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THE EVALUATION OF A SEMI-AUTOMATED PROCEDURE FOR CLASSIFYING CORN AND SOYBEANS WITHOUT GROUND DATA

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I. ABSTRACT

In response to a need for automatic, accurate and robust technology for estimating proportions of corn and soybeans with Landsat data, numerous procedures have been developed. While some of these procedures have provided proportion estimates which are accurate in the sense of having little bias towards one crop or another, they generally exhibit relatively high variance in their estimates, greatly reducing the confidence in their results. A corn and soybean estimation procedure which addresses the variance problem by its unique self-adaptation to segment-specific conditions is presented and evaluated. The evaluation attests to the success of the concept, and provides direction for additional studies aimed at improving the accuracy of the procedure.

II. INTRODUCTION

The development of technology aimed at achieving large area crop estimates using Landsat Multispectral Sensor (MSS) data, without the benefit of ground observed training data, has been the subject of research since the launch of Landsat 1 in 1973. With the world's growing population, it has become important to develop procedures which can provide crop proportion estimates for large regions in a timely, accurate and efficient manner.

This paper evaluates a technology developed to produce estimates of corn and soybean acreage in the central U.S. Corn Belt (Iowa, Illinois and Indiana). The technology was designed to fulfill the need for an estimation technique that uses multitemporal Landsat MSS as the primary information source, is independent of direct ground identification of training samples, and can be implemented in a controlled, formal environment for testing. Three unique aspects of this technology are that 1) it is essentially automatic, requiring human analysts only during the initial acquisition screening and selection, 2) it classifies the entire scene using a combination of objective labeling and nearest neighbor classification and 3) it has the ability to adapt to segment-specific growing conditions.

III. BACKGROUND

Several semi-automatic and automatic procedures have been developed to estimate crop proportions using Landsat, both for small grains and for summer crops (corn and soybeans).[1] While several of these procedures have produced good results measured in terms of bias, in general this low bias is achieved at the expense of a relatively high variance.[2] With this high variance, the low bias is a much less meaningful descriptor of performance. While it may be accurate to state that a procedure's estimation errors are not significantly different from zero, it may be equally accurate to state that the same results are not significantly different from a bias of, say 5% (see Fig. 1). An in-depth study which compared an analyst-intensive technique and a very similar technique in which the target labeling was fully automated indicated that a likely source of this variance is the inability of an automated procedure to adapt to the spectral conditions which may be present in any particular segment.

IV. DESCRIPTION OF TECHNIQUE

With this background in mind, the procedure presented in this paper had as a goal the reduction of the high variance associated with automatic procedures while, maintaining the favorable bias characteristics. This goal was approached by designing a technique which allows the procedure to adapt itself to segment-specific conditions. This self-adapting capability is based on two assumptions. First, corn and soybean fields which have typical spectral developmental patterns may be readily identified using a set of criteria which are applicable over a large region. Secondly, these "classic" spectral profiles are representative of the remaining, atypical, corn and soybean fields in the scene.

The technology may be divided into four distinct stages (see Fig. 8). The first stage, segment familiarization and data selection, is the only part of the procedure which requires analyst involvement. In this stage, nominal phenological crop calendars are adjusted with the use of image data, and biowindows are defined in which specific growth stages of the crops of interest may be observed. Excessively cloudy or misregistered data is screened out at this time, and expected temporal vegetation development patterns are identified.

The second stage is comprised of feature extraction and stratification operations. The acquisitions selected by the analyst in the first stage are preprocessed using the XSTAR algorithm[3,4] to normalize external effects, such as haze, then are transformed with the Tasseled Cap Transformation[5-7] to extract "Greenness" and "Brightness" features which respond to green vegetation and soil Brightness, respectively. Using a threshold value on the Greenness measure, each pixel is identified as either vegetated or non-vegetated for each acquisition. The data are stratified into crop groups (summer crops, small grains, permanent vegetation, and non-vegetated) using these temporal vegetated/non-vegetated patterns in conjunction with the expected patterns identified in Stage 1.[8,9]

Labeling targets are defined by clustering pixels which are spectrally similar and spatially contiguous into field-like groups with the blob algorithm,[10] reducing the data volume by a factor of 20-30 and increasing the purity of the labeling targets. A single pixel border is stripped from each blob to reduce the number of mixed pixels in the labeling target, then the blobs are stratified into two groups according to size: "big" blobs, which have at least 1 pixel remaining after the strip operation, and "little" blobs, which have nothing left after the border is stripped. The interiors of "big" blobs are used as the primary labeling targets in order to provide a more homogeneous labeling target.

The third stage of the procedure produces the crop labels for the targets defined in the previous stage. The target labeling may be further divided into four steps. In the first step, targets are examined using an objective labeling logic to select targets which have developmental profiles which are typical for corn and for soybeans for that segment. The logic employed simulates the approach taken by an expert analyst and uses criteria which are relatively invariant over a large region as the U.S. Central Corn Belt.[9] Some examples are:

- summer crops generally have a single dominant vegetative phase (during the summer)
- permanent vegetation is generally green throughout the growing season
- soybeans reach a greater maximum Greenness value than corn
- soybeans generally reach this peak after corn reaches its peak
- trees generally reach their Greenness peak before corn

Composite profiles for corn and for soybeans are developed using the "classic" targets labeled in this step (see Fig. 2). These composite profiles form the training set for the classification step (third step) and also are the basis for the development of an additional screening for non-summer crops. The reference profiles are examined in the second step to determine a "normal" growing season length and, this length threshold is applied to all non-labeled targets to select those which are vegetated for a length of time which is significantly different from the norm for summer crops. The profiles exceeding the threshold are labeled "non-summer" (see Fig. 3).

The third step in the labeling stage is the classification of all remaining targets. A nearest neighbor classifier with supremum norm is used in this step, using the reference profiles automatically developed in the first step as the training set. This classifier was chosen due to its ability to measure similarity in profile shape in a manner similar to that used by an expert analyst. The feature space used is defined by the nearness of a given target profile to the corn and soybean reference profiles. A set of linear discriminants partitions the feature space into regions of "corn", "soybeans" and "non-summer", with boundaries between the regions given mixed labels (see Figs. 4,5). At this point, all targets have crop labels, and all of the scene except the non-classic "little" blobs has been classified. To complete the classification process, all blobs "big" and "little", labeled or not, are clustered using a spectral/temporal clustering algorithm.[10] Non-classic "little" blobs are then given the proportional label which describes the cluster to which they have been assigned. With the entire scene now classified, the fourth stage, proportion estimation is a simple enumeration process.

V. EVALUATION

This technology was implemented in a testable form in the procedure code-named C/S-1B. Two evaluations of the procedure are described here, a developmental test using 14 5x6 nautical mile segments of U.S. Corn Belt data from 1978, and a test using an independent 1980 Iowa data set of 50 segments. The evaluations of the 1980 Iowa test were performed with the 22 of 50 sites for which wall-to-wall ground truth data were available. The most detailed evaluations were done with the developmental test results, which are representative of the results obtained with the independent (1980) data.

At the level of overall proportion estimation accuracy, the results are comparable to those obtained with an analyst-oriented procedure on the same data set[11] (see Fig. 6), both in terms of bias and variance of the estimates. More careful examination of the results indicates that particularly in the case of soybeans, the estimates were quite good, with two segments contributing most of the variance. One of these segments (832) had numerous fields of stressed soybeans, which looked much like corn to the labeler (and to the analysts in earlier tests), while the other (864) has had soybean proportions badly overestimated by other procedures as well for undetermined reasons.[12]

The corn estimates are characterized by higher variance than seen for soybeans, and this coupled with the low variance soybean estimates indicates a problem with confusing corn and non-summer crops. When considering data in the U.S. Corn Belt, one typically finds that the greatest peak Greenness values are reached by soybeans, followed by corn, which is followed by non-summer crops. This central spectral position held by corn makes it much more likely that anomalous non-summer crop signatures will be interpreted as corn than as soybeans. Examination of Figure 4C bears this out. In this figure, one can see that "non-summer" targets more closely fit the reference corn profile than the soybean profile. This potential confusion of corn and non-summer signatures is further indicated by a study of the purity of the labeling targets.[11] This study has shown that targets which are predominantly corn and may correctly be labeled corn (with a discrete label) have a lower purity than targets which are predominantly soybean or non-summer. This is particularly true for boundaries of the targets. This will lead to overestimation of corn proportions due to more "non-corn" being associated with corn targets than corn with "non-corn".

The process of labeling the "classic" profiles proved to be of high accuracy. This was expected, as these targets are by definition relatively easy to label. The growing season length screen for non-summer crops also performed well, which also was not surprising since this was effectively capturing "classic" non-summer targets. Examining the performance of the classifier indicated that it did indeed classify profiles based on their overall shape, much like an analyst would do. However, these profiles were by definition the "hard" targets, not fitting "classic" development profiles. Since the classifier was forced to classify all remaining targets, it had to deal with profiles that filled the entire spectrum from "classic" soybeans to "classic" corn, and therefore was not expected to perform with the accuracy of the first two labeling steps. With this in mind, the classifier also lived up to expectations - it did have a lower level accuracy. The final labeling step, the cluster assignment, is not easily evaluated in terms of labeling accuracy due to the nature of the targets being labeled. Because these "little" blobs are normally little (1-10 pixels), minor ground truth misregistration of these typically mixed targets makes any assignment of "correct" labels questionable, at best. For this reason, accuracy was not determined for the fourth labeling step. Figure 7 details labeling accuracy and also indicates what portion of the scene was covered by each step of the labeling process.

Although component-level evaluations were not performed for the 1980 data due to the desire to maintain the independence of the data set for future tests, overall proportion estimation accuracy was determined (see Fig. 6). The results are very encouraging, with the variance of the estimates being comparable to that seen for analyst-oriented procedures. There is still a problem with the confusion of corn and non-summer crops, and it is conjectured that this is due to the same factors which caused the problem in the developmental test data.

VI. CONCLUSIONS

It is evident that considerable progress has been made toward creating an automatic, self-adapting procedure which has favorable bias and variance characteristics. The procedure is efficient, requiring very little analyst time, and the profile matching classification with the automatically defined training set appears to allow the procedure to adapt itself to segment-specific conditions without the need for direct ground observed measurements. The bias in favor of corn must be addressed, however, with target definition being a primary focus of that investigation.

The procedure was designed for operation under U.S. Corn Belt conditions, and as such succeeds in adapting to variations within that region. For a procedure to succeed in a foreign environment, it must be able to adapt to a much wider range of growing conditions and farm management practices. It is in the definition of a technique which has this regional self-adapting capability that a major challenge lies.

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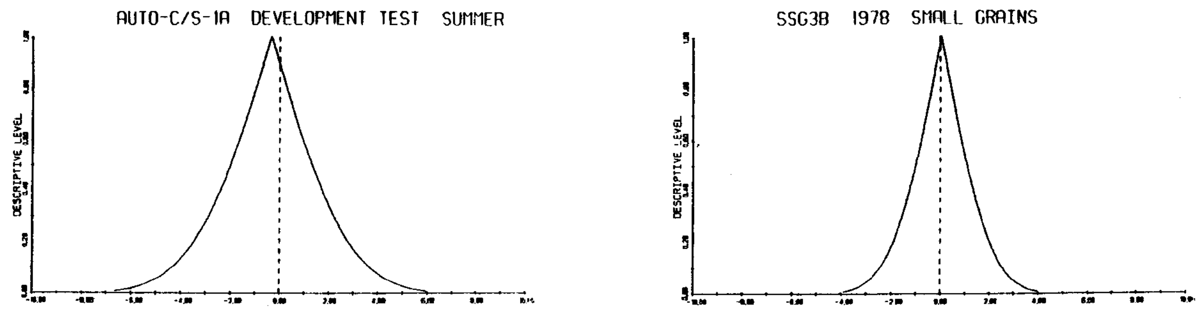

Figure 1. Descriptive Level of the Variance About the Mean Estimate

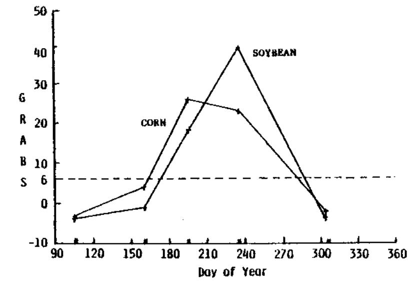

Figure 2. Reference Profiles

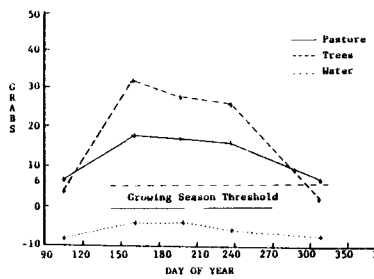

Figure 3. Profiles Labeled "Non-Summer"

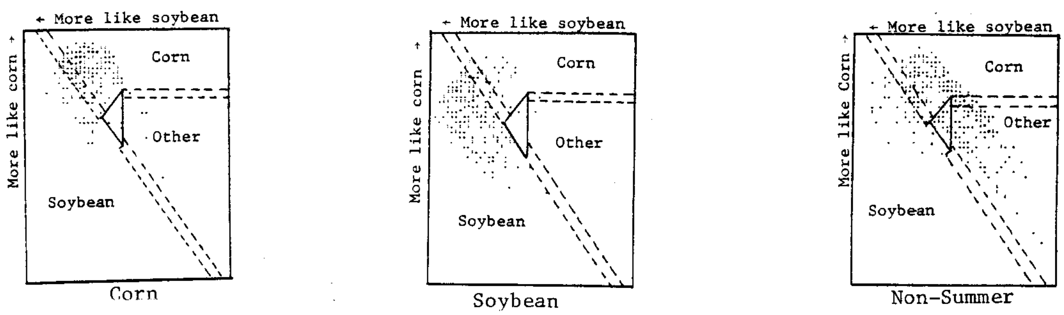

Figure 4. Position of Crops in Feature Space of Classifier, Showing Relationship to Linear Discriminants

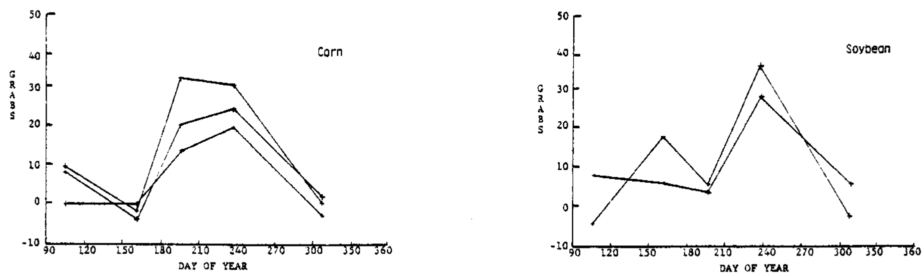

Figure 5. Profiles Labeled by Nearest Neighbor Classifier

Development Test

	CORN	SOYBEAN	SUMMER
$\bar{e}$	1.64	-0.38	1.26
S_e	9.45	7.82	9.78
R.M.E.	4.33	-1.50	0.41
M.A.E.	7.63	5.50	7.34
$\bar{p}$	37.91	-5.35	63.25
n	14	14	14

$\bar{e}$	Mean Estimation Error
S_e	Standard deviation of Error
R.M.E.	Relative Mean Error
M.A.E.	Mean Absolute Error
$\bar{p}$	Mean Ground Truth Proportion
n	Number of Test Sites

1980 Iowa Data

	CORN	SOYBEAN	SUMMER
$\bar{e}$	4.41	1.82	6.32
S_e	5.96	3.32	8.74
R.M.E.	10.98	9.97	10.81
M.A.E.	5.93	2.75	7.68
$\bar{p}$	40.18	18.24	58.42
n	18	18	22

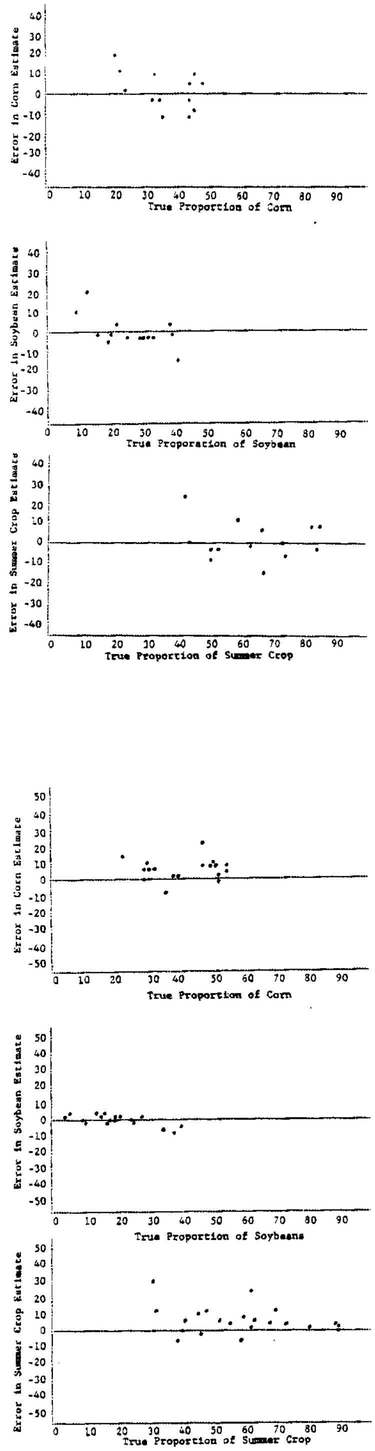

Figure 6. C/S-1B Test Results

Labeling Step	Crops Identified	% Scene Covered (Cumulative)	Accuracy
1	Corn, Soybean, Non-Summer	30-75	93-99
2	Non-Summer	50-90	95-99
3	Corn, Soybean, Non-Summer	90-98	70-85
4	Corn, Soybean, Non-Summer (Mixed Labels)	100	--

Figure 7. C/S-1B Labeling Performance

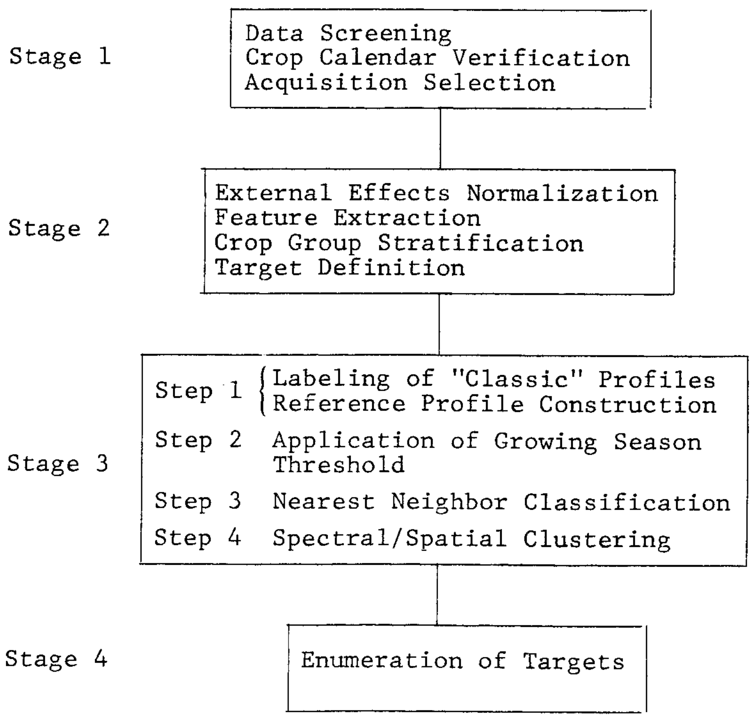

Figure 8. Structure of the Proportion Estimation Procedure

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