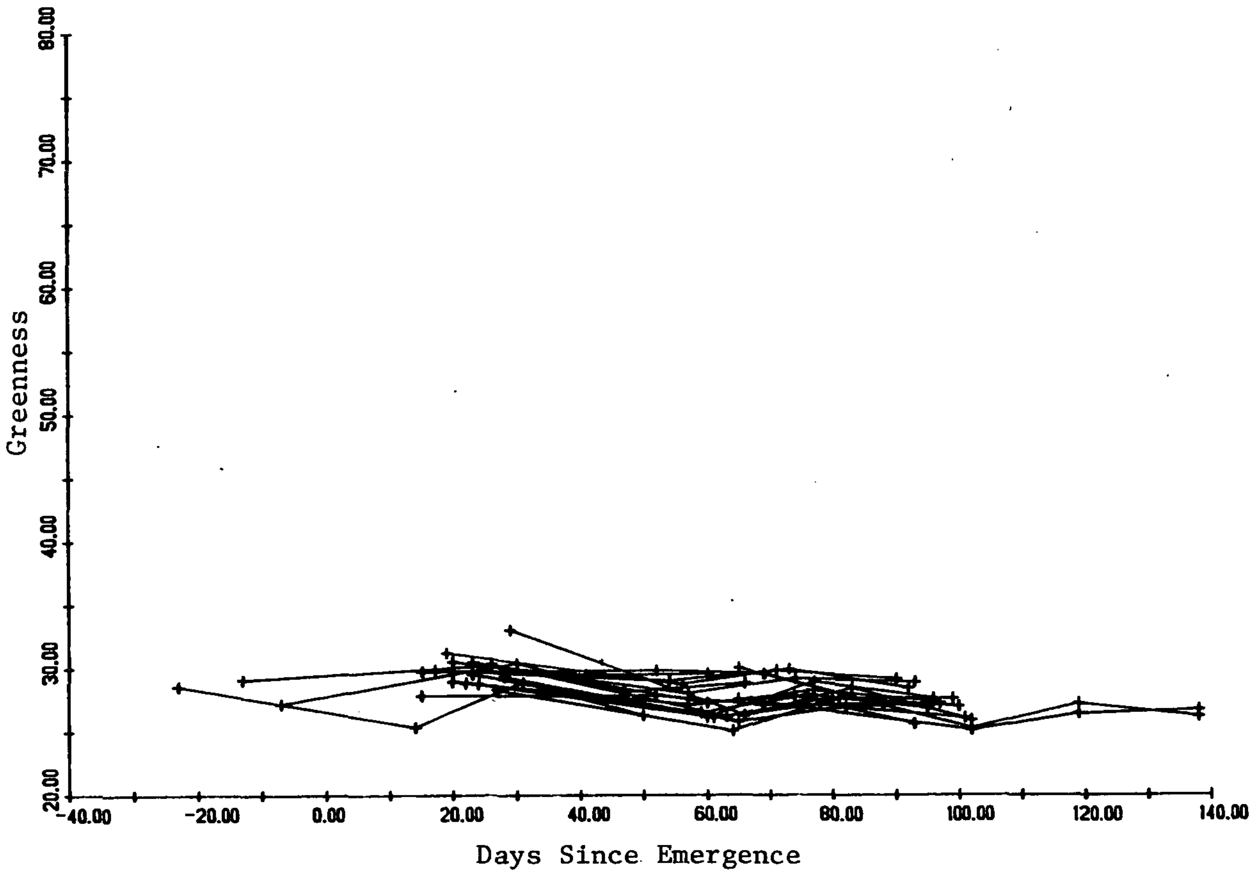


FIGURE 10. IRREGULAR GRAIN GREENNESS TRAJECTORIES - SEGMENT 1498

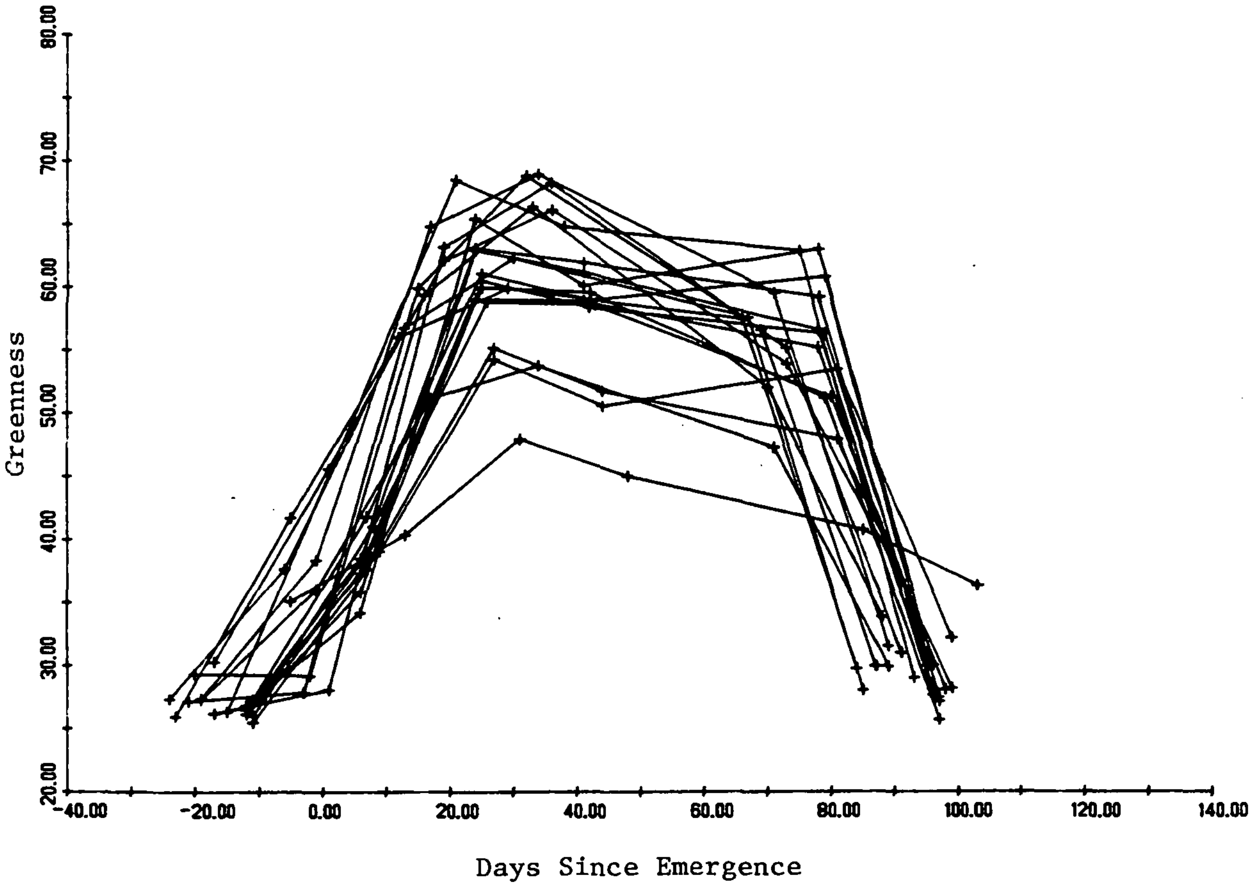


FIGURE 11. IRREGULAR GRAIN GREENNESS TRAJECTORIES - SEGMENT 1619

is ambiguously defined. The incidence of such ambiguous labels can be minimized through use of a spectral-spatial clustering algorithm like SUPERB, but where they do occur, their treatment is a problem more complex than simply assigning the "correct" label.

The third case is that in which cultural or environmental influences have substantially altered the physical and, therefore, the spectral character of the field. In many of these cases it is probably not desirable to label a field as a normal crop, since it will add little or nothing to the final production of the region. While this is dependent on the yield estimation component of the system, and is thus, to some degree, beyond the scope of this work, it again influences the evaluation of test results for labeling techniques. If grain fields that have been green chopped for silage or extensively damaged by hail are not going to contribute to the production figure, then the "correct" label for such fields may not be grain but rather non-grain.

Brightness

As previously described, Brightness development over time is a more complex process than Greenness development. The interaction of soil and plant canopy results in greater variability in spectral patterns exhibited by a single crop, and particularly in Brightness values early and late in the season. This situation is clearly illustrated in Figures 12 and 13. At the same time, however, patterns in Brightness development are important for crop discrimination, as described in Section 4.5.2.

There is clearly a need for more work in this aspect of the labeling process, in terms of characterizing the shapes of crop Brightness profiles, detecting those shapes in data of unknown type, and adjusting expectations in response to soil Brightness and crop condition changes.

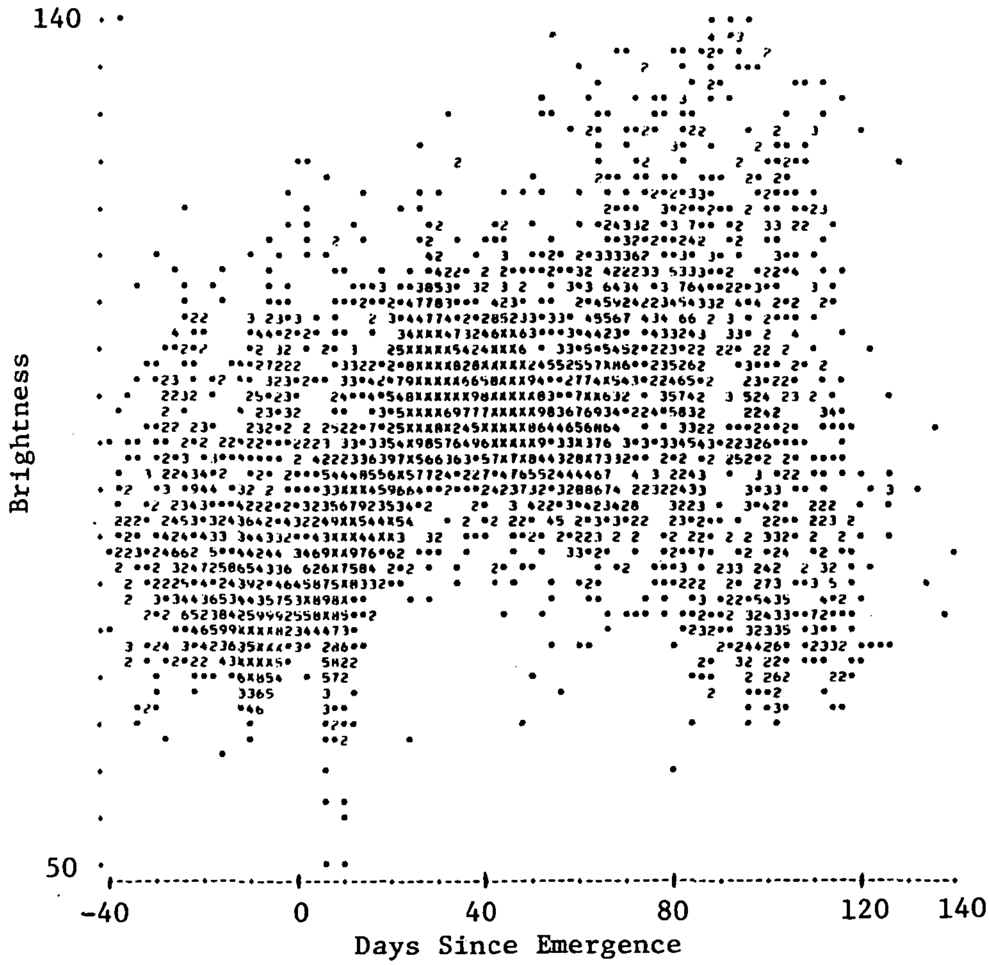


FIGURE 12. COMPOSITE OF ALL SHIFTED GRAIN DATA - BRIGHTNESS

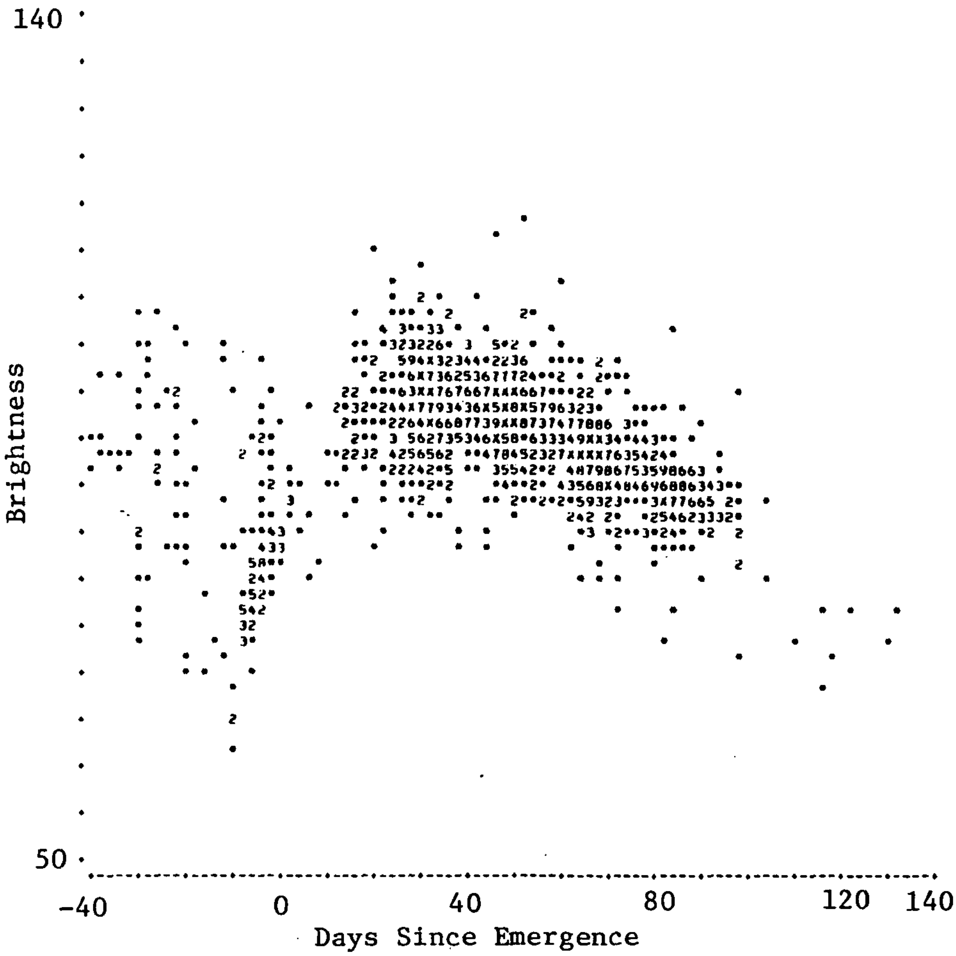


FIGURE 13. COMPOSITE OF ALL SHIFTED CORN DATA - BRIGHTNESS

Acquisition Dependence

A key element of profile fitting already mentioned is the spacing and frequency of acquisitions. Profile-based procedures such as this one may work well or poorly, entirely as a function of the set of available data acquisitions. Two reasonably different profiles may look very different (Figure 14a) or identical (Figure 14b) depending on where the acquisitions fall. This problem, while very significant, is largely outside the control of any labeling procedure. It does, however, point out both the need for frequent coverage and an inherent limitation in multitemporal spectral analysis techniques. The problem may be aggravated by automated profile-based labelers, which must operate on a simpler level than the human mind, but it is a factor in all labeling techniques.

4.5 EVALUATION OF PROCEDURE CONFIGURATIONS

4.5.1 PROFILE SETS

Section 3.3.2 describes the various sets of profiles evaluated. Previous sections have already discussed the influences of some of the described variations. The general trend through all eight sets tested was a decrease in errors of omission and an increase in errors of commission as the number of non-grain profiles was reduced. This is particularly true for the grass profile, which attracted many blobs from many other crop groups, as well as many grains. The best results, based either on combined grain/other accuracies or on the best mix of accuracies for the two crops, were achieved when both the grass and flax profiles were omitted.

The subsetting intended to simulate that which could be done using historical statistics had the same effect as omission of other profiles, but the relative gain, weighting grain accuracy against non-grain accuracy, was of uncertain significance.

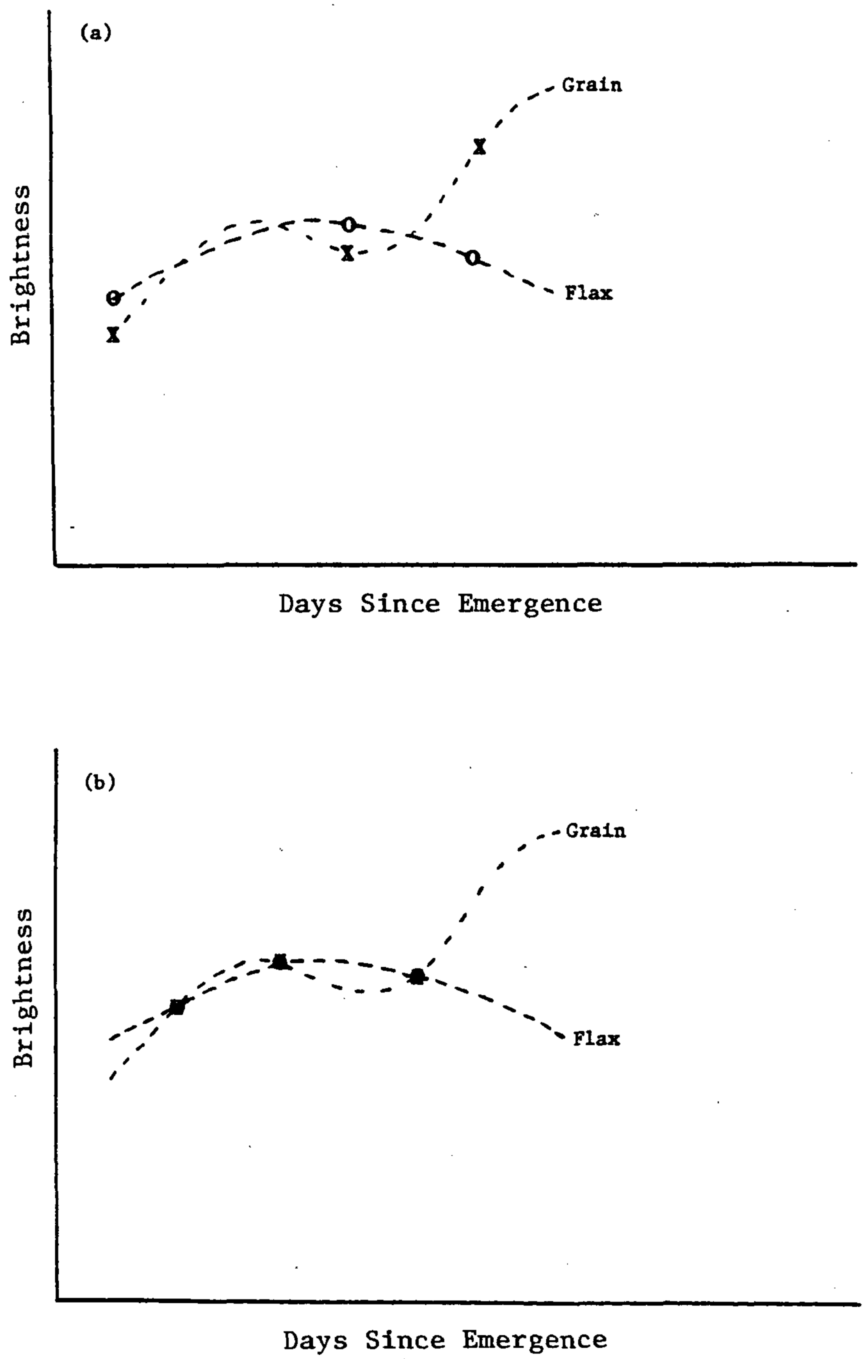


FIGURE 14. ACQUISITION TIMING EFFECT ON CROP SEPARABILITY

4.5.2 TEST STATISTIC WEIGHTINGS

Section 3.3.3 describes the various weightings evaluated. When used by themselves or in most pairs, the three features (Greenness, Brightness, and shift) yielded worse results than when all three were used. When only one was used, the best grain labeling accuracies were obtained with Brightness correlation, and the worst with Greenness fit. The explanation for the superiority of Brightness as a single discriminant may have to do with the Brightness dip which occurs in grains around the time of heading (see Figure 15). This dip is not apparent in any of the other crops for which profiles were constructed. The dip probably results from a combination of shadowing effects from the heads, and the more opaque quality of the heads. Although there are problems associated with Brightness as a discriminant (see Section 4.4.2), it nonetheless produced the best single feature results.

Figure 16 illustrates a likely explanation for the low accuracies achieved with Greenness fit used alone. When shifted so that their peaks line up, the Greenness profiles of all the crops look very similar, varying primarily in their temporal spread. Since the tails of the profiles tend to be the most noisy, it could be expected that many grain blobs would fit the longer profiles fairly well simply as the result of a higher than expected early or late Greenness value.

In this test, grain labeling accuracies were maximized by those weightings which downplayed Greenness fit and emphasized Brightness correlation and shift: the 0-1-1 and 1-2-3 weightings achieved the best results (refer to Tables 3 and 4). These weightings were also best for maximizing overall accuracy (grain and non-grain) when all profiles were used. However, since the flax and grass profiles resemble grain most in Greenness, omission of one or both of these profiles

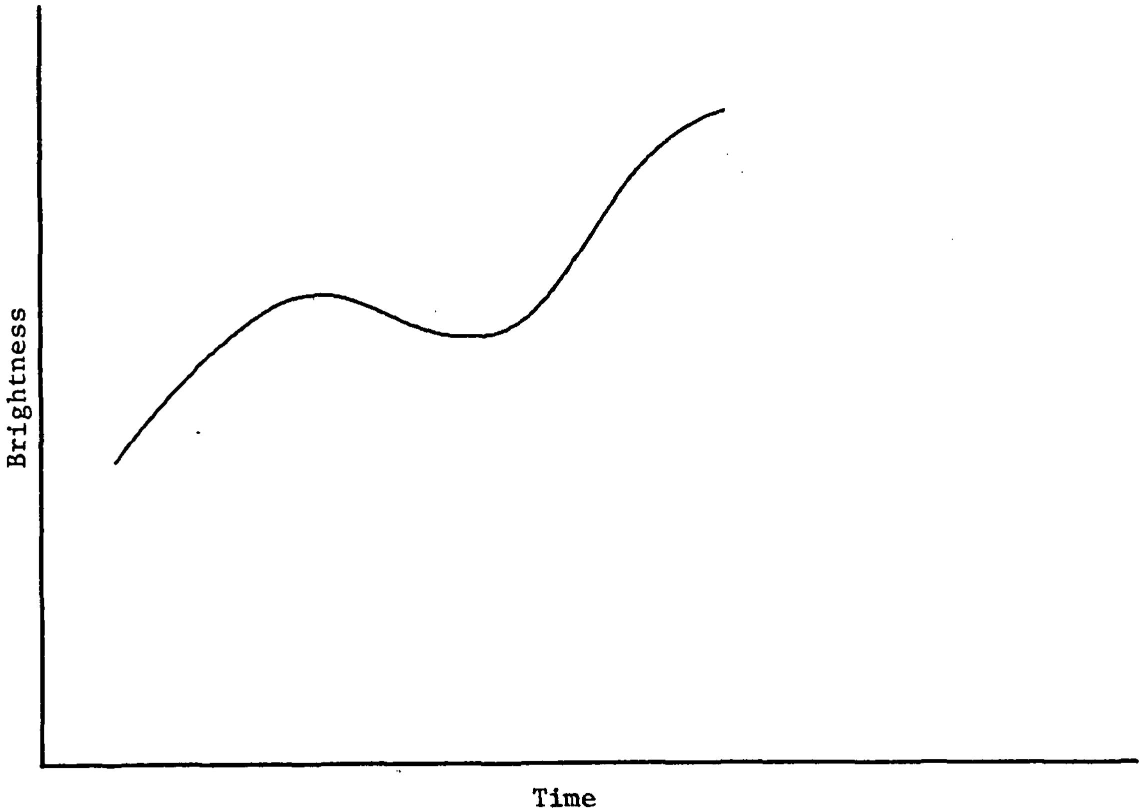


FIGURE 15. SMALL GRAINS BRIGHTNESS PROFILE

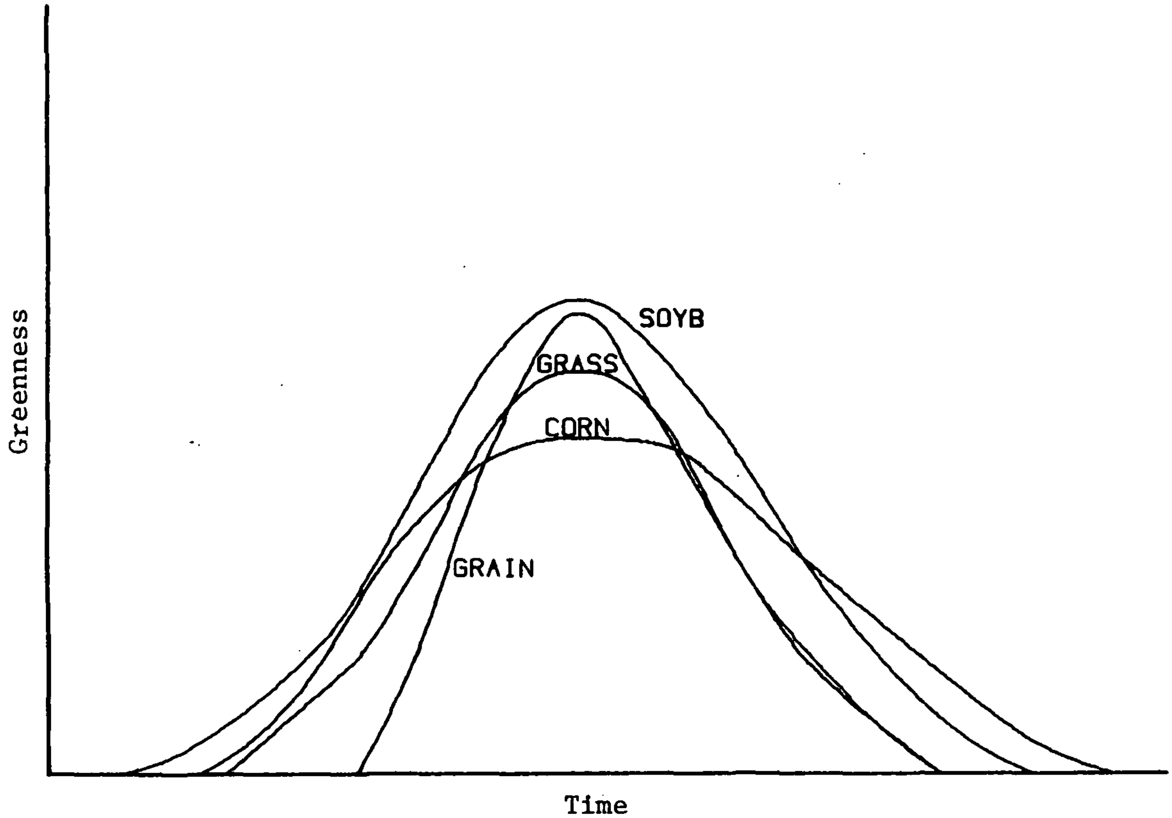


FIGURE 16. COMPARISON OF GREENNESS PROFILES

allowed the emphasis on Greenness fit to be increased. When both were excluded, the 1-1-1 and 1-1-2 weightings produced the best results (see Tables 3 and 4).

4.5.3 PROBABILITY THRESHOLDS

Any increase in the probability threshold will almost certainly reduce the number of blobs assigned to a crop code. In terms of grain vs. non-grain, a higher probability threshold will result in a purer sample (decreased errors of commission) but also increase errors of omission.

Of the thresholds considered (see Section 3.3.4), the 0.5 and 0.667 values were found to be best in terms of both accuracy with which a crop was called itself (grain called grain, corn called corn, etc.) and overall grain/non-grain accuracy.

The incremental change in grain accuracy can be compared to that in non-grain accuracy as a further evaluation of the probability thresholds. Comparison of the 0.0, 0.5, and 0.667 thresholds showed a substantial gain achieved when going from the 0.0 to the higher levels, particularly in configurations excluding the grass and flax profiles. The incremental gains or losses incurred by moving from the 0.5 to 0.667 levels appear insignificant, although the highest total labeling accuracies for all data regardless of type were achieved with the 0.667 threshold. In terms of overall grain and non-grain accuracies, the best threshold was either 0.5 or 0.667, depending on the test statistic weighting used (see Tables 3 and 4). Different effects were also observed between individual segments (Tables 5 and 6).

5.0
CONCLUSIONS

A labeling technique requiring minimal analyst resources has been developed and tested on an extensive and independent data set. Results of that test suggest that the technique, as it is currently defined, can achieve spring grain labeling accuracies similar to those achieved with analyst-intensive techniques, though with lower non-grain accuracies.

Among the procedure configurations tested, the best labeling accuracies were obtained using:

Profile Sets: Exclude grass and flax
Test-Statistic Weighting: 1-1-1
Probability Threshold: .667

Some other statistic weightings, particularly those that increase emphasis on Brightness, should be considered in the future.

Test results also suggest that the accuracy of the technique could be substantially improved through particular modifications. These modifications, and some implications of the test for profile-based labelers and multitemporal labeling techniques in general, are described below.

Modifications Suggested

As detailed in Section 4.3.2, the pasture class is a major source of erroneous grain labels. As suggested in that section, a fairly simple technique, based on either visual or digital detection of field shapes, could be used to identify the pasture class prior to labeling, and so allow substantial improvements in non-grain labeling accuracy. It is clearly desirable that such a technique be developed and added to the labeling procedure as described in this report.

The second major area of interest is that of characterizing and using Brightness development patterns in labeling. There are several obstacles to effective use of this information, but the importance of Brightness as a discriminant feature, described in Section 4.4.2, provides ample incentive to address the problems.

As a whole, our understanding of Brightness and its relationship to crop physical characteristics is less developed than that of Greenness. This understanding, and the resultant development of techniques for detecting soil Brightness and crop condition and using that information to adjust expected crop Brightness profiles, could allow substantial increases in the ability of this or similar labeling techniques to accurately detect grains, and perhaps other crops as well.

Other Implications

The test and evaluation of this labeling procedure on a large data set has raised several issues which relate to the whole discipline of crop identification using Landsat. First, only about half of the blobs in the entire data set of 64 segments met the acquisition requirements for labeling. One might conclude from this fact that profile-based techniques are impractical for use in area estimation systems due to their acquisition constraints. We suggest, however, that the mathematical requirements imposed by this procedure are in fact indications of practical requirements for any labeling procedure, that while an analyst or simple classifier may produce labels using less information than the three acquisitions required by this technique, they will be unable to produce accurate labels in most such cases. Others have observed similar limits [9,10].

Clearly, then, there is a need to design systems which can provide more frequent coverage, and also to develop procedures that can extract the maximum information possible from the limited set of available acquisitions.

A second implication relates to any multitemporal analysis technique which assumes characteristic patterns of temporal-spectral development for crop classes. Results described earlier clearly indicate that at least some data of a particular crop class (as identified in ground data) show little if any similarity to the expected spectral development pattern. Those deviations caused by errors in the ground data or misregistration of data between dates are beyond the control of labeling techniques, but are probably an insubstantial portion of the total. The remainder of the unexpected patterns either point out an inherent flaw in the pattern matching approach, or suggest the need for finer definition of the crop classes. While there is a range of spectral development patterns one would expect from normal fields of a given crop type, our understanding of the effects of crop variations on spectral development, particularly with regard to Tasseled-Cap Greenness, leads us to conclude that the deviant patterns observed represent not a normal range of variability, but the result of drastic cultural or environmental events (e.g., green chop for silage, abandonment, hail damage). Fields altered so significantly will contribute little if anything to regional crop production, and as a result, are probably best assigned to the non-grain (or non-crop of interest) category. Thus it can be said that this and similar techniques best detect "producing grains" (or other crops) rather than all fields containing plants of a given species. As an input to a crop production estimation system, this is probably more useful information.

The test and evaluation reported herein has provided an indication, though not an absolute proof, of the utility of multitemporal profiles and related features as the basis for automatic labeling techniques. Techniques such as this one, which use the integrative powers of the human analyst to provide a context within which a more efficient and objective computerized technique can assign labels, show great promise for advancing the accuracy and efficiency of this most difficult step in crop area estimation systems. With the understanding provided by this and similar tests, combined with continual advances in our understanding of features in Landsat data and their relationship to crops and crop condition, substantial improvements in the state-of-the-art of labeling should be possible.

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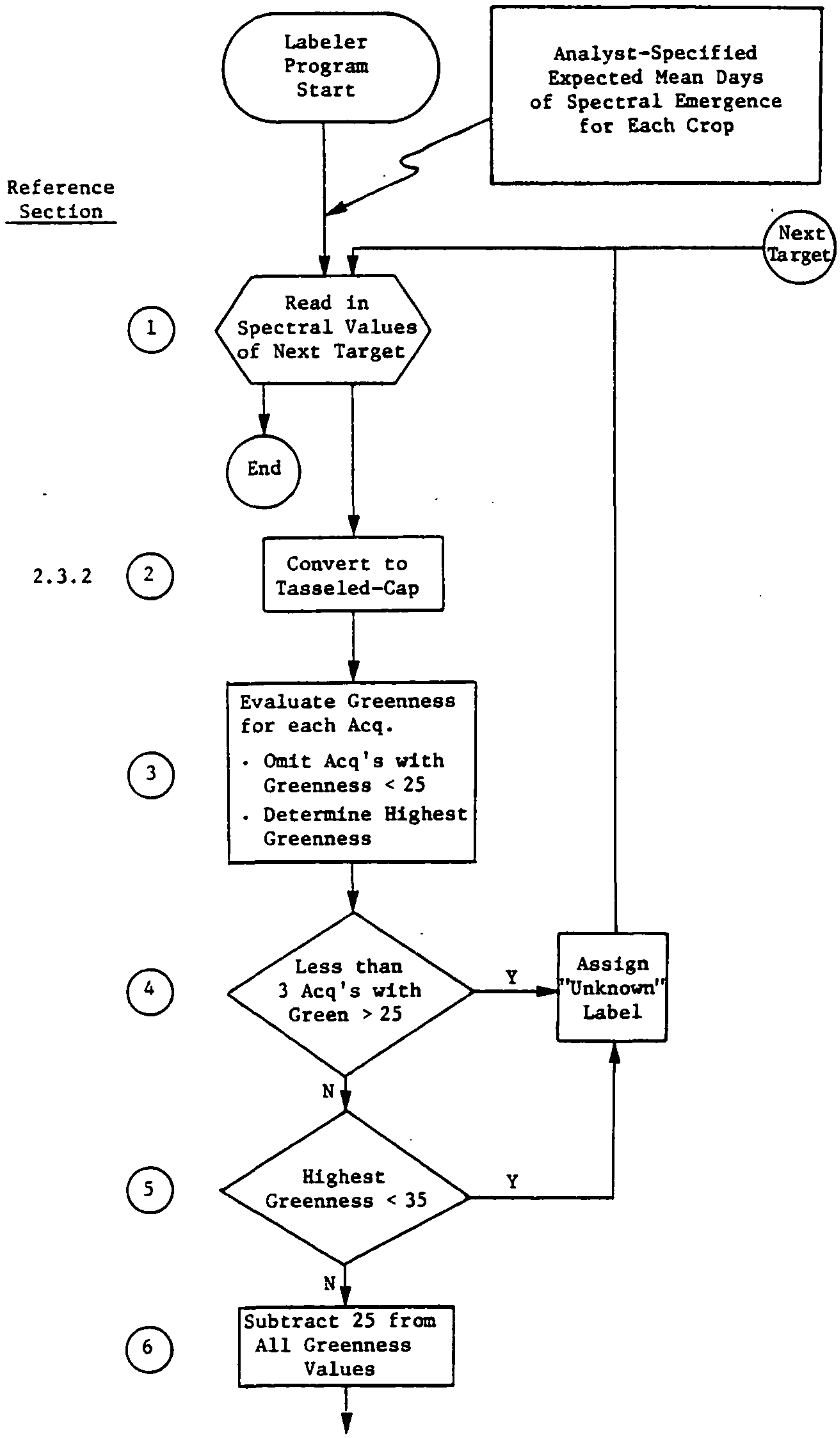
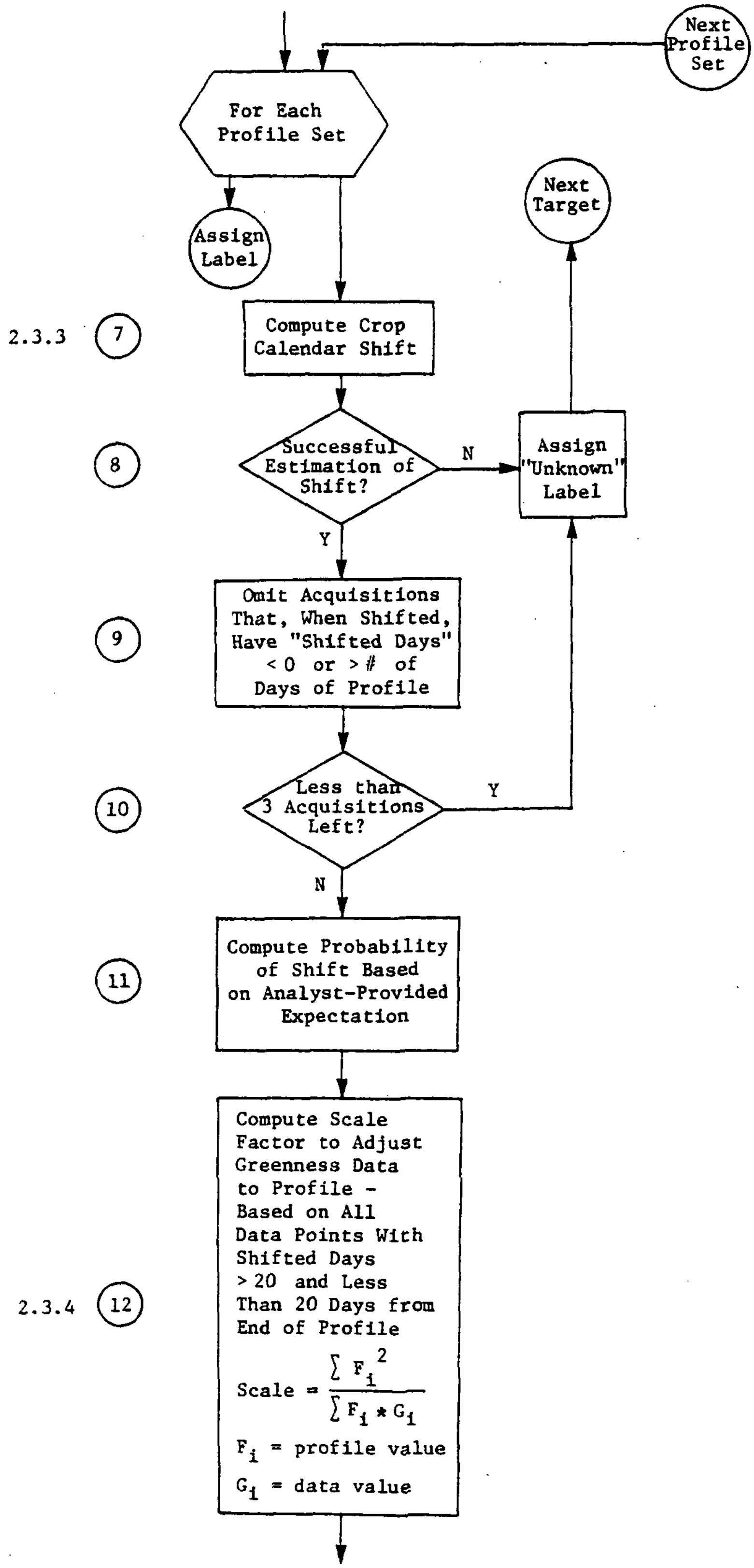
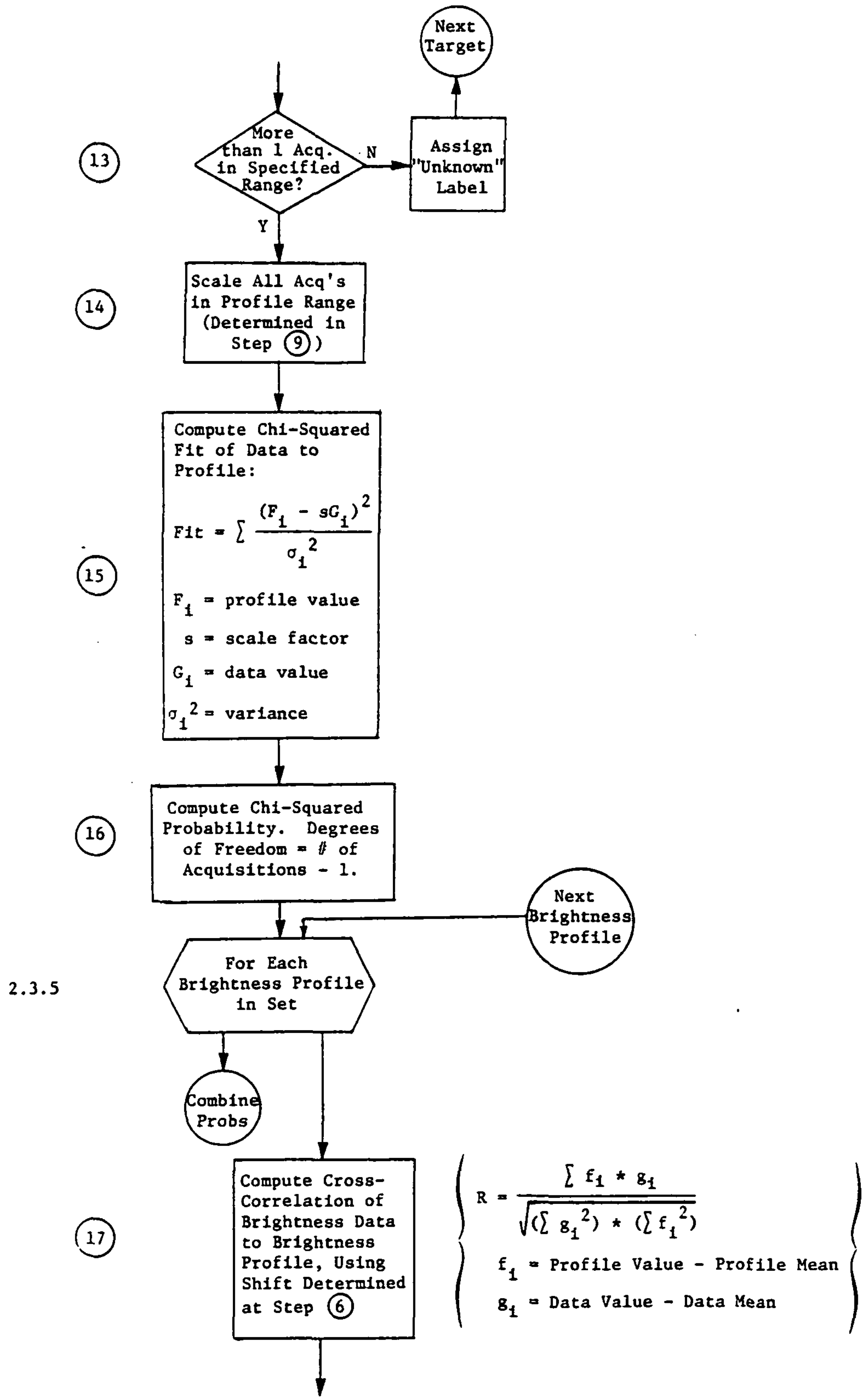
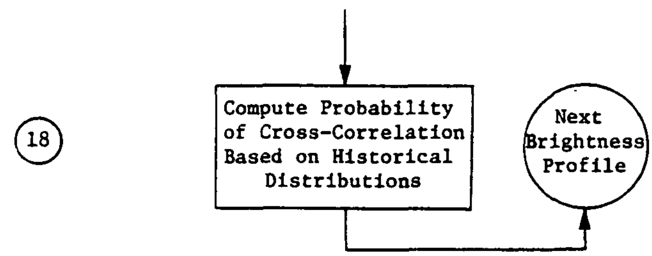
APPENDIX A

GRAIN LABELER FLOW DIAGRAM



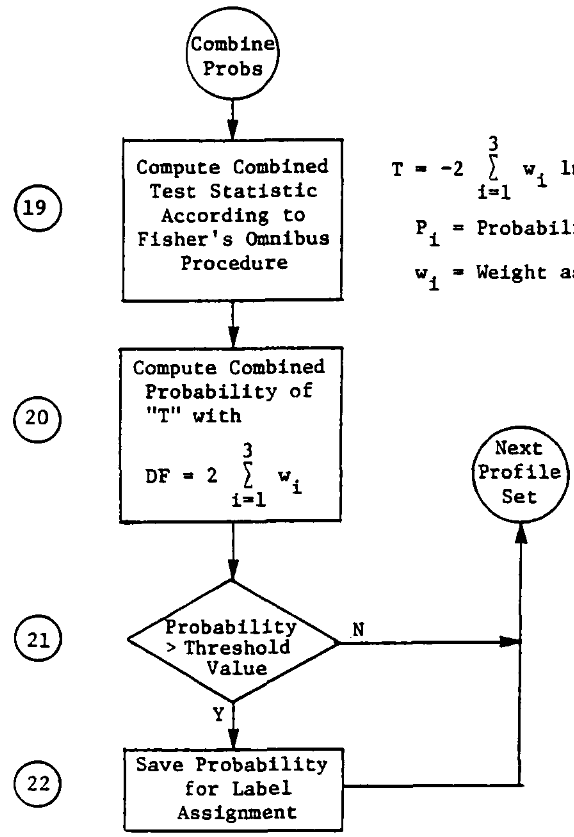

Next Profile Set
For Each Profile Set
Assign Label
Next Target
2.3.3
7
Compute Crop Calendar Shift
8
Successful Estimation of Shift?
N
Assign "Unknown" Label
Y
9
Omit Acquisitions That, When Shifted, Have "Shifted Days" < 0 or > # of Days of Profile
10
Less than 3 Acquisitions Left?
Y
N
11
Compute Probability of Shift Based on Analyst-Provided Expectation
2.3.4
12
Compute Scale Factor to Adjust Greenness Data to Profile - Based on All Data Points With Shifted Days > 20 and Less Than 20 Days from End of Profile
Scale = $\frac{\sum F_i^2}{\sum F_i * G_i}$
F_i = profile value
G_i = data value


Next Target
13
More than 1 Acq. in Specified Range?
N
Y
Assign "Unknown" Label
14
Scale All Acq's in Profile Range (Determined in Step 9)
15
Compute Chi-Squared Fit of Data to Profile:
$Fit = \sum \frac{(F_i - sG_i)^2}{\sigma_i^2}$
F_i = profile value
s = scale factor
G_i = data value
σ_i^2 = variance
16
Compute Chi-Squared Probability. Degrees of Freedom = # of Acquisitions - 1.
Next Brightness Profile
2.3.5
For Each Brightness Profile in Set
Combine Probs
17
Compute Cross-Correlation of Brightness Data to Brightness Profile, Using Shift Determined at Step 6
$R = \frac{\sum f_i * g_i}{\sqrt{(\sum g_i^2) * (\sum f_i^2)}}$
f_i = Profile Value - Profile Mean
g_i = Data Value - Data Mean



NOTE: Where more than one Brightness profile are present in a profile set, select the one with the greatest cross-correlation.

2.3.6



$$T = -2 \sum_{i=1}^{3} w_i \ln P_i$$

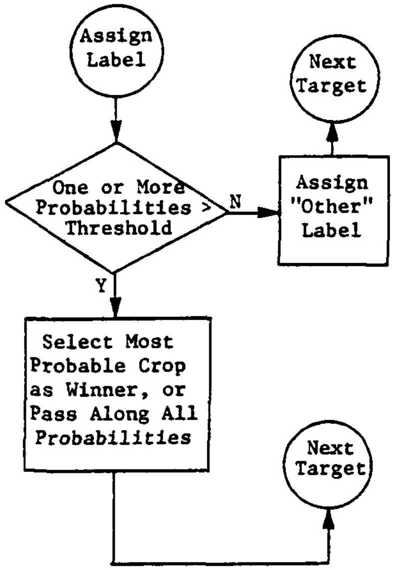
P_i = Probability associated with i^{th} test

w_i = Weight assigned to i^{th} test

2.3.7

23

24


Assign
Label
One or More
Probabilities >
Threshold
N
Y
Assign
"Other"
Label
Next
Target
Select Most
Probable Crop
as Winner, or
Pass Along All
Probabilities
Next
Target

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