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DEVELOPMENT OF PROCEDURE M FOR MULTICROP INVENTORY, WITH TESTS OF A SPRING-WHEAT CONFIGURATION

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16. Abstract

The usefulness of remotely sensed data for agricultural monitoring and inventory is increasing. The Large Area Crop Inventory Experiment (LACIE) pioneered the development of technology and use of Landsat data for global inventory of wheat production. An outgrowth of ERIM's research and development activities in support of LACIE is a multicrop area estimation procedure, Procedure M, which is described in this report.

Procedure M is a flexible, modular system that can operate within the LACIE framework. Its distinctive features are refined preprocessing (including spatially varying correction for atmospheric haze), definition of field-like spatial features for labeling, spectral stratification and unbiased selection of samples to label, and crop area estimation without conventional maximum likelihood classification.

To address a key problem identified in LACIE, namely the separation of spring wheat from other spring small grains, Procedure M was configured initially with a two-step labeler -- first analyst labeling of samples as either 'Spring Small Grain' or 'Other' and then additional machine labeling of the spring small grain samples as 'Spring Wheat' or 'Other Spring Small Grain'. The machine labeler employs the concept of estimating the relative crop calendar of individual samples using multitemporal profiles of the 'Greenness' spectral feature and establishing the decision criterion accordingly.

Testing and evaluation was conducted using data from 26 5x6-mile LACIE segments spanning four states and two crop seasons and for which "wall-to-wall" ground observations of crop type were available.

Results are presented which show that Procedure M produces area estimates that are accurate and have low variance for the two-class (Spring Small Grain vs. Other) case, given ground truth labels. The machine labeler produced encouraging but higher variance spring wheat estimates. Accuracy was good in many segments; however, certain subsets exhibited systematic bias errors. The nature of these errors suggests effects of sustained moisture stress and leads to optimism that an improved labeler can be developed.

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PREFACE

This report describes part of a comprehensive and continuing program of research concerned with advancing the state-of-the-art in remote sensing of the environment from aircraft and satellites. The research is being carried out for NASA's Lyndon B. Johnson Space Center (JSC), Houston, Texas, by the Environmental Research Institute of Michigan (ERIM). The basic objective of this multidisciplinary program is to develop remote sensing as a practical tool to provide the planner and decision-maker with extensive information quickly and economically.

Timely information obtained by remote sensing can be important to such people as the farmer, the city planner, the conservationist, and others concerned with problems such as crop yield and disease, urban land studies and development, water pollution, and forest management. The scope of our program includes:

1. Extending the understanding of basic processes.
2. Discovering new applications, developing advanced remote-sensing systems, and improving automatic data processing to extract information in a useful form.
3. Assisting in data collection, processing, analysis, and ground-truth verification.

The research described herein was performed under NASA Contract NAS9-15476 and covers the period from May 15, 1977 through November 14, 1978. I. Dale Browne/SF3 was the NASA Contract Technical Monitor. The program was directed by Richard R. Legault, Vice-President of ERIM and Head of the Infrared & Optics Division, Quentin A. Holmes, Program Manager, and Robert Horvath, Head of the Analysis Department. During a major portion of the program Richard F. Nalepka was ERIM's Principal Investigator.

The contract work was divided into several tasks. Work on two tasks is reported elsewhere--yield forecasting procedures incorporating Landsat data in Reference 36 and analysis of color image products in Reference 37.

During the final quarter of the contract year, the work carried out on the remainder of the tasks was focused on the development of a multi-crop acreage estimation system, Procedure M. This final contract report describes and evaluates that procedure and the components derived from the preceding work.

The authors of this report (listed alphabetically) are: R. Cicone, E. Crist, R. Kauth, P. Lambeck, W. Malila, and W. Richardson. Significant software support was provided by D. Rice. In addition, the following members of the ERIM staff contributed to the reported work: R. Balon, J. Gleason, S. Lindner, B. McCann, J. More, O. Mykolenko, J. Ott, and T. Wessling. Consultation provided by E. Jebe, R. Hieber, W. Holsztynski, H. Horwitz, F. Pont, and G. Suits is gratefully acknowledged, and appreciation is expressed to D. Dickerson for her secretarial support.

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1
INTRODUCTION

Procedure M is a technique for estimating acreages of multiple crops based upon remotely sensed data. Procedure M is an embodiment of techniques and viewpoints developed at ERIM and throughout the research community during the last several years under the stimulus of the Large Area Crop Inventory Experiment (LACIE). This report describes the development and testing of Procedure M as configured for spring wheat and other spring small grains. LACIE was designed to estimate the production of wheat. The techniques employed by LACIE were found to reliably estimate winter wheat and spring small grains. The further estimation of spring wheat production using Landsat multispectral scanner data, in the face of the spectral similarity of the other spring grains, has been recognized as one of the most difficult problems brought to the fore by the LACIE program.

Before proceeding to the details of Procedure M and its testing, a broad context for the development of large-scale remote sensing techniques is discussed and a perspective of Procedure M is given in terms of that context and the background of research in agricultural remote sensing.

1.1 GENERAL CONTEXT

The broad class of systems which may be used to affect, control, or monitor environment can be called environmental management systems. In the most general terms, an environmental management system consists of an information gathering system, a forecasting system, a decision making system, and an action taking system, as shown in Figure 1.1

Briefly, an information gathering system obtains data regarding both the current state of the environment and actions that affect the environment. A forecasting system requests and obtains information from the information system and, in view of a specific set of planned actions and a likely set of unplanned actions, produces an objective prediction

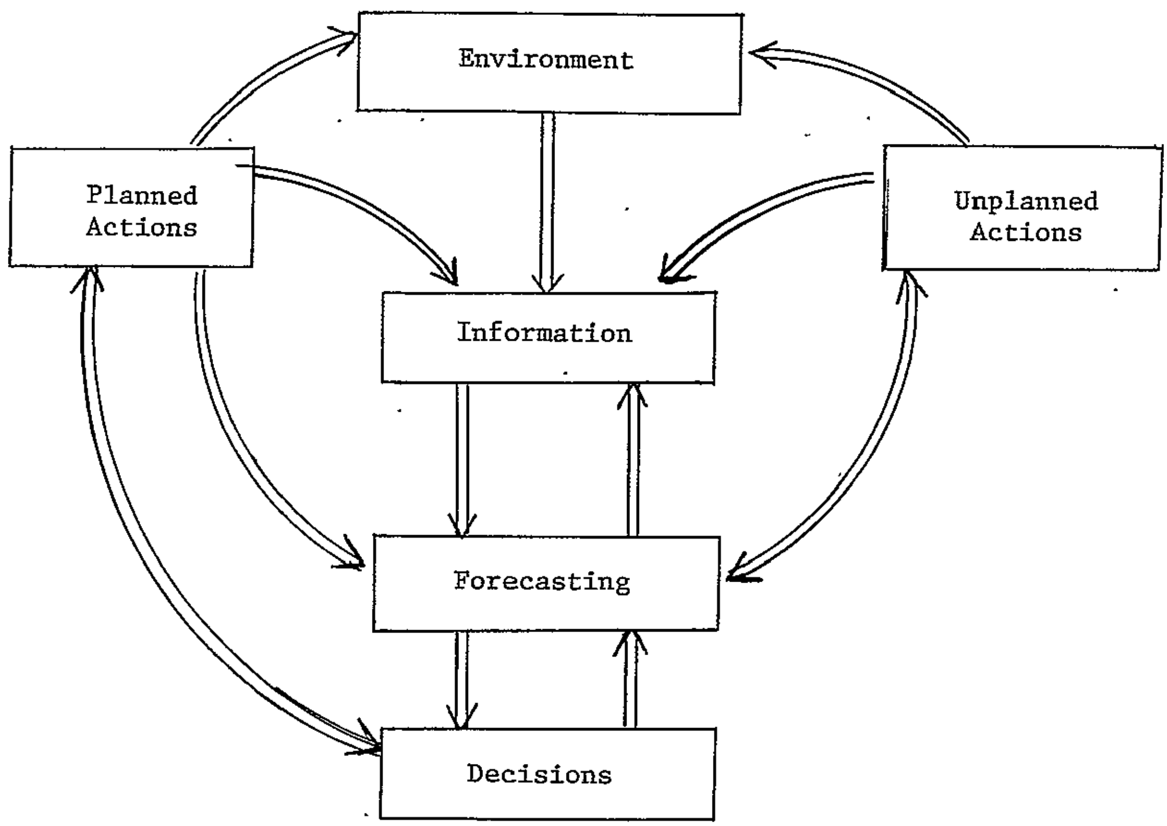

FIGURE 1.1 AN ENVIRONMENTAL MANAGEMENT SYSTEM

of the future environmental state. The decision making system hypothesizes a set of planned actions and obtains predictions of the environmental state from the forecasting system. It decides among alternative sets of actions. The action taking system carries out the planned actions and reports actions as they occur.

Because of long lead times for technology development, it is natural to first develop the information gathering component of an environmental management system, then the forecasting component, and last of all to create the possibility for coherent planned action by introducing a decision making system. In developing the information and forecasting systems it is wise to consider the characteristics needed when operating in conjunction with a decision making system. Notably these are accuracy, objectivity, and timeliness.

By accuracy we mean that the system error distribution must be small enough that the outputs are useful for decision makers. Practically speaking this means that any particular system forecasting capability will be validated by independent test before being accepted as part of the system, and that the acceptance criteria will be set so that the system has a high likelihood of performing with useful accuracy.

By objectivity we mean, basically, believability. Some of the procedures which insure objectivity are that the forecasting process is visible to the decision makers in all essential elements, that the forecasts arise from fixed procedures applied to a data base, that the data base be subject to a rigorous quality assurance procedure, that the actual quantities forecasted are quantities that will subsequently be known with accuracy significantly better than the forecast accuracy, that the system publishes its estimated error distribution along with its forecasts, and that the system publishes posterior comparisons of its forecasts with the subsequently known forecasted quantities.

By timeliness we mean that a forecasting system produces regular predictions of a set of forecasted quantities. In addition, considering the way decision making processes usually proceed, the forecasting system is likely to be called upon to produce special reports in a near-real-time mode. This emphasizes a special need for a large, quality assured, data base, only a sample of which is routinely accessed for regular scheduled forecasts.

1.2 BACKGROUND IN AGRICULTURAL REMOTE SENSING

An important aspect of the world environment is the state of agriculture -- the amount and kind of food products available region by region throughout the world. For many years there has been a gradual development by the U.S. Department of Agriculture (USDA) of all aspects of an environmental management system in the United States regarding domestic agriculture. Regarding foreign agriculture, only the information gathering and forecasting functions have been attempted by the USDA.

In the last several years, remote sensing techniques have been in the process of being developed to assist significantly in the process of information gathering, for numerous types of environmental management problems. The National Aeronautics and Space Administration (NASA) in particular has supported the development of aircraft and spacecraft remote sensing instruments and information extraction techniques. ERIM has been deeply involved in this effort, developing the first airborne multispectral scanners [1,2] and having a continuous 15-year history of improving instruments and increasing understandings of the underlying physical processes and the techniques of processing the data to obtain the desirable information from it [3-11].

Specific applications to agricultural problems have been initiated and led by NASA's Johnson Space Center (JSC) over the past decade. One of these was the Corn Blight Watch Experiment (CBWE) (1970), with airborne scanner data and photography [12]. The purpose of the CBWE was to track the spread of the Southern Corn Leaf Blight northward across the nation.

With the launch of the Earth Resources Technology Satellite (now Landsat) in July of 1972, it became possible to consider the application of the spaceborne Multispectral Scanner (MSS) data to the task of Crop Production Forecasting over world or national regions. An early attempt was the Crop Identification Technology Assessment for Remote Sensing project (CITARS) [13]. This project involved efforts by the Earth Observations Division of the Johnson Space Center (JSC), Purdue University's Laboratory for Applications of Remote Sensing (LARS), and ERIM in an intensive effort to apply then current state-of-the-art information extraction techniques in an evaluation of the feasibility of inventorying corn and soybeans in Indiana and Illinois.

The possibility of using the Landsat plus collateral data to monitor the wheat production in the world's major wheat producing regions arose out of the experience gathered in CITARS and elsewhere, plus the occurrence and impact of major wheat crop failures around the world. The Large Area Crop Inventory Experiment (LACIE) was initiated by NASA and carried out jointly with the USDA and the National Oceanic and Atmospheric Administration (NOAA), to test the feasibility of using Landsat MSS data, weather data, and historical data to estimate the production of wheat at harvest in seven major wheat producing countries [14]. LACIE ran through three phases -- crop harvest years 1975 through 1977. Currently in transition year, the feasibility of extending LACIE technology to the discrimination among spring small grains and to the problem of production inventory of corn, soybeans, and soft red wheat is being explored.

In each of these exercises, the attempt was to use and evaluate existing techniques and, in each case, the existing techniques were found wanting in some respects. That this would be true was recognized in advance. One of the stated purposes of the LACIE was to "research and develop alternate approaches and techniques...where required to meet performance goals..." [15]. And indeed there has been substantial growth in the technology of information extraction during the LACIE program.

At JSC, Procedure 1, which embodies a fundamental re-thinking of the methods of using remotely sensed data in estimation procedures, was developed and implemented in LACIE by NASA/EOD and Lockheed Electronics Company (LEC) personnel [16,17]. Among other contributors supported by LACIE are LARS, UCB, and ERIM. LARS provided field measurements data for the development of detailed insights into the multitemporal-spectral description of crop canopies, and has advanced the art of sampling design for remote sensing surveys. The Remote Sensing Program at the University of California at Berkeley (UCB) has developed advanced techniques of photointerpretation, sampling designs, and partitioning.

Several of ERIM's tasks have been in developing advanced techniques for acreage estimation, including preprocessing techniques, training techniques, and unbiased sampling and estimation techniques. These have been incorporated into Procedure M, a procedure for acreage estimation of multiple crops which further develops the basic approach of Procedure 1.

A viewpoint that has been reinforced by the LACIE experience is the essential need for validation of the estimation procedures. In addition to its estimated quantities, as stated above, we believe that every forecasting or estimation system ought to produce estimates of the error distribution of its forecasts. We have attempted to follow this philosophy in the development of Procedure M. One of the most valuable legacies of LACIE is a large supply of accurate ground truth information and associated Landsat data and in-place procedures for continuing to acquire more of it. Without such data, tests of the types described in this report are impossible. In our view, real progress in the development of remote sensing is now fully dependent on such tests.

Section 2 describes Procedure M and its components. Then Section 3 describes both overall performance evaluations and component evaluations, while a summary and conclusions are presented in Section 4.

2
DESCRIPTION OF PROCEDURE M

Procedure M is a research system for performing crop area (proportion) estimation based on labels assigned to samples of multispectral scanner data by ground truth, by analysts, by machine/analyst combination, or by machine. It can operate in the LACIE Framework and is a multicrop generalization of the previously developed Procedure B [18,19]. Between segment selection and final aggregation, the six major steps of the procedure are data preprocessing and selection, spatial feature definition, data stratification, sampling of entities for labeling, labeling, and proportion estimation, as shown in Figure 2.1. Each of these steps uses state-of-the-art techniques. However, the system is modular so that it can easily be modified, configured for different purposes, or used as a test bed to evaluate alternative components or groups of components.

The key elements of the two-class Procedure B were used as the basis for Procedure M, because their functioning is understood and test results have been good, showing nearly unbiased proportion estimates using ground truth labels [20]. In generalizing the elements to multiple crops, a number of improvements were made in the overall design and in various components and their implementation.

2.1 OVERALL DESCRIPTION OF PROCEDURE M CONFIGURED FOR SPRING WHEAT

Procedure M was configured initially for the problem of inventorying spring wheat and other small grains, through incorporation of a two-step procedure for discriminating between (i.e., labeling) spring wheat and other spring small grains data.* This two-step procedure utilizes analyst interpretation to distinguish between the 'Spring Small Grain' and 'Other' classes and a machine algorithm to further distinguish between 'Spring Wheat' and 'Other Spring Small Grain'.

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*Spring wheat, spring barley, oats, rye, and triticale were considered to form the 'Spring Small Grain' class.

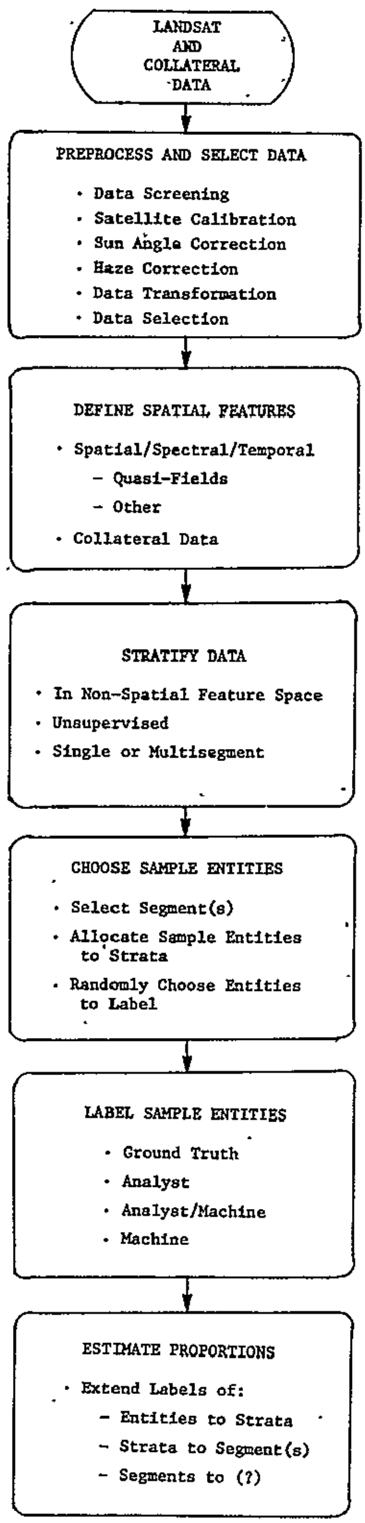

FIGURE 2.1 BLOCK DIAGRAM FOR PROCEDURE M IN LACIE CONTEXT

2.1.1 COMPARISON OF LACIE PROCEDURE 1 AND PROCEDURE M FOR SPRING WHEAT

At this point in the discussion, it is appropriate to identify the major similarities and differences between LACIE's Procedure 1 and Procedure M for spring wheat inventory. Points of comparison are presented in Table 2.1, both operating in the LACIE framework. The major differences are that the Procedure M configuration includes more preprocessing, defines and labels quasi-fields rather than individual pixels, uses a different sampling strategy, incorporates a machine labeler for distinguishing between spring wheat and other spring small grains, and does not use maximum likelihood classification to produce the crop proportion estimates.

2.1.2 GENERAL DESCRIPTION OF COMPONENTS OF PROCEDURE M FOR SPRING WHEAT

An overview and general description is given below for each of the components (modules) of Procedure M as configured and tested for spring wheat inventory. Details of five of the key components on which substantial development work was performed during the contract year are presented later in Section 2.2, while specifics of the configuration tested are presented in Section 3.1.1 and appendices. The discussion below follows the sequence of data processing operations in Procedure M and starts at the point, in LACIE, where sample segments have been allocated and selected.

The first data operations involve preprocessing to screen, normalize, and transform the Landsat data for subsequent selection and processing, as indicated in Table 2.2. The screening operation flags garbled data and data from clouds, cloud shadow, and water, and computes a haze diagnostic parameter. This diagnostic parameter is then used with the spatially varying XSTAR algorithm (discussed more fully in Sections 2.2.5 and 3.2.4) to adjust for variations in atmospheric haze across the scene and normalize the data to a reference atmospheric condition and reference sun angle. Correction for the response of different Landsat MSS sensors also is incorporated. These normalizations increase the stability and interpretability of the data and reduce scene-to-scene variability. The

TABLE 2.1 COMPARISON OF LACIE PROCEDURE 1 AND PROCEDURE M FOR SPRING WHEAT

SIMILARITIES

- Use of 5x6-mile LACIE Segments of Landsat Data
- Use of Analyst for Labeling 'Spring Small Grain' vs. 'Other'
- Labeling of a Sample of Data from Each Segment

MAJOR DIFFERENCES

Function	LACIE Procedure 1	Spring Wheat Procedure M
• Preprocessing	Sun Angle Correction Analyst Screening	Sun Angle Correction Machine Screening Satellite Calibration Haze Correction Tasseled-Cap Data Transformation
• Entities to be Labeled	Pixels	Interiors of Quasi-Fields
• Sample Selection for Labeling	Fixed Selection from 209-Dot Grid	Random Selection from 40 Spectral Strata
• Labeling of 'Spring Wheat' vs. 'Other Spring Small Grain'	Analyst	Machine Algorithm
• Proportion Estimation	Maximum Likelihood Ratio Classification for Two-Class Stratification, followed by Bias Correction	Aggregation of Stratified Sample Estimate

TABLE 2.2 LANDSAT DATA PREPROCESSING AND SELECTION

- Screen to
  - Exclude or Flag: Bad Data, Clouds, Cloud Shadows, Water
  - Compute Haze Diagnostic

- Correct for Landsat MSS Sensor Calibration

- Correct for Sun Angle
- Correct for Atmospheric Haze

  (Spatially Varying XSTAR Algorithm)

- Transform Data: Tasseled-Cap Linear Combinations

- Select Segments (Analyst) -- Criteria are:
  - Acquisitions Exist for Adequate Separability of Spring Small Grains from Other Crops
  - Acquisitions That Will Provide a Good Definition of the Field Pattern Present

- Select Acquisitions (Analyst) -- Criteria Include:
  - Acquisition(s) at the Dough or Ripening Stage of Wheat Development
  - Acquisition(s) Near and After Peak Green Development Stage
  - Other Acquisitions that Provide Good Definition of Field Pattern and Spectral Separability of Spring Small Grains from Other Crops

- Select Spectral Features:
  - Brightness and Greenness, for Each Selected Acquisition Date

final preprocessing step is a transformation of the corrected Landsat channel values to Tasseled-Cap space, using linear combinations [21,22]. The first two combinations or principal directions, Brightness and Greenness, contain a majority of the variability and information in the Landsat data and have physical meaning.

The other aspect of preprocessing is the selection of data for processing. As indicated in Table 2.2, this includes selection by the analyst of segments and acquisitions according to the stated criteria. Only the Brightness and Greenness spectral features for selected acquisitions are subsequently used in the procedure.

The second component detects spatial features in each scene (Table 2.3). An approximation of the field pattern is defined or extracted from multitemporal data by using a clustering algorithm (BLOB) that employs both spectral and spatial variables [23]. A set of BLOB parameters which is optimized for various times of the growing season has been established and produces good results, as discussed further in Sections 2.2.4 and 3.2.3. The algorithm actually defines quasi-fields which frequently, but not necessarily, follow farm field boundaries. For instance, if two adjacent farm fields have the same or similar crops they may be assigned to the same quasi-field. Conversely, if some spectral anomaly, such as a bare area, is present within a farm field, two different quasi-fields, one for the bare area and one for the remainder, may be assigned to it.

A key next step in field definition is that of stripping away the edge pixels from each defined quasi-field. These pixels are the ones most likely to contain mixtures of two or more different crop types and are most susceptible to errors induced by spatial misregistration of data channels acquired on different dates. By eliminating these edge pixels from calculations of spectral data means and requiring the analyst to label only quasi-field interiors, we believe that major sources of analyst labeling errors are likewise removed. It remains only to demarcate for the analyst those quasi-field interiors that are to be labeled (See the example in Figure 2.2) and to count the number of pixels in each quasi-field.

TABLE 2.3 SPATIAL FEATURE DEFINITION

- Apply Spectral/Spatial Clustering
  - BLOB Algorithm
  - Up to Four Dates: Biostages 1-4
  - Brightness and Greenness Each Date

- Operate on Each Defined Quasi-Field (Blob)
  - Count Number of Pixels
  - Strip Away Edge Pixels
  - Compute Spectral Means
  - Display Boundary to Analyst (if selected)

- Results:
  - Quasi-Field Interiors Defined for Selection and Labeling
  - Effects of Mixture Pixels and Spatial Misregistration Minimized for Labeling

FIGURE 2.2 EXAMPLE MAP OF QUASI-FIELD (BLOB) INTERIORS

Because there may typically be 300 to 500 interiors defined by BLOB for a LACIE segment and because it is not practical to require the analyst to label them all, some sampling is required. In Procedure M for spring wheat, the sample selection process has two stages -- a spectral stratification followed by sample allocation and selection.

The spectral stratification process as employed for spring wheat is summarized in Table 2.4 and discussed more fully in Sections 2.2.3 and 3.2.2. In essence, it is a second clustering operation, this time using only the spectral means of field interiors as the items to be clustered. As noted in Table 2.4, two passes of the ERIM clustering algorithm are utilized, which is a refinement of the stratification process used previously in Procedure B. For the spring wheat inventory problem, it was decided to define 40 spectral strata for each segment, a number based on prior experience and results with Procedure 1 and Procedure B. In a multisegment configuration, Procedure M stratification could use collateral features as well as spectral features for stratification.

We also decided to allocate and sample 100 quasi-fields for labeling, among the 40 spectral strata (Table 2.5). The number of samples assigned to each stratum is made proportional to the size (total number of pixels) of the stratum. An unbiased method for choosing the samples allocated to each stratum was developed and is described in Section 2.2.2.

The most critical stage in crop inventory procedures is labeling the crop type of the designated samples (fields or pixels). In the configuration of Procedure M tested and described in this report, a two-step labeling procedure is followed, as summarized in Table 2.6. In the first step, the analyst labels each designated quasi-field as either 'Spring Small Grain' or 'Other'. In the second, a machine algorithm operates on those quasi-fields designated 'Spring Small Grain' by the analyst and assigns a proportional label among two classes: 'Spring Wheat' or 'Other Spring Small Grain'. If the acquisition needed to make this determination is not available, the label 'Unidentifiable Spring Small Grain' is assigned.

TABLE 2.4 SPECTRAL STRATIFICATION OF SEGMENT

- Cluster Quasi-Field Spectral Means to Produce a Specified Number of Strata (B Clusters)
  - Employ ERIM Clustering Algorithm as Follows:
    - On a First Pass, Adapt Cluster Means as Clusters Grow
    - On a Second Pass, Assign Cluster Membership on Basis of Final Means from First Pass
  - Produce 40 Strata -- Number Chosen Based on:
    - The Design and Experience of Procedure 1
    - Prior Procedure B Test Results

TABLE 2.5 ALLOCATION AND SAMPLING OF QUASI-FIELDS FOR LABELING

- Allocate 100 Quasi-Fields (Blobs) for Labeling Among the Strata with Number Proportional to Stratum Size (Total Number of Pixels)
- Choose the Quasi-Fields Allocated to Each Stratum in an Unbiased Manner

TABLE 2.6 LABELING PROCEDURE

Step 1: 'Spring Small Grain' vs. 'Other'

- This Function Operationally is Performed by an Analyst
- Ground Truth Was Used in Designating a Quasi-Field Label for T & E Purposes (A Quasi-Field was Labeled Grain if It was More Than 50% Grain)

Step 2: 'Spring Wheat' vs. 'Other Spring Small Grain'

- Machine Algorithm is Automatically Applied to Each Quasi-Field Called 'Spring Small Grain' by Analyst
- If the Proper Acquisition is Not Available, the Quasi-Field is Labeled 'Unidentifiable Spring Small Grain'
- Otherwise, Two Classes are Designated Proportionally:
  - Spring Wheat
  - Other Spring Small Grain

Result: Each selected quasi-field is either labeled proportionally among the spring small grain classes or else is labeled 100% unidentifiable spring small grain or 100% non spring small grain.

For the initial testing and evaluation reported herein, ground observations were used as a substitute for analyst labels in Step 1. The machine algorithm of Step 2 has the key elements identified in Table 2.7. It is designed to capitalize on the fact that barley ripens more rapidly and/or somewhat differently than spring wheat and to detect the spectral manifestations of this process. Details of this algorithm are presented in Sections 2.2.1 and 3.2.1.

The final step of Procedure M is to take the crop labels assigned to the selected quasi-fields and use them to compute crop proportion estimates for the segment. As indicated in Table 2.8, a proportional label is computed for each spectral stratum, using the labeled quasi-fields within it. The stratum proportions are then aggregated to produce various segment proportion estimates. One is the two-class estimate represented by the proportion of spring small grains. Another is the three-class estimate which divides the spring small grains class into 'Spring Wheat' and 'Other Spring Small Grain'. The two-class estimate will reflect the accuracy of analyst labeling. The three-class estimate may be unreliable or have high variance if too few of the analyst-labeled spring small grain fields have suitable acquisitions for the machine labeler to further discriminate among them. A reliability flag will accompany the estimates.

This concludes the general description of Procedure M for spring wheat. Details of five key components are presented in Section 2.2.

2.2 DESCRIPTION OF SELECTED COMPONENTS OF PROCEDURE M

Development aspects and characteristics of several key components of Procedure M, as configured for spring wheat, are described below. The order of discussion is the reverse of that in the preceding section -- we begin with the machine labeler and work backwards through the data flow to the preprocessing phase that performs atmospheric haze correction. In between, are discussions of the unbiased sampling strategy, spectral stratification, and spatial feature definition.

TABLE 2.7 ELEMENTS OF MACHINE ALGORITHM FOR DISCRIMINATING AMONG SPRING SMALL GRAINS

- A Reference Profile of Green Development vs. Day of Year (Day of Peak Greenness is a convenient reference point)
- A Calculation of Crop Calendar Shift for Each Field or Pixel, Relative to the Reference Profile
- A Characteristic Distance, in the Brightness-Greenness Plane, for Each Date (Values Increase as the Grain Ripens)
- A Decision Threshold on the Computed Characteristic Distance, as a Function of Days Since Peak Greenness

TABLE 2.8 PROPORTION ESTIMATION

- Utilize Quasi-Field (Blob) Labels to Compute a Proportional Label for Each Spectral Stratum (B Cluster) (Based on Total Pixels)

- Generate Intermediate Segment-Level Proportion Estimates, Based on the Proportional Label and Total Number of Pixels in Each Stratum

  - Spring Wheat
  - Other Spring Small Grain
  - Unidentifiable Spring Small Grain
  - Other

- Adjust Intermediate Proportion Estimates by Partitioning Unidentifiable Spring Grains into 'Spring Wheat' and 'Other Spring Small Grains' in Accordance with Their Raw Proportions to Produce Final Proportion Estimates for the Segment:

  - Total Spring Small Grain Proportion
  - Spring Wheat Proportion; Other Spring Small Grain Proportion

- Flag Potentially High-Variance Spring Wheat Estimates (Based on Number of Quasi-Fields in Unidentifiable Spring Small Grain Class)

  - For Our Tests, Only a Total Spring Small Grains Estimate was Produced if More Than 50% of the Selected 'Spring Small Grain' Quasi-Fields Were Labeled 'Unidentifiable'

2.2.1 DESCRIPTION OF MACHINE LABELER

While the discrimination of spring small grains from other cover types in the spring wheat configuration of Procedure M is carried out by analyst interpreters, the finer discrimination of spring wheat from other spring small grains is entirely a machine function. This second phase, which begins when the analyst has identified those fields in the training sample that are spring small grains, is itself a two-step process: estimation of crop calendar shift, followed by label assignment.

2.2.1.1 Estimation of Crop Calendar Shift

Basic Concept. Observed through time, a spring small grains pixel or field should exhibit a pattern, in Tasseled-Cap Greenness, such as that represented in Figure 2.3(a). In the absence of system noise or other outside influences, one could reasonably expect that other spring small grains pixels, observed at identical points in time, would have a similar appearance if their growth stages were the same. However, a more common occurrence is illustrated in Figure 2.3(b), where observations at the same point in time show a high degree of signal variation.

The underlying assumption of crop calendar shift estimation is that a large part of this variation is the result of differences in stage of development at the time of observation.* By fitting a model form to data like those in Figure 2.3(a) (See Figure 2.3(c)), and then shifting the model form along the day-of-year axis, we find that the sets of observations, while showing much variability on the day of acquisition, are in fact different points along a common curve form (Figure 2.3(d)), differing only in their stage of development at the time of observation. Conversely, by shifting each set of observations to a common reference time, within-day signal variablility can be substantially reduced (Figures 2.3(e) and (f)). In addition, since previous studies at ERIM [24,25]

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*We gratefully acknowledge the work of Dr. Gautam Bahdwar of NASA/JSC in first using spectral profiles to more closely estimate the stage of plant development. The shift procedure presented here is an extension of his work.

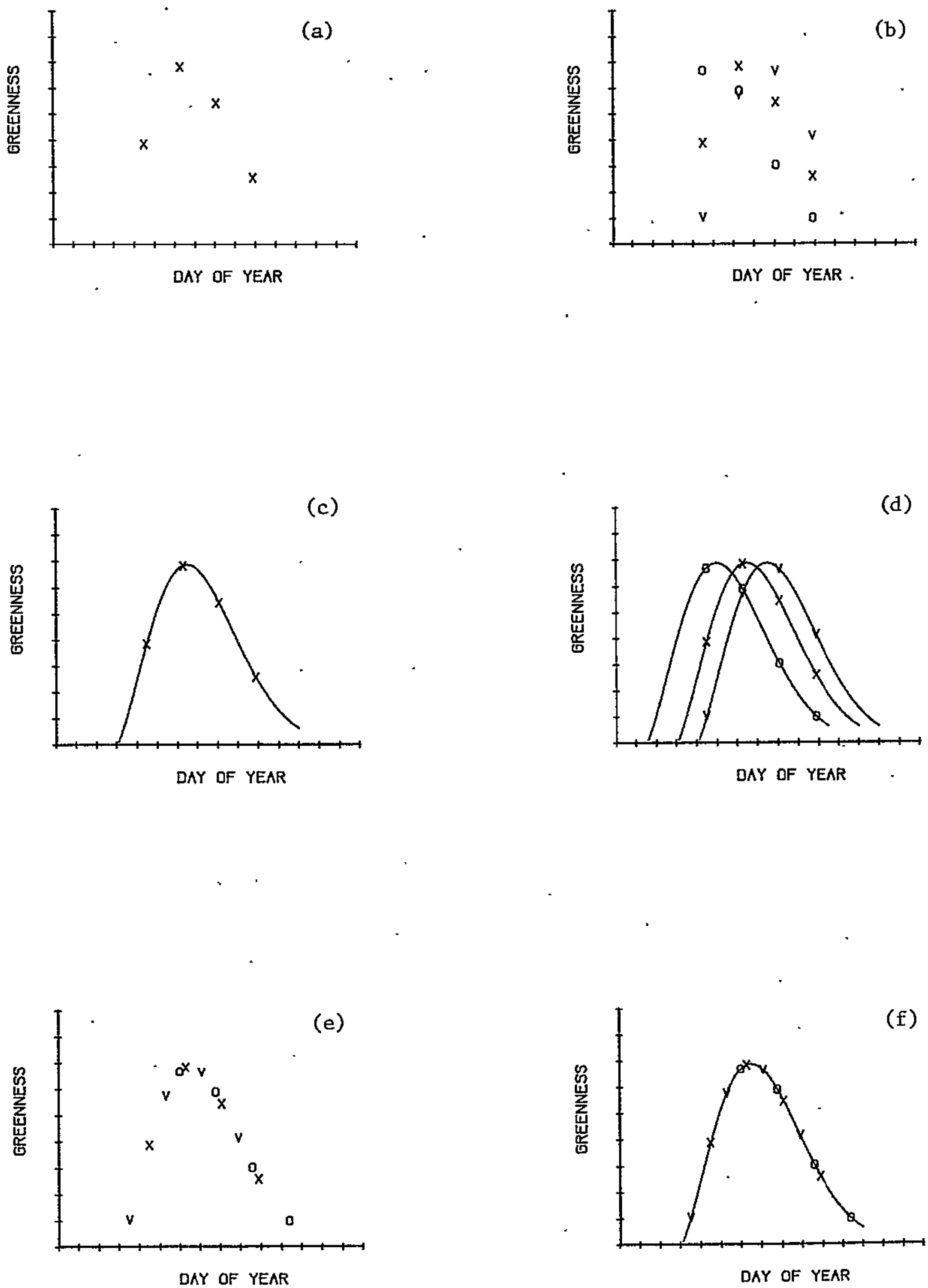


FIGURE 2.3 BASIC CONCEPT OF CROP CALENDAR SHIFT BASED ON GREEN DEVELOPMENT PROFILE

have suggested that effective spring wheat and barley separation can only be accomplished in a relatively narrow day span around the dough stage of development, application of the crop calendar shift allows for proper selection of the acquisition to use in the label assignment step. Figure 2.4 is an example of real data with and without the crop calendar shift applied.

General Approach. The model form used in Procedure M for spring wheat is illustrated in Figure 2.5. A cross-correlation calculation, which is independent of differences in overall signal magnitude, is used as the goodness-of-fit criterion. In order to obtain a stable estimate of the shift to be applied, at least three acquisitions must fall in the time interval between plant emergence and harvesting, while additional acquisitions in this range result in a more accurate shift estimation.

It should be noted that a single profile is used for all spring small grains and all sample segments. A study of differences in shift between more specific (segment or crop) profiles and more general (multi-segment or all small grains) profiles indicated that, for 85-95% of the pixels tested, shift differences were within a range attributable to noise (± 2 days or less). In light of the added complexity introduced by either trying to adjust the reference profile for each new sample segment or testing with a different profile for each small grains crop, it is a significant advantage to be able to use one common profile.

Implementation. The actual crop calendar shift estimation in Procedure M for spring wheat is carried out on two levels: field-by-field and then pixel-by-pixel. The field-level shift provides an approximation of the final shift for each pixel and also serves to identify those spring small grain quasi-fields lacking the required number of acquisitions within the reference time interval. Such fields are labeled 'unidentifiable spring small grains' and are removed from further consideration by the labeler.

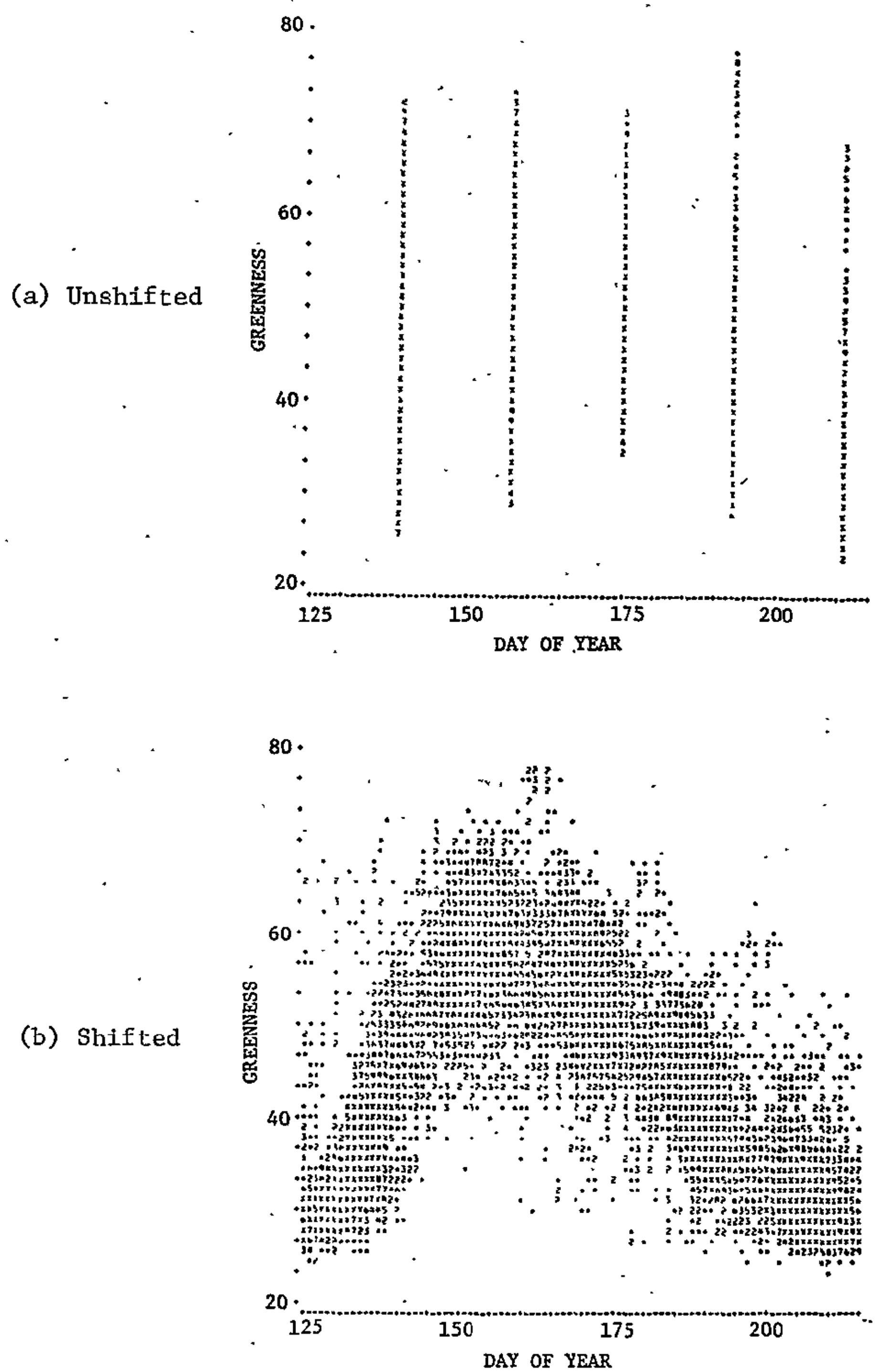
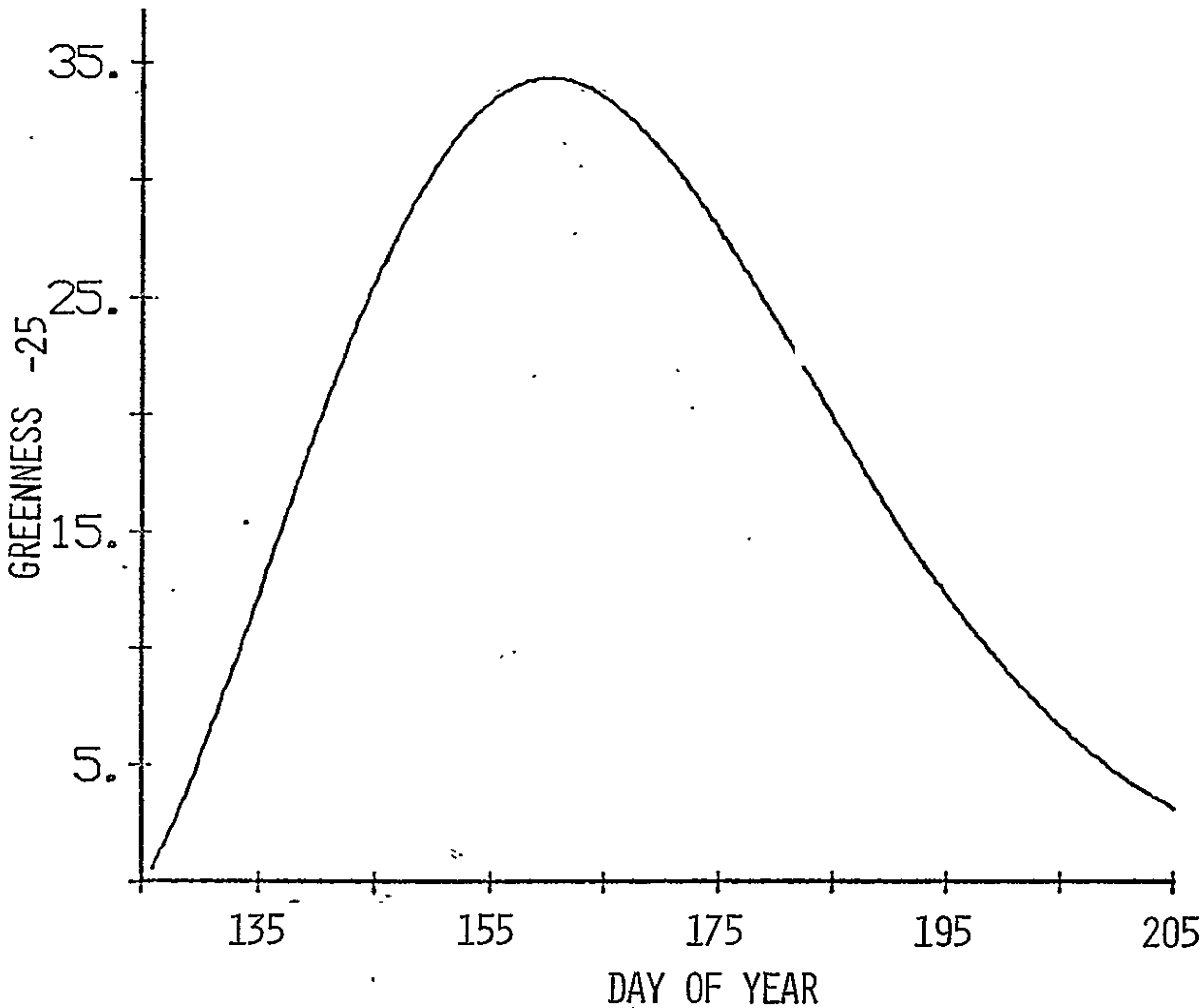


FIGURE 2.4 DATA FOR SPRING WHEAT PIXELS - SEGMENT 1663



Model Form: $F(T) = AT^B e^{CT^2}$

$F(T) = [(\text{Greenness}) - 25]$

$T = [(\text{Day of Year}) - 125]$

$A = 0.65163$

$B = 1.2957$

$C = -0.52415 \times 10^{-3}$

FIGURE 2.5 GREEN DEVELOPMENT PROFILE MODEL

At the pixel level, each interior pixel of the given quasi-field is examined individually, and a fine tuning of the field shift is made. This second level of shift estimation provides for more accurate estimation of crop development for each pixel and also accommodates differences in stage of development within a field shape (as when several small fields are grouped together into one quasi-field by the spectral/spatial clustering algorithm).

2.2.1.2 Label Assignment

Background. Studies at ERIM over the past two years clearly demonstrated the marked spectral similarity of the various spring small grains, even when view multitemporally. However, our tests on both Phase 2 and Phase 3 LACIE data have also indicated that, in the acquisition most likely to correspond to the dough stage of plant development, barley tends to be somewhat more advanced, and spectrally brighter, than spring wheat [24,25]. After heading, barley fields seem to ripen at a faster rate and/or follow a short-cut in the trajectory illustrated in Figure 2.6 in Brightness-Greenness space, such that by the dough stage they are farther from the green arm (a line approximately parallel to the spectral path followed by developing green vegetation) than are spring wheat fields at the same point in time. This separability is lost as the fields complete the ripening process and begin to be harvested, primarily because the signatures at these times are considerably more variable.

By providing an estimate of the actual stage of development of each pixel at each acquisition date, the crop calendar shift makes possible a clearer understanding of the spectral relationship between spring wheat and barley, and thus a more precise definition of the labeling criterion.

It should be noted that the labeling criterion we have devised is based on spring wheat and barley separation. Too few rye or triticale fields were present in the training data to allow any decision logic to be established for these crops. Oats, too, occurred with significantly

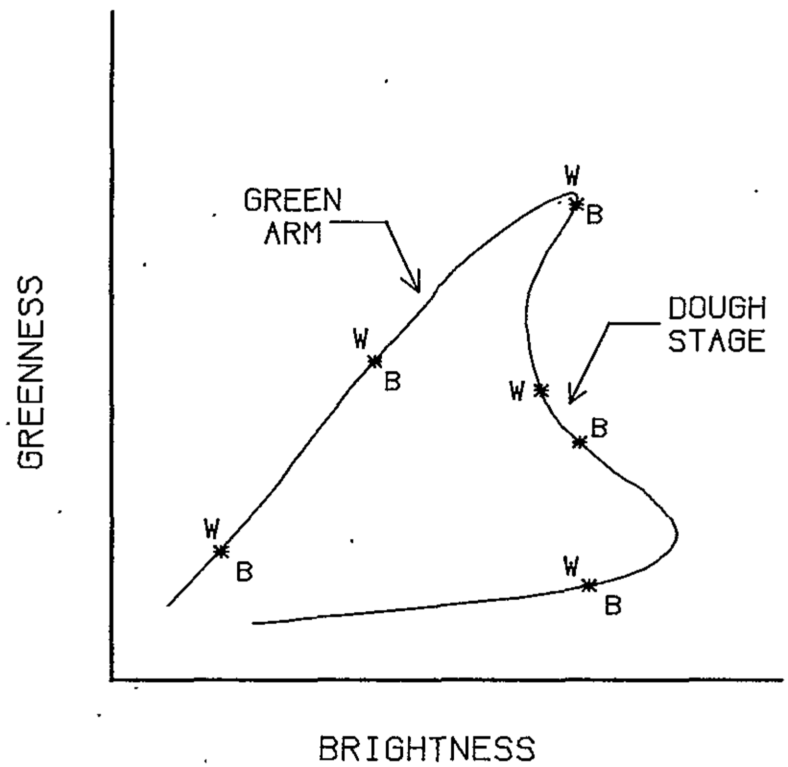


FIGURE 2.6 TEMPORAL PATTERN OF SPRING SMALL GRAINS

lower frequency than spring wheat and barley. In addition, limited past work had shown few spectral differences between spring wheat and oats [26].

Development. Four Phase 3 LACIE blind sites (1498,1515,1640,1663) were used to develop the labeling criterion. These sites were chosen based on the availability of acquisitions in the reference time interval and around the dough stage of development, as well as the presence of sufficient numbers of spring wheat and barley pixels to adequately characterize the behavior of the two crops. Atmospheric corrections were applied using the spatially varying XSTAR algorithm and a crop calendar shift was estimated for each interior pixel.

Examination of Brightness-Greenness scatter plots for each shifted day of the year after peak Greenness (Day 160 on the reference scale) suggested that adequate separability could be obtained on Reference Days 186 through 203. In this day range, optimum linear discriminant analysis was carried out, using greenness and brightness as the discriminant variables. The decision lines selected by this process showed a marked similarity in slope from day to day, differing only in the value of their y-intercept, and had similar slopes and intercepts from segment to segment for each day. Accordingly, a reference line was defined having the same slope as the set of decision lines, and the distance from that line was used as the discriminant (see Figure 2.7). Optimum discriminant values were again calculated, using the newly defined distance, and again the chosen values were very similar from segment to segment for each day in the chosen range. Further, the mean decision values for the four segments, when plotted against a time axis, defined a straight line. Thus the final decision measure, common to all four segments, was a simple linear function of day of year (after shifting) and distance from the reference line (see Figure 2.8).

Using this measure on the four segments from which it was developed, we achieved an average labeling accuracy for spring wheat and barley of 75% to 85%. Table 2.9 gives a segment-by-segment breakdown of the results.

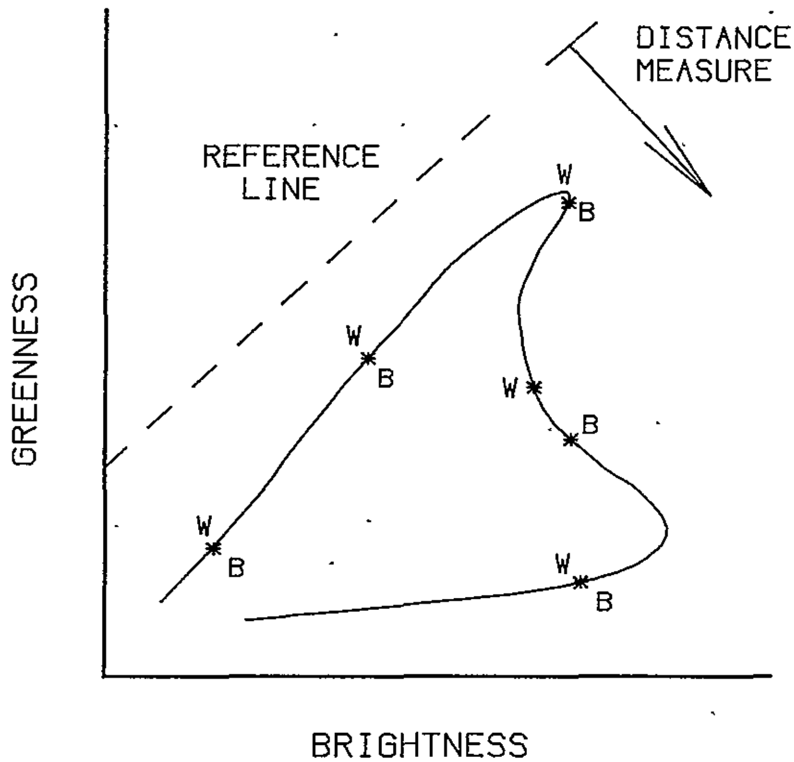
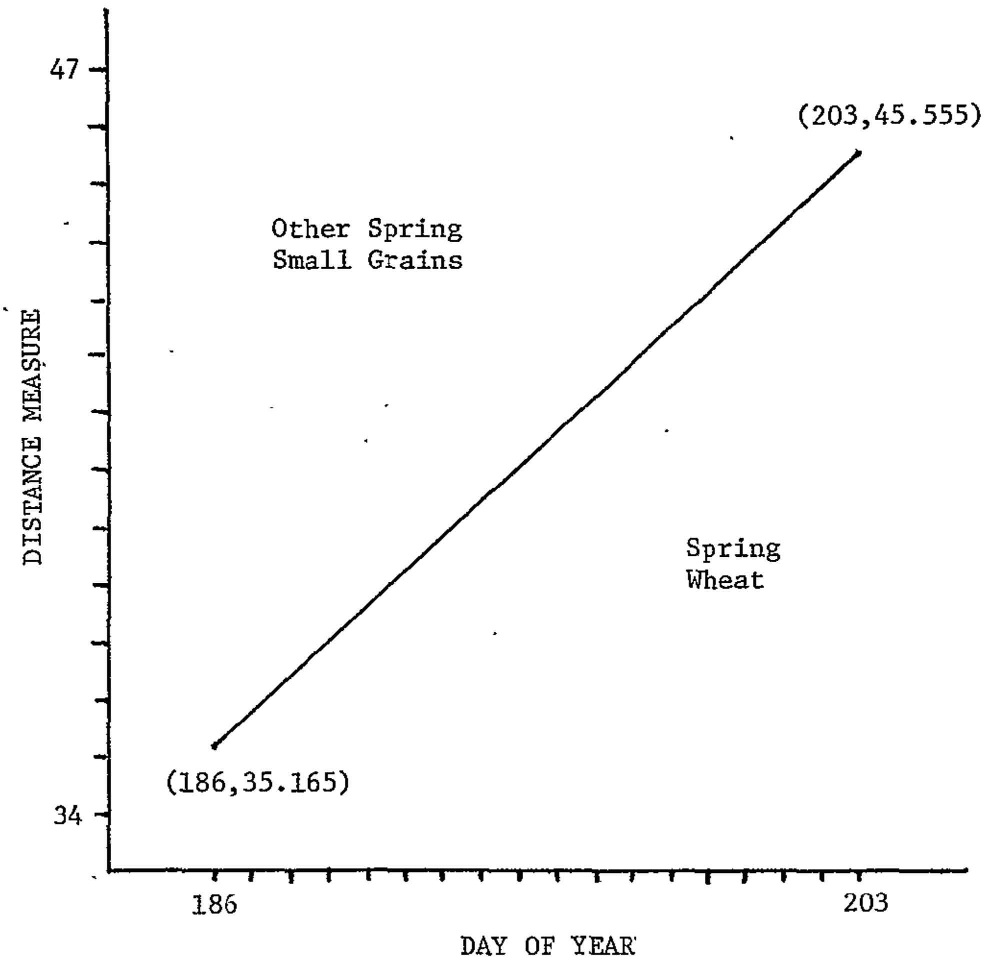


FIGURE 2.7 DISTANCE USED IN LABELING CRITERION



Distance = 0.611 * Shifted Day - 78.513

FIGURE 2.8 SPRING WHEAT DECISION RULE

TABLE 2.9 LABELING RESULTS FOR DEVELOPMENT SEGMENTS

1498

	True Spring Wheat	True Barley
Est. Spring Wheat	745	103
Est. Barley	229	292
Correct	76.5%	73.9%

1515

	True Spring Wheat	True Barley
Est. Spring Wheat	2125	379
Est. Barley	445	1975
Correct	82.7%	83.9%

1640

	True Spring Wheat	True Barley
Est. Spring Wheat	4397	827
Est. Barley	891	1241
Correct	83.2%	60.0%

1663

	True Spring Wheat	True Barley
Est. Spring Wheat	3624	282
Est. Barley	442	858
Correct	89.1%	75.2%

2.2.2 UNBIASED SAMPLING STRATEGY

This section is concerned with how to choose a random sample of quasi-fields from a stratum in such a way that the percent wheat in the sample is an unbiased estimate of the percent wheat in the stratum.* Although "wheat" plays a role in the discussion, the result applies to other crops and attributes whether estimated singly or in groups. Also, the sampled entities are called "fields", for convenience.

At first glance, it would appear that there isn't a problem. Why do we need to do anything more complicated than draw a simple random sample, that is, we decide on the number k of fields to sample and then, giving all samples of k fields equal probability, choose one at random?

The answer is that this simple scheme results in a biased estimate. To produce an unbiased estimate, we sample the first field with probability proportional to size and the remaining k-1 fields with equal probability, a technique first described by H. Midzuno in 1951 [27], [28] and [29].

Because this technique defies intuition and could become a source of doubt and controversy, a more extended discussion of it than is provided by the references will be given here.

Suppose we are sampling k fields from a total of B in the stratum and that each field, i, has n_i pixels and has a proportion p_i of wheat. Then $n_i p_i$ is the number of wheat pixels in Field i.

The proportion $\hat{p}$ of wheat in the sample is

$$\frac{\sum n_i p_i}{\sum n_i}$$

*Bias that may be introduced by omitting some strata from the aggregation process is discussed in Section 3.1.2.1.

where the sums are taken over all fields in the sample. The proportion p of wheat in the stratum is the same expression except that the sums are taken over all fields in the stratum. The problem is to find a probabilistic method of selecting the sample so that the wheat proportion in the sample is an unbiased estimate of the wheat proportion in the stratum.

That the simple random sample is not such a method is shown by the following example. Suppose we have three fields, a, b and c, in the stratum, we are sampling just one field, and the n_i's and p_i's are as follows:

Field	n_i	p_i	$n_i p_i$
a	50	0.6	30
b	20	0.2	4
c	10	0.1	1
TOTAL	80		35

p is 35/80 = 0.4375. $\hat{p}$ is 0.6, 0.2 or 0.1 depending on whether a, b or c is chosen as the sample. According to the simple random sampling scheme, each of these samples has equal probability, 1/3, of being chosen. The expected value of $\hat{p}$ is obtained by multiplying the probability of each sample by $\hat{p}$ for that sample and summing. So

$$\mathcal{E}\hat{p} = \frac{1}{3} \times 0.6 + \frac{1}{3} \times 0.2 + \frac{1}{3} \times 0.1 = 0.3$$

which is $\neq$ 0.4375. Thus $\hat{p}$ is a biased estimator of p.

But if we apply the Midzuno technique to this special case where just one field is chosen, we choose that field with probability proportional to size. Then Field a has a probability 50/80 of being chosen, Field b, 20/80 and Field c, 10/80.

The expected value of $\hat{p}$ is

$$\frac{50}{80} \times 0.6 + \frac{20}{80} \times 0.2 + \frac{10}{80} \times 0.1 = \frac{35}{80}$$

which = p. Thus the Midzuno technique is unbiased in this example.

The part of the Midzuno technique that strains our intuition is choosing fields subsequent to the first with equal probability. Let us see how this technique handles the choice of two fields in our example. There are three possible samples, (a and b), (a and c) and (b and c). The probability of each sample, the wheat proportion in each sample, and the product of the two for computing $\mathcal{E}\hat{p}$ are given in the table below:

Sample	Sample Probability	Wheat Proportion $\hat{p}$	Sample Probability x Wheat Proportion
a and b	$\frac{50}{80} \times \frac{1}{2} + \frac{20}{80} \times \frac{1}{2}$	$\frac{(50 \times 0.6) + (20 \times 0.2)}{50 + 20}$	$\frac{30 + 4}{80 \times 2}$
a and c	$\frac{50}{80} \times \frac{1}{2} + \frac{10}{80} \times \frac{1}{2}$	$\frac{(50 \times 0.6) + (10 \times 0.1)}{50 + 10}$	$\frac{30 + 1}{80 \times 2}$
b and c	$\frac{20}{80} \times \frac{1}{2} + \frac{10}{80} \times \frac{1}{2}$	$\frac{(20 \times 0.2) + (10 \times 0.1)}{20 + 10}$	$\frac{4 + 1}{80 \times 2}$

The sample probability of (a and b) is computed by realizing that this sample can come about in two ways: either a can be chosen first with probability 50/80 and b is then chosen with probability 1/2 or b is chosen first with probability 20/80 and then a is chosen with probability 1/2.

To get the expected value of $\hat{p}$, we multiply the sample probability by $\hat{p}$ for each sample and sum. The number of pixels in the sample appears in the denominator of the wheat proportion and in the numerator of the sample probability. This factor cancels when we multiply the two and we are left with the uncluttered expressions in the right hand column. When this column is summed, we get

$$\mathcal{E}\hat{p} = \frac{2\ (30 + 4 + 1)}{2 \times 80} = \frac{35}{80}$$

which = p. And so again, the unbiasedness of the Midzuno technique is exhibited.

An algebraic proof of the unbiasedness of the Midzuno technique, built on the insights of the previous example, is presented in Appendix A.

We note that in the example just given, we chose a sample with probability proportional to the size of the sample (i.e., the number of pixels in the sample): sample (a and b) had probability (50 + 20) x constant; (a and c), (50 + 10) x constant; (b and c), (20 + 10) x constant. This conclusion holds in general (See Appendix A). Thus we can think of the Midzuno technique as <u>a random mechanism for selecting a sample of k quasi-fields with probability proportional to size</u>. A more direct mechanism would be to enumerate all possible samples, give each a probability proportional to size, compute cumulative probabilities for the sequence of samples, choose a random number between 0 and 1 and observe at which sample it falls within the cumulative probabilities. We don't use this mechanism because as k and B increase it becomes rapidly impractical. If k=5 and B=150, for example, we would have to compute 590 million probabilities. We are fortunate to have a practical mechanism that achieves the same end.

2.2.3 SPECTRAL STRATIFICATION

In order to increase the efficiency of the sampling of quasi-fields to be labeled, the population of quasi-fields is split up into strata. It is well known [30] that if the stratification has some relation to the attribute being estimated and if the strata are sampled in proportion to their size, a more precise estimate is obtained from the sample.

In Procedure M the stratification is done by an algorithm BCLUST which groups together quasi-fields that are spectrally similar for all the biophases observed. The effect is to concentrate the crops of interest into a few of the spectral strata.

The first step is to put the quasi-fields of a segment in random order. Omitted from the list are the so-called "small fields", namely, those that have no interior pixels. (An "interior pixel" is one that faces pixels from the same quasi-field on all four sides.) The small quasi-fields, usually stringy boundary areas between real fields, are omitted because they are difficult to label and subject to registration errors. The parameters of the algorithm setting up the quasi-fields are chosen so that few of the pixels in the segment are in small quasi-fields.

The large quasi-fields are clustered using the multitemporal spectral mean vectors. The means are computed over the interior pixels only, because these pixels are less likely to be subject to registration errors or to mixed spectral responses and they therefore more purely represent the crop or material present in the quasi-field. Thus the intent of stratifying the data according to crop or material is further realized.

The distance measure used in the clustering is

$$d_i = \sum_{j=1}^{nchan} w_j^2 (x_j - \overline{x}_{ji})^2$$

where

$x_1, \ldots, x_{nchan}$ is the data vector (a quasi-field mean)

$\overline{x}_{1i}, \ldots, \overline{x}_{nchan,i}$ is the mean vector of cluster i

nchan is the total number of multitemporal spectral channels

d_i is the distance from the data vector to cluster i

w_j is a weight on channel j

Each new data point x is assigned to the cluster i for which d_i is smallest, except that if the minimum d_i is greater than a parameter τ, a new cluster is created with its mean initially at x. As each point enters a cluster, it is included in the calculation of the cluster mean by the updating formula

$$\text{new } \bar{x}_i = \frac{n_i}{n_i + 1} \text{ old } \bar{x}_i + \frac{1}{n_i + 1} x$$

where n_i is the former number of points in cluster i.

The number of clusters created depends on the weights $w_1, \ldots, w_{nchan}$ and τ. The larger τ is in relation to the weights, the smaller the number of clusters. Appendix B discusses how these parameter values were set.

The present implementation of BCLUST has a provision for repeating automatically with appropriate changes in τ until a desired number of clusters is achieved. Other options include switches for turning off the creating and updating capabilities, a provision for seeding clusters with arbitrary values or with the means from a previous run, the use of a data transformation matrix rather than merely a set of weights, and a provision to start with a small value of τ and increase it asymptotically to a desired final value. This last option has the effect of seeding the clusters with the first data vectors and tends to produce clusters that are more uniform in size.

BCLUST also has the capability of incorporating collateral information into the distance formula when strata are being formed from a pool of quasi-fields from several segments. The collateral information such as a moisture index or crop calendar figure, is a single value for the whole segment. This capability of BCLUST is not used in Procedure M for spring wheat which operated only on single segments.

In running BCLUST for Procedure M, we have used the repeated run option to converge to a desired number of clusters, then used the means of the converging run as seeds to make another pass through the data with no creating or updating. We have also used the Tasseled Cap channels Brightness and Greenness, and have set the weights in inverse proportion to the effective ranges of the variables. The specific parameters used are presented in Appendix B.

2.2.4 DEFINITION OF SPATIAL FEATURES

An aerial photograph of an agricultural area shows that the scene is divided into areas called fields, usually rectangular or some other simple shape, within which the color is nominally uniform. A field in Landsat data is similarly defined: a group of neighboring pixels in some simple shape whose spectral characteristics are very likely to be uniform.

Because of the one-acre resolution of Landsat data, it does not seem possible to reconstruct, without further information, the fields that would be evident in higher resolution data. But we can define groups of pixels that we call quasi-fields that have properties similar to fields, namely that their pixels are spatially close and spectrally similar.

Several purposes are served by such a definition:

1. Using the quasi-field as the unit of analysis rather than the pixel increases processing efficiency through a data compression factor of about 30.
2. Averaging the pixel values over a quasi-field smooths out noise in the data.
3. Stripping away the edge pixels of the quasi-field allows working with the relatively pure interior pixels. Purity refers not only to a uniform spectral response but also to the invariance of the associated ground truth, as demonstrated

in tests on Kansas and North Dakota segments [20,23]. This purity contributes to the success of labeling techniques, whether carried out by humans or by computer programs. It also contributes to the grouping of quasi-fields into meaningful strata that reduce sampling error.

The algorithm used by Procedure M to create quasi-fields is called BLOB; other possibilities might have been AMOEBA [31] or ECHO [32]. BLOB is a clustering algorithm similar to BCLUST (Section 2.2.3) but based on the spatial channels, line number and point number, in addition to the spectral channels.

The distance function for deciding which quasi-field a pixel belongs to is:

$$d_i = \sum_{j=1}^{nchan} \frac{(X_j - \overline{X}_{ji})^2}{V_j} + \frac{(L - \overline{L}_i)^2}{V_L} + \frac{(P - \overline{P}_i)^2}{V_P}$$

where

$x_i, \ldots, x_{nchan}$ is the spectral data vector for a pixel

L is the pixel line number

P is the pixel point number

$\overline{X}_{1i}, \ldots, \overline{X}_{nchan,i}$ is the spectral mean vector of quasi-field i

$\overline{L}$ is the mean line number of quasi-field i

$\overline{P}$ is the mean point number of quasi-field i

nchan is the number of spectral channels

d_i is the distance from the pixel to quasi-field i

V_j, V_L and V_P are weights attached to the spectral and spatial variables in the distance function

The pixel joins the quasi-field with the smallest d_i provided that this value is less than a parameter τ. Otherwise the pixel starts a new quasi-field. The mean vector for a quasi-field is computed from all the pixels in the quasi-field by an updating formula as in BCLUST.

The numbers $V_1, \ldots, V_{nchan}, V_L, V_P$ and τ are parameters of the algorithm that affect its performance. The larger τ is relative to the others, the larger the quasi-fields are and the fewer there are of them. Increasing τ also reduces the number of quasi-fields with no interior pixels, fields that are left out of the stratified sampling. Large values of V_L and V_P relative to $V_1, \ldots, V_{nchan}$ have the effect of emphasizing the spectral, rather than the spatial, variables , and may produce quasi-fields that are not very cohesive geographically. Relatively small values of V_L and V_P emphasize the spatial variables and may produce compact quasi-fields that are not as homogeneous spectrally as one would like and may subdivide large fields. Information regarding the parameters of BLOB are reported in Appendix B.

It is possible that clouds may obscure field patterns. When the BLOB algorithm is applied to multiple time periods, it is now possible to avoid data that are cloud covered. This was accomplished by a modification that first excludes any channel data that have been flagged by the screening process (i.e., using only cloud-free data) in computing d_i, and adapting the τ distance factor to reflect the use of fewer channels of information.

The BLOB algorithm allows the use of an alternate distance function that favors the formation of rectangular fields. When used, the line and point coordinates L and P are rotated by a linear transformation to obtain ℓ and p that measure in the North-South and East-West directions, respectively. Then the last two terms of the distance function are replaced by

$$\max \left[\frac{(\ell - \bar{\ell}_i)^2}{V_\ell}, \frac{(p - \bar{p}_i)^2}{V_p} \right]$$

Using this distance function, all points equi-distant from the spatial mean of a quasi-field form a North-South/East-West rectangle rather than an ellipse.

2.2.5 ATMOSPHERIC HAZE CORRECTION

An atmospheric haze correction, preceded by data screening and followed by a data transformation (to the Tasseled-Cap linear channel combinations), forms the preprocessing component of Procedure M. During the research leading to Procedure M, it became increasingly apparent that an atmospheric correction algorithm was needed which would compensate not only for large scale (segment-to-segment) atmospheric variations, but for smaller scale (within segment) variations as well. For this purpose the application of the XSTAR haze correction algorithm [33,34] (which was developed during a previous effort) was changed from a global application (a fixed correction throughout a segment) to a spatially varying application (a variable correction within each segment). The resulting algorithm is called the spatially varying XSTAR haze correction [35].

In principle, the spatially varying XSTAR algorithm calculates its haze diagnostic within a moving window (which has a 15 pixel diameter between half amplitude points), using only those pixels which have passed the screening procedure, and then applies its correction to the pixel at the center of the window. However, in the detailed implementation of the procedure the application of the moving window is quantized as described below. This quantization reduces the execution time for the procedure on the computer, with the result that the spatially varying XSTAR procedure costs slightly less than twice as much to run as the former global XSTAR procedure cost.

The spatially varying XSTAR procedure follows six steps, as outlined in Table 2.10. In the first step, the SCREEN procedure [33,34] is applied to the data to flag pixels (e.g., bad data, dense clouds, cloud shadows, or water) which are not usable in the haze diagnostic procedure. However, for the spatially varying XSTAR correction, two of the SCREEN thresholds are relaxed somewhat, as described in Reference 35. This allows more extreme haze concentrations to be diagnosed and corrected than had been the case previously with the global XSTAR correction (which needed to

TABLE 2.10 STEPS IN SPATIALLY VARYING XSTAR HAZE CORRECTION PROCEDURE

- Screen Data (Using Less Stringent Cloud and Dense Haze Thresholds)
- Calculate Mean Signal Values for 5 Line by 5 Pixel Blocks (Using Only "Good" Pixels)
- Calculate Spatially Smoothed Mean Values for Blocks, Using a Moving Window Filter
- Use Spatial Interpolation/Extrapolation to Estimate Mean Values for Blocks Which Have an Insufficient Number of Good Pixels
- Calculate XSTAR Correction Appropriate at Each Block Center
- Interpolate XSTAR Correction to Apply to Each Pixel

exclude pixels within haze concentrations which were not typical of the majority of the segment to be corrected). The relaxed thresholds also help the correction algorithm to track haze variations more accurately.

The second step of the spatially varying haze correction procedure divides the scene into 5 line by 5 pixel blocks, and calculates a mean value for each block, using only signal values from the "good" pixels within the blocks. ("Good" pixels are those pixels which pass the SCREEN procedure.) Mean values for blocks with no good pixels or with fewer good pixels than half the average number of good pixels per block (truncated to integer form) are not used. For these "unknown" blocks, mean values are estimated by interpolating or extrapolating from neighboring block mean values, as described in Steps 3 and 4 below.

In the third step of the procedure, the mean values of the 5 line by 5 pixel blocks are smoothed, using a non-recursive moving window filter. The filter approximates a Gaussian shape, with a 3 block diameter between half amplitude points. In this stage, smoothed mean values are calculated for all blocks with "known" mean values, and for all blocks with at least one near neighbor (either along-track or across-track) which has a "known" mean value. The smoothed mean value is the weighted average of the available "known" mean values within the window of the filter.

Step 4 of the spatially varying XSTAR procedure is used to assign smoothed mean values to blocks which still have "unknown" mean values after Step 3. In this step only those blocks which have "unknown" mean values, but which have at least one near neighbor (either along-track or across-track) with a smoothed mean value, are assigned smoothed mean values according to the procedure of Step 3. Step 4 is iterated until all blocks have smoothed mean values.

In Step 5 of the procedure, the smoothed block mean values are used as XSTAR haze diagnostics, and the multiplicative and additive correction factors appropriate for each block center are calculated from them.

Finally in Step 6 the multiplicative and additive correction factors calculated from the block means in Step 5 are interpolated between block centers (in two dimensions) to determine the appropriate correction factor for each pixel. These correction factors are then applied pixel by pixel. For this step a curvilinear interpolation is used which employs an approximately Gaussian interpolation weighting function, described in Reference 35. Pixels which are near the borders of the scene, so that only one or two block centers are within the interpolating range (±4 lines and ±4 pixels) of the pixel, are corrected by interpolating the correction factors calculated for only those blocks whose centers are within the interpolating range.

The spatially varying XSTAR procedure results in an effective atmospheric haze correction (for Landsat agricultural MSS data) with a 15 pixel (∿1.2 x 0.9 km) spatial resolution of haze variability. The performance characteristics of this haze correction are discussed in Section 3.2.4.

3
TEST AND EVALUATION OF PROCEDURE M CONFIGURED FOR SPRING WHEAT

Procedure M utilizes a statistical sampling strategy to inventory crop acreage. The procedure is constructed in a modular way and was designed to function within the LACIE framework. This section presents an evaluation of a spring wheat configuration of Procedure M in estimating spring small grain and spring wheat acreages in the Northern Great Plains. The evaluation considers the performance of the overall procedure in providing acreage estimates (Section 3.1), as well as the performance of the individual components (modules) that comprise the procedure (Section 3.2).

3.1 TEST AND EVALUATION OF SYSTEM PERFORMANCE

Test and evaluation of Procedure M performance is presented in three parts -- the experiment design, results, and a summary.

3.1.1 EXPERIMENT DESIGN

The major objective of the evaluation was to gain an understanding, in a statistical sense, of the overall performance of Procedure M as configured for spring wheat. That is, the experiment was to characterize the procedure's performance in terms of bias and variance of crop proportion estimates. In addition to spring wheat and other spring small grain estimates, the accuracy of the total spring small grain estimates were to be evaluated.

The specific software configuration employed to conduct this evaluation is described in Appendices B and C. Experiment parameters are listed in Table 3.1. Note that both Phase 2 and Phase 3 segments were used. This was done to evaluate whether the machine labeling procedure for spring wheat, described in Section 2 and developed using Phase 3 sites, could be extended to another crop year, represented by the Phase 3 sites.

TABLE 3.1 EXPERIMENT PARAMETERS

- 26 Northern Great Plains Phase 2 and Phase 3 LACIE Blind Sites
- Up to 7 Acquisitions for Each Site
  - 3 or 4 Chosen for Field and Strata Definition
  - 3 or 4 Chosen for Automatic Labeling
- 4 Stratification Cases (B Clusters -- 1,20,40,60)
- 5 Field Sample Cases (Quasi-Fields or Blobs -- 40,60,80,100,120)
- 50 Estimates Per Case (Random Field Sample Replicates)
- 26,000 Proportion Estimates Total

The 26 segments chosen for evaluation were selected so that they would geographically represent the major spring wheat growing regions in the United States Northern Great Plains (Figure 3.1). The proportions of segments planted to spring small grains vary from about 70% to near 9%, as is illustrated in Figure 3.2 in which segments are ranked according to their spring small grain proportions. The specific acquisition dates available and used for these segments are listed in Appendix D.

Procedure M for spring wheat utilizes 100 labeled samples drawn from 40 spectral strata. This experiment sought to characterize the performance of other sampling strategies as well. Unstratified sampling was carried out in addition to sampling from within 20, 40, and 60 strata to enable measuring the variance reduction (R factor) due to stratified sampling. The R factor is a measure of the efficiency of stratified sampling and is defined as:

$$R_{mn} = \frac{\sigma_{mn}^2}{\sigma_{1n}^2}$$

where

- m is the number of strata
- n is the number of fields sampled
- σ^2 is the measured variance of the procedure (over the 50 random field sample replicates)
- σ_{1n}^2 is the measured variance for the one-stratum case (i.e., unstratified)

Once samples are drawn, the quasi-fields are labeled. To evaluate the efficiency of the procedure in terms of its variance characteristics juxtaposed to the gains that might be achieved in the efficiency of labeling, sets of 40, 60, 80, 100 and 120 samples were drawn and results using them were compared.

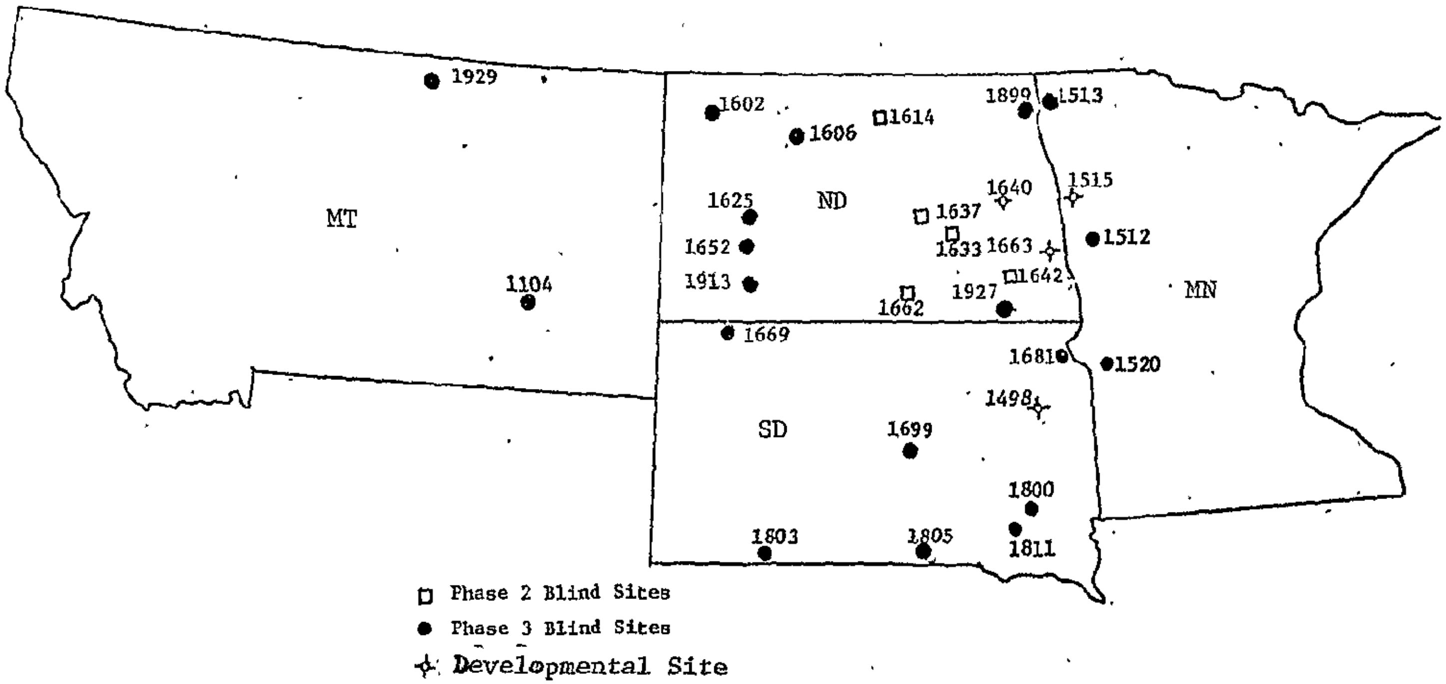


FIGURE 3.1 TEST SITE LOCATIONS

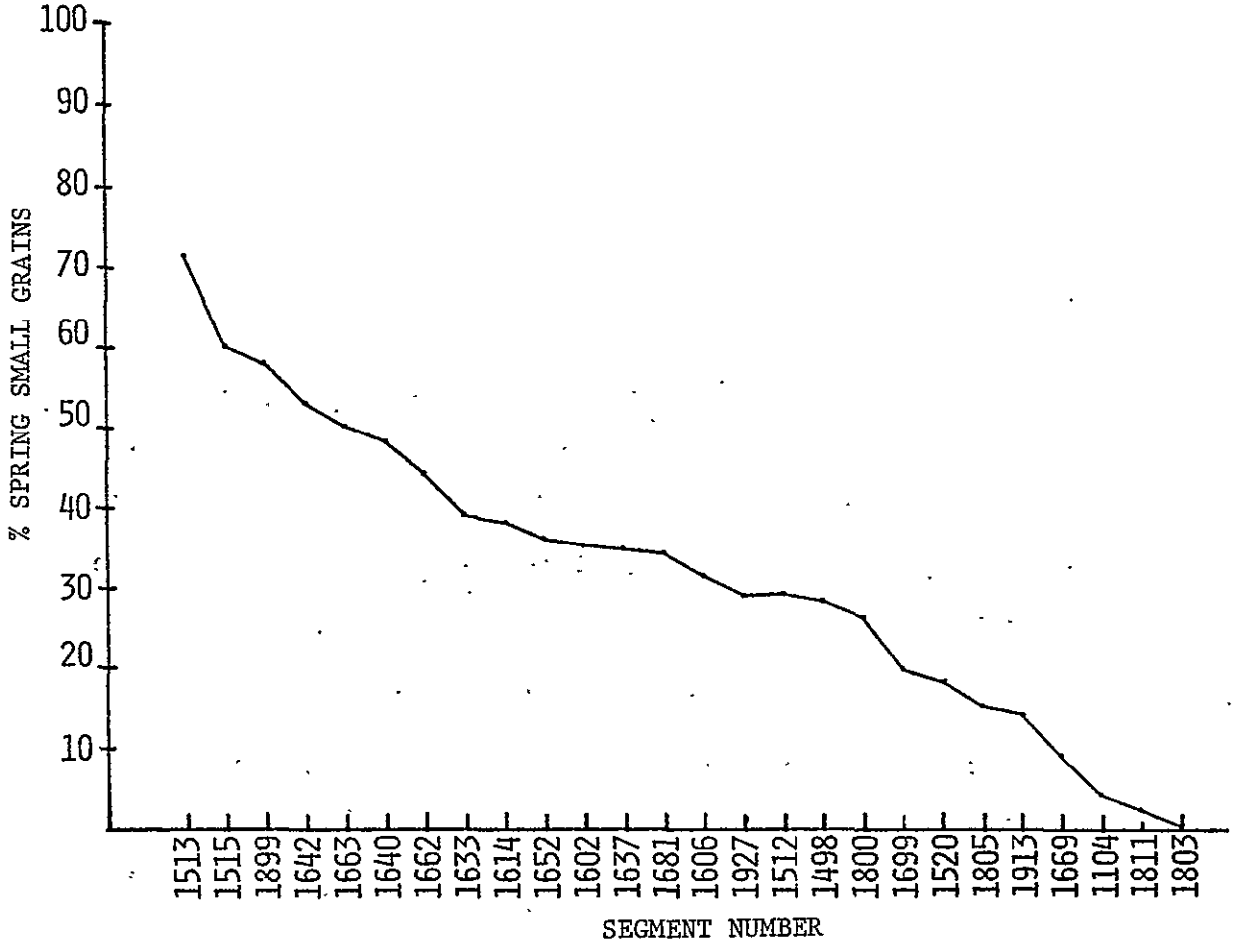


FIGURE 3.2 AMOUNT OF SPRING SMALL GRAIN PER SEGMENT

The spring wheat configuration of Procedure M uses the previously described two-step labeling mechanism. The first step involves analyst interpretation and labeling of samples as 'Spring Small Grain' or 'Other'. Ground truth* was used as a substitute for analyst interpreter labels in this experiment. The second step involves a further discrimination of the grain samples by the machine labeler. These labels are then utilized in aggregating a segment spring wheat proportion estimate.

To characterize both bias and variance characteristics of the procedure, estimates were made by replicating the process of drawing 50 sets of samples for each combination of stratification and field sampling cases.

3.1.2 SYSTEM PERFORMANCE RESULTS

The results presented in this section consider both portions of the two-stage labeling mechanism. First, three aspects of the performance of the procedure in estimating total spring small grains are presented:

(1) Average performance using 40 strata and 100 labeled samples

(2) Bias due to ignoring certain strata

(3) Parametric evaluation of sampling variance

This analysis evaluates the performance of the two-class procedure with respect to ground truth labels.

Then, three aspects of the performance of the procedure in estimating three classes -- spring wheat, other spring small grains, and other -- are presented:

(1) Average performance using 40 strata and 100 labeled samples

(2) Performance for various partitions of the segments

(3) Parametric evaluation of sampling variance

*Wall-to-wall ground truth provided by JSC and prepared in subpixel format by Lockheed Electronics Company and ERIM personnel was used.

This three-class analysis evaluates the performance of the procedure with the machine labeler. The intent is to show not only areas of strength but also to make recommendations to improve the spring wheat labeling accuracy and to evaluate whether the labeling strategy employed can meet needs in an operational setting.

3.1.2.1 Spring Small Grain Estimates (Two-Class)

Performance Using 40 Strata and 100 Labeled Samples. Overall, the small grain proportion in the 26 LACIE blind sites was 32.3%. The average estimate made using Procedure M was 34.3% -- an absolute error of 1.9% and a relative error of 6%.* This estimate is the average of 50 replicates of 100 labeled samples from 40 strata in each of the segments. There was no statistically significant difference between this estimate and those derived similarly from other combinations of strata and sample size, although their variance reductions (sampling efficiencies) were significantly different.

Figure 3.3 illustrates the accuracy of these average estimates on an individual segment basis. The average standard deviation about each of these points was 2.5%, while their RMS error about the 45° line was 3.66 and the R^2 about the regression line was 0.987. Overall, the estimates were accurate with a slight positive bias introduced as the percentage of small grain in the segment increased.

Bias Due to Ignoring Certain Strata. Procedure M samples only quasi-fields with interior pixels. Assuming that the estimate for these fields is unbiased, the expected bias due to not sampling from the smaller fields is given by the expression:

$$b = \frac{N - M}{N} (P_s - P_u)$$

---

* $\frac{E-T}{T}$ where E is the estimate and T the true grain proportion.

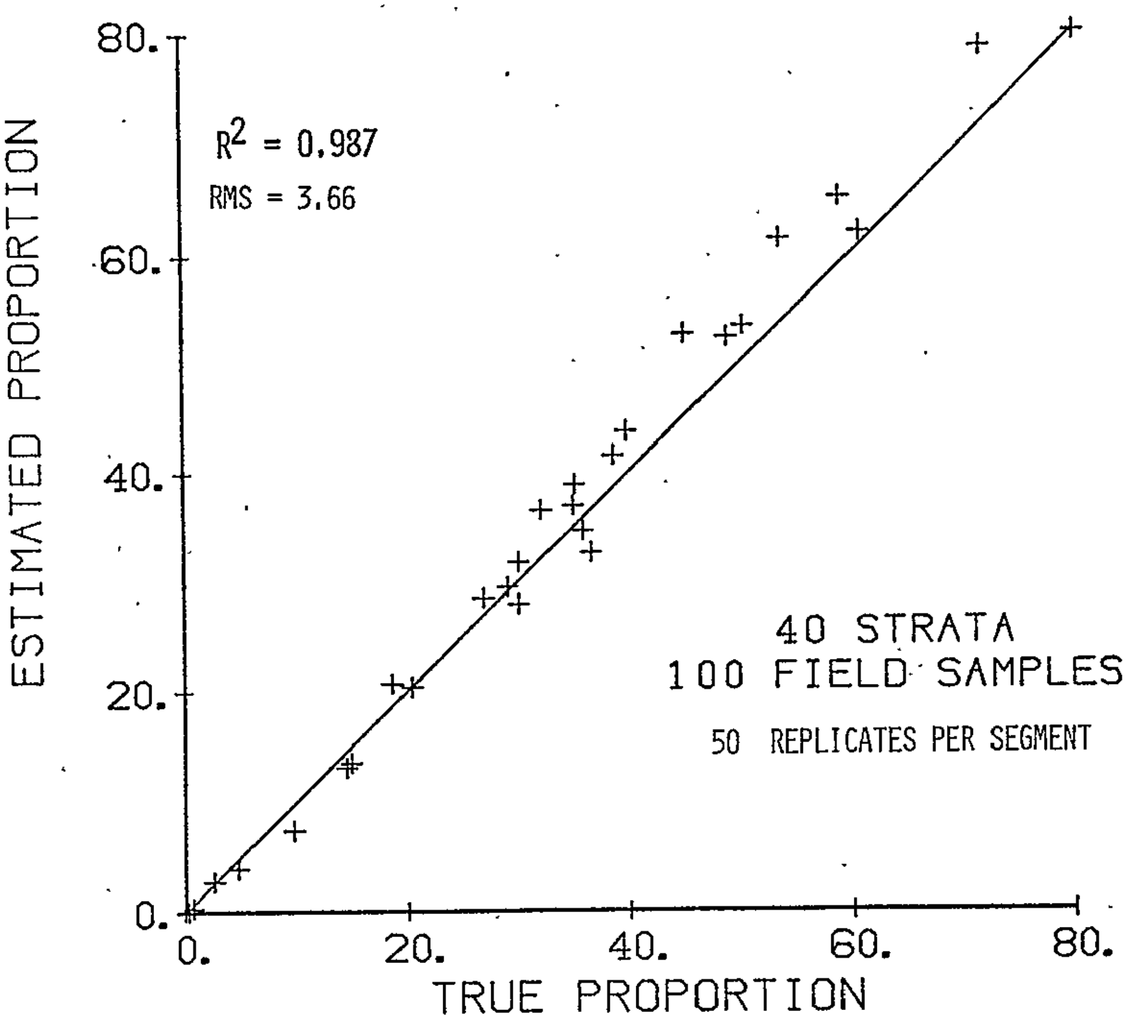


FIGURE 3.3 PROCEDURE M SEGMENT ESTIMATES OF TOTAL SPRING SMALL GRAINS

where

P_s is the crop proportion in the quasi-fields from which samples are drawn

P_u is the crop proportion in the quasi-fields from which no samples were drawn

N is the total number of pixels

M is the total number of pixels in the sampled strata

If $P_s \cong P_u$ or if $M \cong N$, no significant bias is introduced. The expected bias in the 26 sample segments was computed to be 1.9% which is about equal to the absolute error that was measured. Hence Procedure M was found to be virtually unbiased with respect to the fields that were sampled.

Figure 3.4 provides a comparison on a segment-by-segment basis of the expected bias (dashed line) and the measured bias. The segments are ordered as in Figure 3.2. With the exceptions of Segments 1652 and 1662, the estimates and expectations track closely. The unexpected bias encountered in Segment 1652 was the result of inadequate ground truth labels (See footnote in Section 3.1.2).

The bias encountered is well understood to be a function predominantly of ignoring the small-field strata. Three techniques are under consideration to eliminate this bias. One strategy is to increase the number of pixels in quasi-fields having interior pixels. This can be accomplished by relaxing the parameter settings in the BLOB program.* A second strategy involves a post bias correction algorithm based on a relationship that may exist between average field size and grain proportions. The third strategy, suited for areas dominated by smaller fields, is to sample the small-field stratum directly. What is implied is an

*Currently these parameters are fixed for all segments (See Appendix B). In the Northern Great Plains results, an average of about 70% of each segment was represented by quasi-fields with interior pixels.

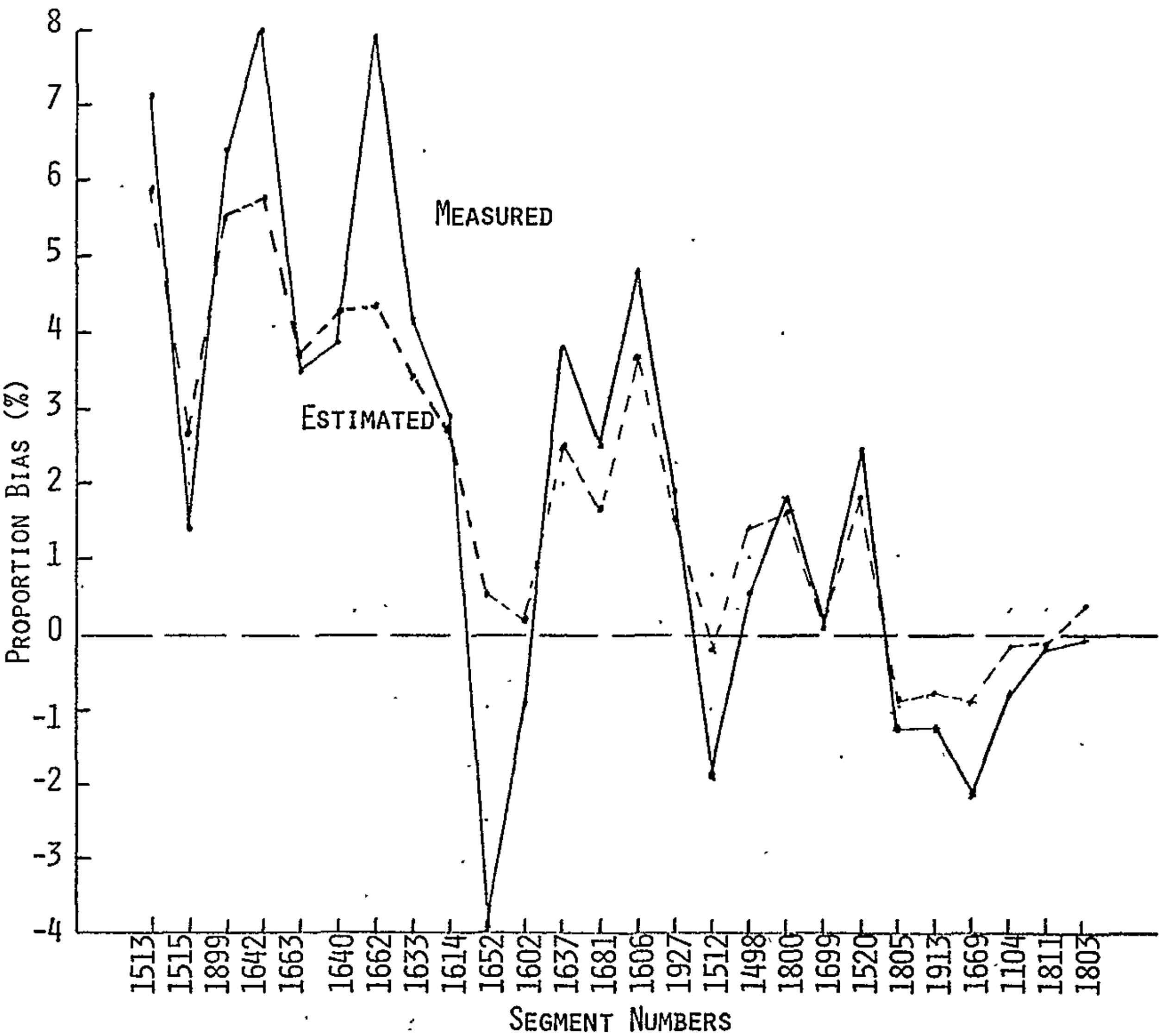


FIGURE 3.4 TWO-CLASS TOTAL SPRING SMALL GRAINS BIAS

initial stratification of an area into two strata, small fields and large fields and the employment of sampling strategies suited to each stratum.

Parametric Evaluation of Sampling Variance. The efficiency of Procedure M in terms of its variance reduction characteristics is as critical to its usefulness as is its bias characteristics. In this section the variance of the spring small grain estimate derived using Procedure M is discussed. Integral to this procedure is the concept of stratified sampling. It has been shown that a reduction in variance can be achieved using a stratified sampling approach [30]. Here, empirical evidence will be provided to illustrate the degree of sampling efficiency that can be achieved using Procedure M.

Results of the empirical tests are summarized in Figure 3.5. This plot illustrates the dependence of the measured variance (represented by its square root) on the number of labeled samples and the number of strata. The standard deviation,

$$\sigma_{mn} = \sqrt{\left(\frac{1}{26} \sum_{i=1}^{26} \sigma_{mni}^2\right)} ,$$

is plotted versus the number of labeled samples, on a semi-log graph for each of the four strata parameters, where as before,

m = 1, 20, 40, or 60 denotes the number of strata

n = 40, 60, 80, 100, or 120 denotes the number of labeled samples

σ_{mni} denotes the standard deviation of 50 observations from Segment i using n labeled samples and m strata.

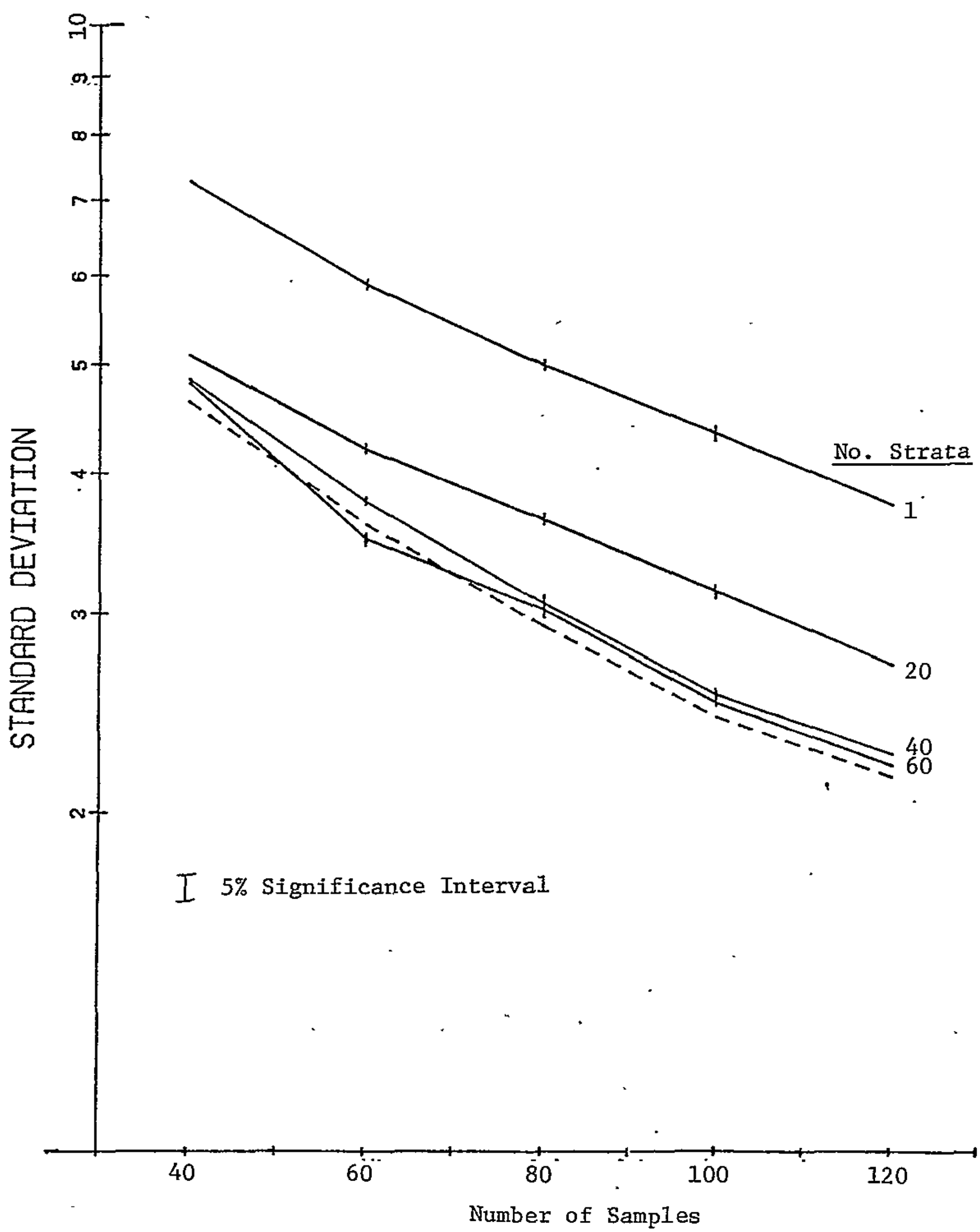


FIGURE 3.5 PROCEDURE M STRATIFIED SAMPLING VARIANCE, SPRING SMALL GRAIN

The top curve, for one stratum, represents unstratified sampling. Note that for 20, 40, and 60 strata, the variance encountered is substantially reduced. The bar labeled '5% Significance Interval' has length

$$\log \sqrt{F(1-.05,1274,1274)} = \log \sqrt{1.0967} = \log(1.04725)$$

Any two standard deviation estimates whose vertical distance on the graph exceeded the length of the bar are significantly different by the F-test at the 5% level. A dashed line is drawn below the curve for 40 strata at a distance equal to the length of the bar. This shows geometrically that the curve for 60 strata is not significantly lower than the one for 40 strata, except for a sample size of 60.

The choice of using 40 strata in Procedure M for spring wheat seems to be supported by this analysis. The choice of using 100 labeled samples is not as good as using 120 labeled samples in the sense that $\sigma_{40,120}$ is significantly smaller than $\sigma_{40,100}$ at the 5% level. On the other hand, the additional cost of 20 more labels may not be warranted by the reduction of variance gained by using 120 samples, since the standard deviation is already well below 3% at the segment level.

The R (variance reduction) factor presented in Section 3.1.1 also provides insight into the efficiency of stratified sampling. For example, a procedure with R = 0.344 would need only 34.4% of the labeling effort required to obtain the same variance using unstratified sampling. Table 3.2 provides a matrix of R factors measured in conducting this evaluation of Procedure M. Since R is a ratio of sampled variances, it has an F distribution. Any two variances with

$$0.9118 < R < 1.0967 \quad (F(.05,1274,1274) \text{ to } F(.95,1274,1274)$$

are not significantly different.*

---

*Recall, average estimates were not significantly different, regardless of strata or sample settings.

TABLE 3.2 R FACTOR MATRIX (Reduction of Variance)**

# Strata \ # Samples	Relative to Unstratified*					Relative to 40 Strata*				
	40	60	80	100	120	40	60	80	100	120
1	1.0	1.0	1.0	1.0	1.0	2.25	2.43	2.65	2.91	2.76
20	0.49	0.51	0.53	0.52	0.52	1.11	1.24	1.41	1.52	1.44
40	0.44	0.41	0.38	0.34	0.36	1.0	1.0	1.0	1.0	1.0
60	0.44	0.35	0.37	0.33	0.35	0.87	0.86	0.98	0.97	0.95

*R factors are defined as follows:

$$R = \frac{\sigma^2_{m,n}}{\sigma^2_{1,n}} \qquad R = \frac{\sigma^2_{m,n}}{\sigma^2_{40,n}}$$

**If $0.9118 < R < 1.0967$, then variances resulting from parameter settings are not significantly different.

3.1.2.2 Spring Wheat, Other Spring Small Grains Estimates (Three Class)

Performance Using 40 Strata and 100 Labeled Samples. The second stage of the Procedure M labeling process labels the spring small grain quasi-fields proportionally among spring wheat and other spring small grain, except when the proper acquisition is missing. Of the 26 segments processed, three had acquisition histories inadequate for separating the small grains (See last entry in Table 2.9). Hence, spring wheat estimates were made for 23 segments. The overall results achieved for these segments appear in Table 3.3. Spring wheat was underestimated by 2.6%, and other spring small grains were overestimated by 3.8%. Figures 3.6 and 3.7 illustrate the average estimates on a segment-by-segment basis. The average standard deviation for a segment was under 2%. The spring wheat estimates made for other combinations of strata and sample sizes were not significantly different from the estimates made using 40 strata and 100 samples.

Though these results are encouraging, they do not compare in terms of accuracy with those achieved in making a total spring small grain estimate. The RMS error in these average spring wheat estimates was 8.6% as opposed to 3.7% for all spring grains. The accuracy of the three-class estimates is closely tied to labeler performance. While an in-depth evaluation of the labeler will be presented in Section 3.2.1, a systematic pattern to the measured error does appear in these results and will be discussed in this section.

Performance for Various Partitions of the Segments. It is of interest to determine whether the error measured in the spring wheat estimates is systematic in nature as opposed to random. If systematic, techniques to improve performance can be explored within a procedural context. In order to evaluate this possibility, the 23 segments

TABLE 3.3 SPRING SMALL GRAIN ESTIMATES USING 40 STRATA AND 100 LABELED SAMPLES (23 Segments With 50 Replicates Per Segment)

	Estimate (%)	True (%)	E-T (%)	$\frac{E-T}{T}$
Spring Wheat	15.4	18.0	-2.6	-0.15
Other Spring Small Grains	15.5	11.6	3.9	0.33

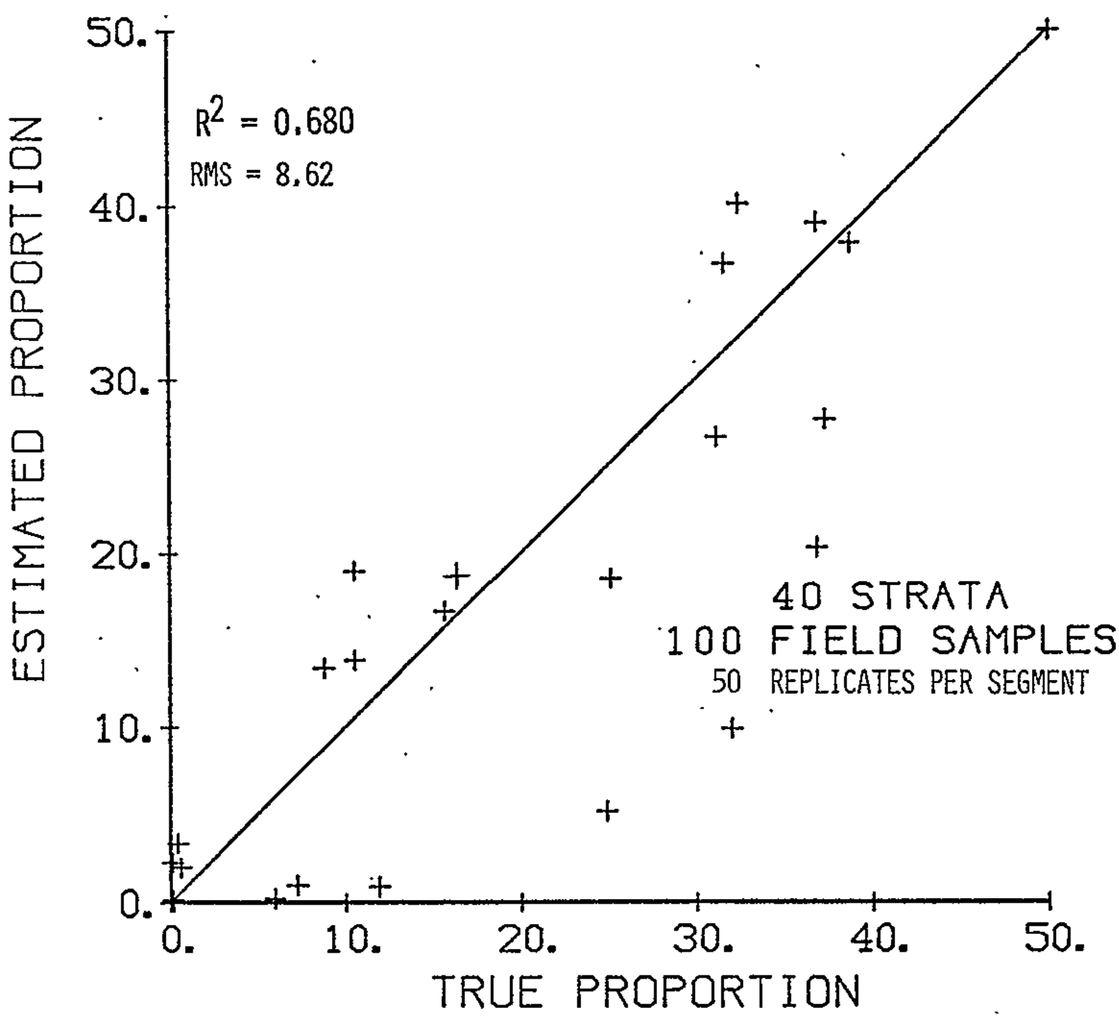


FIGURE 3.6 PROCEDURE M SEGMENT ESTIMATES OF SPRING WHEAT

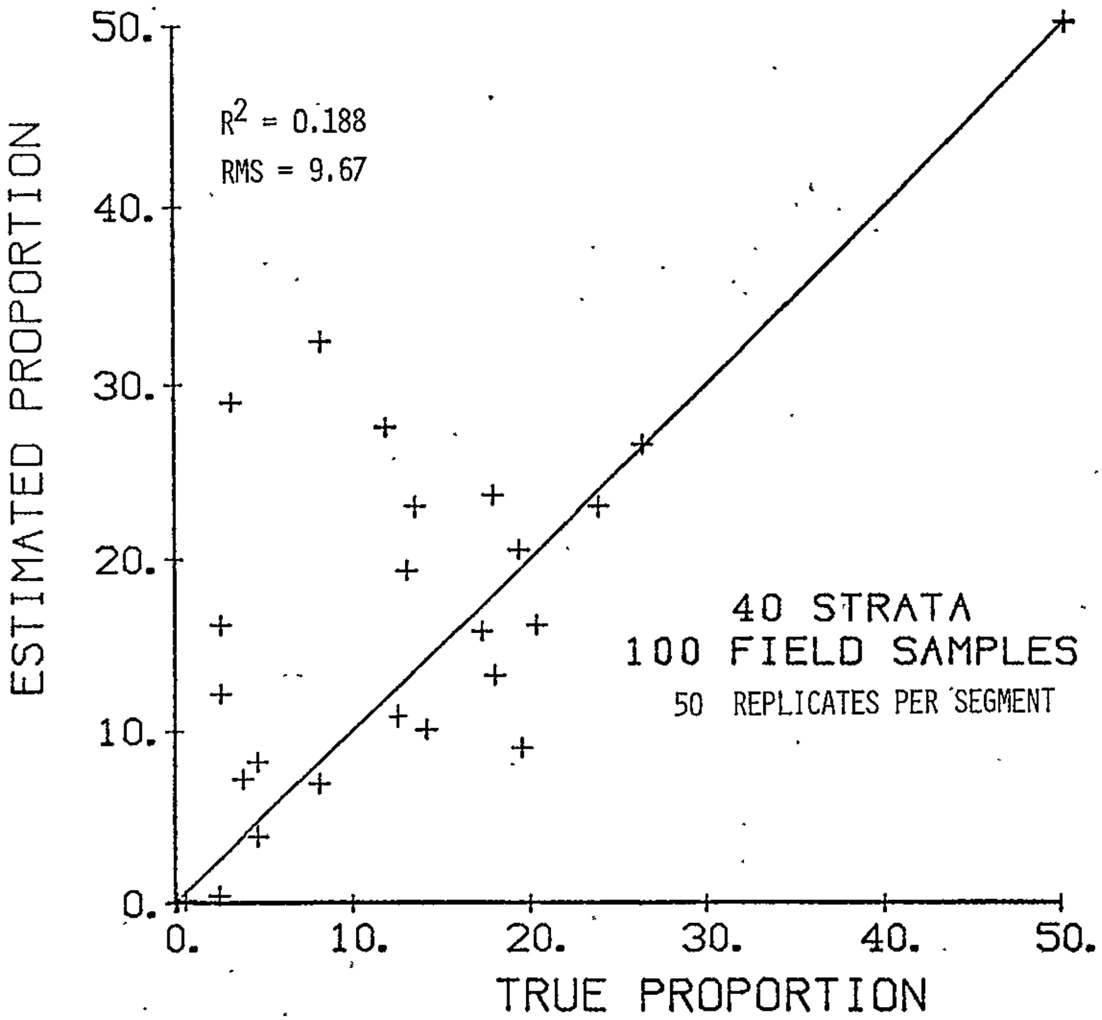


FIGURE 3.7 PROCEDURE M SEGMENT ESTIMATES OF OTHER SPRING SMALL GRAINS

processed were partitioned into groupings as follows (Table D.3 in Appendix D identifies the segments in each category):

Label	No. of Segments	Description
Acceptable	23	Spring wheat estimates made
Developmental	4	Phase 3 sites used for labeler development
Problem Segments	4	Displayed poorest results
Phase 2	5	1976 Blind Sites
Phase 3	18	1977 Blind Sites
Red River	8	Developmental geographic region

Figure 3.8 illustrates, using scatter diagrams, the performance attained within partitions in estimating spring wheat acreage. What is immediately evident is that two of the partitions, Problem Segments and Phase 2, contribute much of the error in an RMS sense. For both developmental segments and those located near the same river valley, accurate spring estimates are achieved. Section 3.2.1 discusses meteorological conditions that may influence these results in patterns that at first seem geographic or annual in nature.

Results are displayed numerically for these partitions in Tables 3.4 through 3.7. Note in Table 3.7 that the relative spring wheat error in Phase 3 sites is -1.8% as opposed to -32.7% in Phase 2 sites. It is significant that spring wheat is largely underestimated. Four segments labeled Problem Segments exhibit exceptionally poor spring wheat estimates (Table 3.6) with measured relative error of -65.6%. On the other hand, the remaining nineteen segments, exhibiting a relative error of only 3%, estimated a 16.7% spring wheat proportion given 16.2% actual. This estimate was not significantly different from

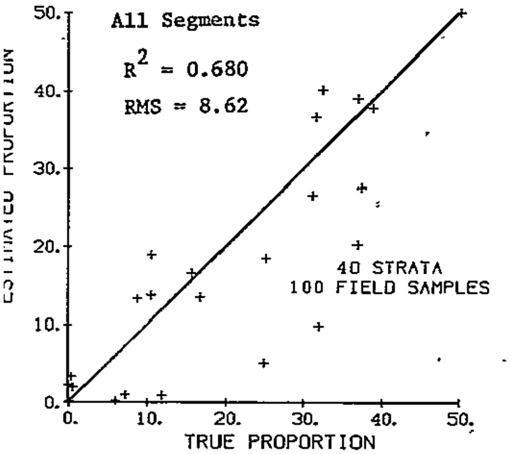


FIGURE 3.8 PARTITIONED RESULTS OF SPRING WHEAT ESTIMATION

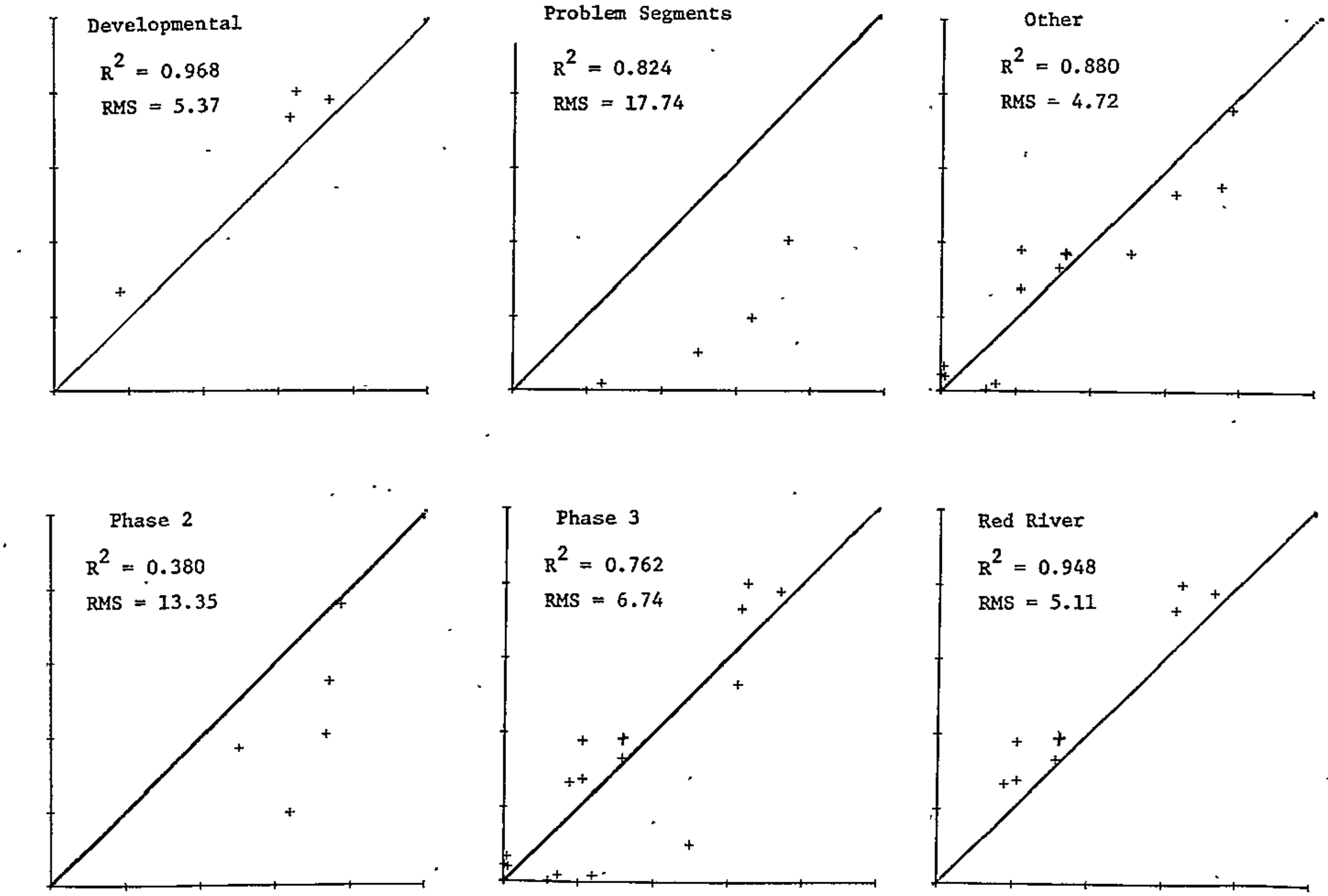


TABLE 3.4 STRATIFIED THREE-CLASS PERFORMANCE RESULTS, Part 1

Stratum	No. of Segments	Spring Wheat Estimate (%)	Spring Wheat True (%)	Spring Wheat E-T (%)	Spring Wheat $\frac{E-T}{T}$	Other Spring Small Grains Estimate (%)	Other Spring Small Grains True (%)	Other Spring Small Grains E-T (%)	Other Spring Small Grains $\frac{E-T}{T}$
Acceptable	23	15.37	17.98	-2.60	-0.145	15.46	11.62	3.84	0.330
Phase 2 Segments	5	22.83	33.92	-11.09	-0.327	24.81	8.99	15.82	1.760
Phase 3 Segments	18	13.30	13.55	0.25	-0.018	12.86	12.35	0.51	0.041

TABLE 3.5 STRATIFIED THREE-CLASS PERFORMANCE RESULTS, Part 2

Stratum	No. of Segments	Spring Wheat Estimate (%)	Spring Wheat True (%)	Spring Wheat E-T (%)	Spring Wheat $\frac{E-T}{T}$	Other Spring Small Grains Estimate (%)	Other Spring Small Grains True (%)	Other Spring Small Grains E-T (%)	Other Spring Small Grains $\frac{E-T}{T}$
(A) Acceptable	23	15.37	17.98	-2.60	-0.145	15.46	11.62	3.84	0.248
(B) Developmental	4	32.30	27.30	5.00	0.183	17.05	19.76	-2.71	-0.137
A Less B	19	11.81	16.01	-4.20	-0.262	15.12	9.90	5.22	0.527

TABLE 3.6 STRATIFIED THREE-CLASS PERFORMANCE RESULTS, Part 3

Stratum	No. of Segments	Spring Wheat Estimate (%)	Spring Wheat True (%)	Spring Wheat E-T (%)	Spring Wheat (E-T)/T	Other Spring Small Grains Estimate (%)	Other Spring Small Grains True (%)	Other Spring Small Grains E-T (%)	Other Spring Small Grains (E-T)/T
(A) Acceptable	23	15.37	17.98	-2.60	-0.145	15.46	11.62	3.84	0.330
(B) Problem Segments	4	9.05	26.30	-17.25	-0.656	25.26	6.38	18.88	2.959
A Less B	19	16.70	16.22	0.48	0.030	13.39	12.72	0.67	0.053
A Less B and Developmental	15	12.55	13.27	-0.72	-0.054	12.42	10.85	1.57	0.145

TABLE 3.7 STRATIFIED THREE-CLASS PERFORMANCE RESULTS, Part 4

		Spring Wheat				Other Spring Small Grains			
Stratum	No. of Segments	Estimate (%)	True (%)	E-T (%)	$\frac{E-T}{T}$	Estimate (%)	True (%)	E-T (%)	$\frac{E-T}{T}$
(A) Acceptable	23	15.37	17.98	-2.60	-0.145	15.46	11.62	3.84	0.330
(B) Red River Valley	8	24.74	20.29	4.45	0.219	14.52	17.37	-2.86	-0.197
A Less B	15	10.38	16.74	-6.36	-0.380	15.96	8.55	7.41	0.867

the truth at the 0.05 significance level. Table 3.7 indicates that more accurate estimates were made in the vicinity of the developmental segments than otherwise.

Parametric Evaluation of Sampling Variance. The sampling variances measured for spring wheat estimates are parametrically illustrated in Figure 3.9. Again, these represent the aggregated performance with 50 replicates over the 23 segments. A 5% significance bar is provided, as in Figure 3.5. Recall that since this graph is on a semi-log scale, this bar can be displaced to any position on the graph and will encompass curves for sampling parameters whose procedural variances are not significantly different. Once again, for a fixed number of labeled samples, the use of 40 or 60 strata results in variances are not significantly different at the 0.05 level. The variance reduction (R factor) relative to unstratified sampling using 40 strata and 100 labeled samples was 0.48.

The variances illustrated by the parametric curves in Figure 3.9 are attributable to the procedure's sampling strategy and estimation technique. It is of interest to examine how these variances compare to those contributed by other components such as the labeler. The two dashed lines appearing at 5.4% and 9.2% illustrate the RMS between-segment error for the spring wheat estimate of the developmental and other segments respectively. This clearly displays that the sampling efficiency of the procedure is well within the limits of accuracy provided by the labeling mechanism. In other words, the Procedure M framework is accurate and efficient with respect to the labeling source.

Table 3.8 is provided for completeness and contains summary statistics on a segment basis of the Procedure M evaluation using 40 strata and 100 labeled samples.

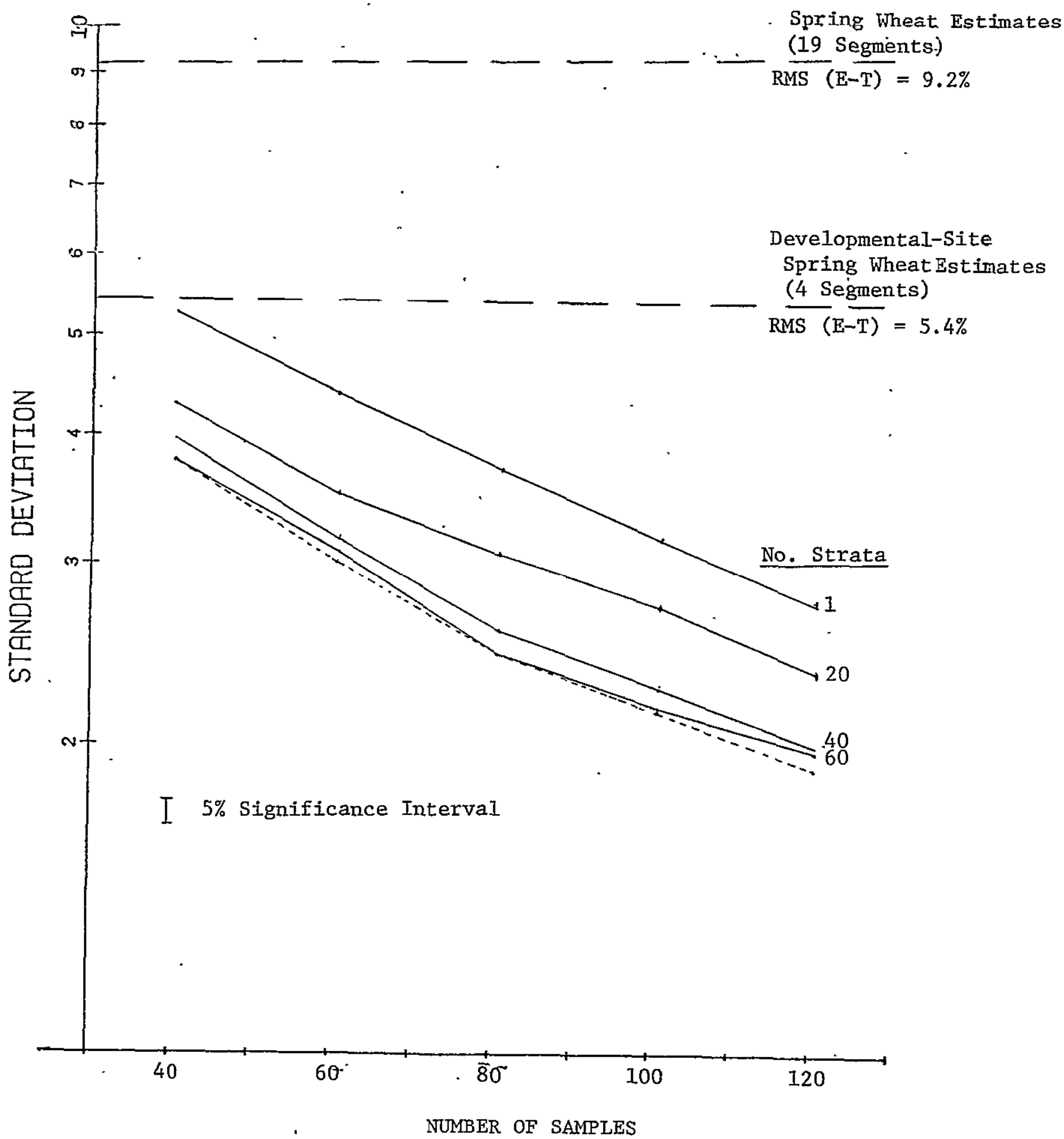


FIGURE 3.9 PROCEDURE M STRATIFIED SAMPLING VARIANCE, SPRING WHEAT

TABLE 3.8 SEGMENT PERFORMANCE RESULTS

40 Strata 100 Labeled Samples 50 Replications

	2-class (Tot. Spring Sm. Grains)				3-class Procedure M: Raw Spring Wheat			3-class Procedure M: Raw Other Spring Sm. Grains			3-class Procedure M: Unknown Spring Sm. Grains		
Segment	Mean Estimate	Sampling Std.Dev.	Expected Bias	Truth	Mean Estimate	Std. Dev. of Est.	Truth	Mean Estimate	Std.Dev. of Est.	Truth	Mean Estimate	Std.Dev. of Est.	Comment
1104	3.9%	1.7%	-0.2%	4.6%	0 %	0 %	0.0%	3.9%	1.7%	4.6%	0 %	0 %	
1498	29.5	3.0	1.4	28.9	13.3	2.3	8.6	16.1	2.7	20.3	0.1	0.2	
1512	27.9	1.8	-0.0	29.8	15.6	2.4	10.4	7.4	1.7	19.5	4.9	1.9	
1513	78.7	2.0	6.0	71.6	0.4	0.1	52.3	0.4	0.2	19.3	78.3	2.0	Rejected
1515	61.9	2.9	2.6	60.6	30.9	3.6	36.8	18.1	2.8	23.8	12.9	2.8	
1520	20.6	3.5	1.7	18.4	10.7	2.5	10.4	5.3	1.6	8.0	4.6	1.6	
1602	34.8	3.9	-0.1	35.7	22.9	2.8	31.1	7.0	1.5	4.6	4.9	2.3	
1606	36.6	2.9	3.6	31.9	7.6	2.4	24.5	3.6	1.5	7.5	25.4	3.2	Rejected
1614	41.5	3.2	2.8	38.5	16.5	2.5	25.1	20.4	3.0	13.5	4.6	1.7	
1633	43.8	2.2	3.2	39.7	20.3	3.1	37.2	11.8	1.9	2.5	11.7	3.0	
1637	38.8	2.6	2.5	35.0	9.7	1.9	31.9	28.4	2.6	3.2	0.7	0.7	
1640	52.5	3.2	4.4	48.6	35.9	3.2	31.5	15.5	2.1	17.1	1.1	0.8	
1642	61.4	3.1	5.7	53.5	28.3	3.5	38.7	17.7	2.6	14.8	15.4	3.3	
1652	32.6	2.7	0.5	36.5	4.2	1.7	24.7	22.5	2.5	11.8	5.9	1.6	
1662	52.7	2.9	5.4	44.9	20.2	2.6	36.8	32.2	2.3	8.1	0.3	0.4	
1663	53.4	1.6	3.5	50.2	37.0	2.6	32.3	12.2	2.0	17.9	4.2	1.6	
1669	7.4	1.9	-0.9	9.5	0.3	0.3	5.9	7.0	1.9	3.8	0.1	0.3	
1681	37.1	2.7	1.7	34.9	16.4	2.4	15.6	20.2	2.3	19.2	0.5	0.6	
1699	20.3	1.9	0.1	20.1	0.9	0.7	7.1	18.0	1.9	13.0	1.4	1.1	
1800	28.4	2.8	1.6	26.8	1.9	0.9	0.5	26.3	2.8	26.3	0.2	0.3	
1803	0.3	0.4	0.2	0.5	0.2	0.2	0.0	0.1	0.3	0.5	0	0	
1805	13.1	2.6	-0.9	14.7	3.1	1.2	0.3	9.8	1.3	14.4	0.2	0.4	
1811	2.7	1.4	-0.2	2.5	2.2	1.4	0.1	0.5	0.4	2.4	0	0	
1899	65.3	3.4	5.6	58.9	7.3	1.6	28.6	13.4	2.5	30.3	44.6	3.8	Rejected
1913	13.0	2.5	-0.8	14.3	0.8	0.8	11.8	11.6	2.4	2.5	0.6	1.0	
1927	31.8	2.9	1.6	29.9	11.5	2.4	16.7	15.7	2.3	13.3	4.6	1.8	

3.1.3 SUMMARY OF SYSTEM PERFORMANCE

Procedure M configured for spring wheat has been parametrically evaluated using 26 LACIE Phase 2 and Phase 3 Blind Sites distributed across the Northern Great Plains. Encouraging results were achieved in estimating total small spring grain and spring wheat proportions. Analysis of results showed that:

1) Procedure M provided accurate total spring small grains proportion estimates with respect to the source of labels.

2) High variance spring wheat estimates were made at the segment level.

3) Poor spring wheat results in certain segments were seemingly systematic in nature and probably related to ancillary conditions; four segments exhibited poorest results; the aggregated estimate based on the remaining 19 of 23 segments for which spring wheat estimates were made exhibited an absolute error of 0.5% and a relative error of only 3%. Implying that the spring wheat discriminant function was accurate when employed within the appropriate stratum (excluding Phase II and moisture stressed segments -- see Section 3.2.1)

4) Within-segment sampling variance is not a key issue with this procedure; accurate labeling of samples is critical.

This overall evaluation does point to the need for a critical analysis of the component parts of Procedure M, in particular the spring wheat labeling mechanism. Section 2.2 provides evaluations of these components. The overall mechanism and procedural concept is sound, exhibiting both accurate and efficient estimates of crops. Improvement in certain components may result in levels of accuracy for spring wheat estimates that were not expected, given the problem's degree of difficulty.

3.2 TEST AND EVALUATION OF COMPONENT PERFORMANCE

In addition to evaluating the overall performance of Procedure M for spring wheat, the tests and analyses were conducted so that the performance of individual system components could be evaluated. Evaluations of four major components -- machine labeler, stratification, spatial feature definition, and haze correction -- are presented below.

3.2.1 EVALUATION OF LABELER PERFORMANCE

For purposes of machine labeler evaluation, 18 segments were used.* This subset excludes the four segments used for development of the machine labeling criterion. An additional six segments had little or no spring wheat present. Since, as will be explained later, spring wheat labeling accuracy served as the primary indicator of labeling success, these six segments offered little or no additional information for evaluation, and were therefore excluded. The locations of the 18 remaining segments are shown in Figure 3.10.

3.2.1.1 Results

Overall accuracy of labeling for spring wheat and barley pixels was 53%, with 81% of the barley pixels receiving correct labels compared to 45% of the spring wheat pixels. Table 3.9 summarizes the overall results by crop and year. (See Appendix E for a segment-by-segment breakdown of results for the entire test set.)

Figure 3.11, which is a plot of overall accuracy by segment (ordered according to decreasing small grains percentage), illustrates the wide variability of results. However, a sub-grouping of the segments is also suggested by the graph. By dividing the 18 segments into two groups based on labeling accuracy (greater than 50%, or less than 50%), a clearer understanding of labeler performance can be gained. Table 3.10 summarizes the labeling accuracy for these two groups, again by crop and year.

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*16 were drawn from the 26 described in Section 3.1. Two additional segments were available for this evaluation but were not available for full scale testing due to incomplete wall-to-wall ground truth.

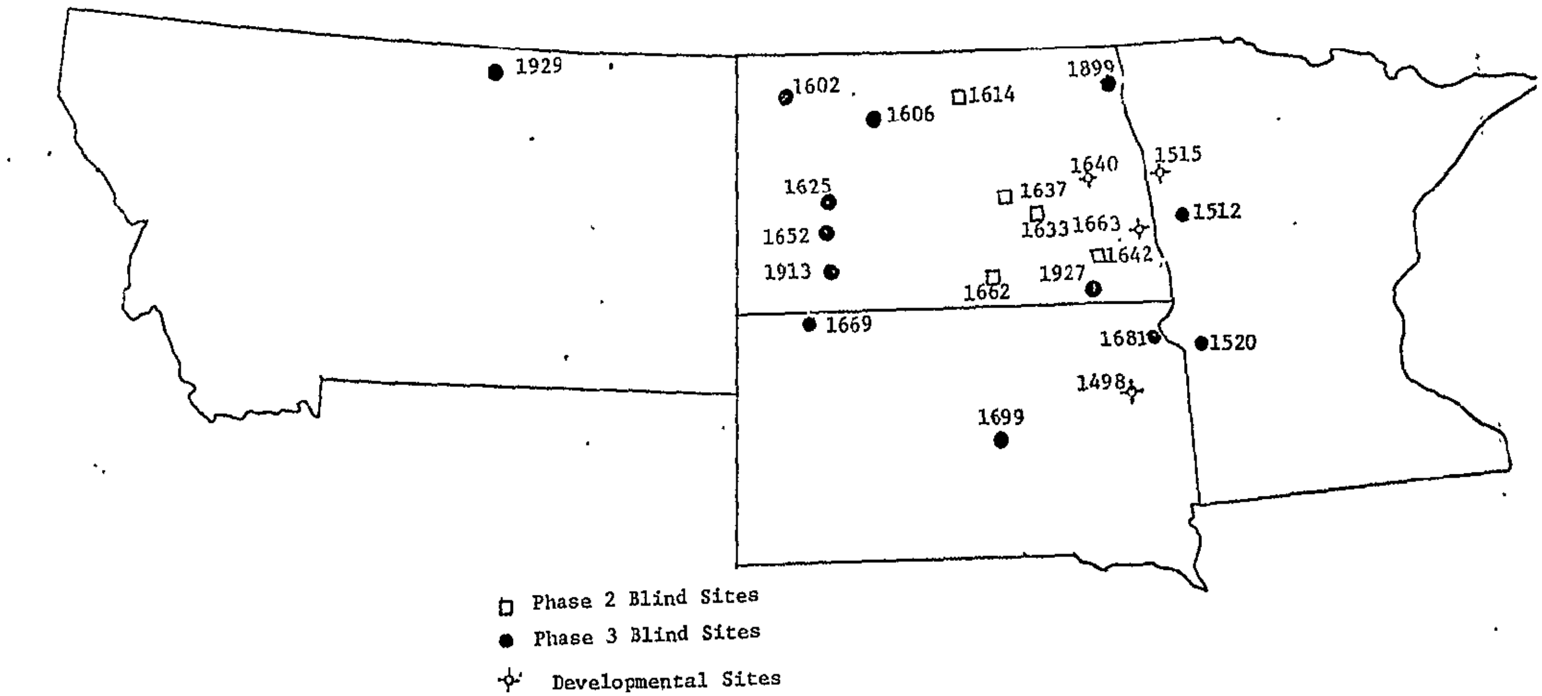

FIGURE 3.10 LOCATION OF SITES USED IN LABELER PERFORMANCE ANALYSIS

TABLE 3.9 LABELING ACCURACY FOR SPRING WHEAT AND BARLEY PIXELS

	Phase 2	Phase 3	Total
Spring Wheat	43%	51%	46%
Barley	72%	86%	81%
Overall	46%	60%	53%

TABLE 3.10 LABELING ACCURACY FOR TWO GROUPS OF SEGMENTS

	"Good" Segments (> 50% Accuracy) 3 Phase 2 Sites 8 Phase 3 Sites			"Bad" Segments (< 50% Accurac 2 Phase 2 Sites 5 Phase 3 Sites		
	Phase 2	Phase 3	Total	Phase 2	Phase 3	Total
Spring Wheat	58%	71%	65%	33%	7%	25%
Barley	71%	80%	77%	74%	99%	91%
Overall	--	--	68%	--	--	34%

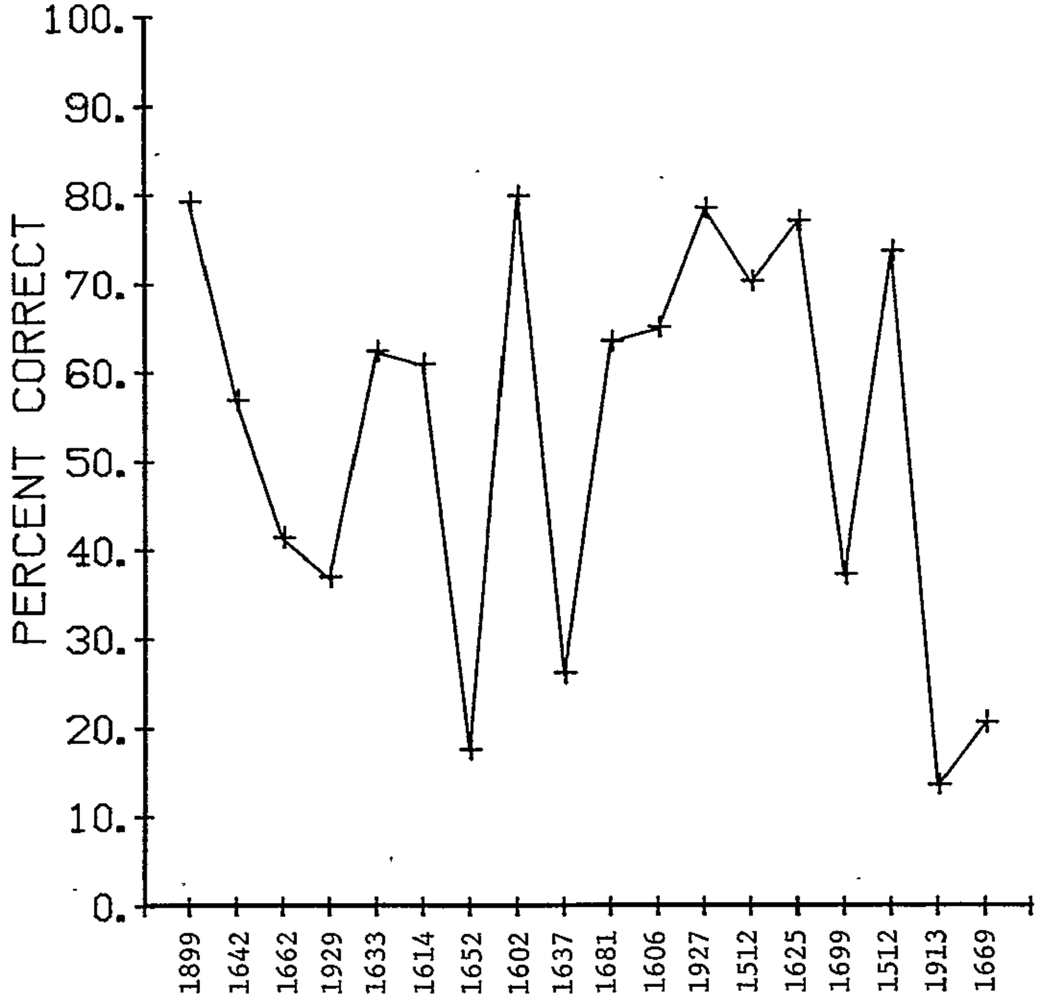

FIGURE 3.11 LABELING ACCURACY FOR SPRING WHEAT AND BARLEY PIXELS, BY SEGMENT

Clearly, the factor that drives the overall accuracy down is the reduced labeling accuracy for spring wheat pixels. In fact, barley labeling accuracy actually increased from the greater-than-50% (good) segments to the less-than-50% (bad) segments.

Although the labeling criterion was developed using spring wheat and barley pixels only, the procedure is meant to label all the small grains (spring wheat, barley, oats, rye, and triticale). For the 28 segments which comprised the entire data set, there were no triticale pixels and only a few rye pixels. There were, however, enough oats pixels to provide an indication of the procedure's success in separating them from spring wheat pixels. Table 3.11 summarizes the results for oats.

3.2.1.2 Evaluation of Results

As described earlier, the decision criterion for labeling is based on a distance in Brightness-Greenness space which increases from the time of heading through the dough stage of development. Since barley fields have been observed to ripen somewhat faster than spring wheat fields, a greater distance on any given day in the critical day range (defined in Section 2.2.1) should indicate a barley pixel.

Consider, however, the result of a localized increase in the rate of crop development. In this situation, distances on a given day should tend to be greater than they would be under normal conditions. One should find, then, that both crops tend to be a greater distance from the reference line than that selected as the spring wheat/barley discrimination value. Thus spring wheat pixels would be mistaken for barley pixels, while barley pixels would be even more likely to be correctly labeled. This is precisely the result we see in Table 3.10, suggesting that the poor results were indeed caused by an increase in the crop develpment rate.

While such an increase could be the result of a number of factors, one of the most likely candidates is environmental stress, and particularly moisture stress. This stress could take the form of perennially low

TABLE 3.11 LABELER RESULTS FOR OATS PIXELS

	Label Assigned	
	Spring Wheat	Other Spring Small Grains
Overall	40%	60%
Good Segments	56%	44%
Phase 2	60%	40%
Phase 3	51%	49%
Bad Segments	18%	82%
Phase 2	23%	77%
Phase 3	2%	98%

moisture (i.e., arid regions) or exceptionally low moisture (i.e., drought). In either case, however, the effect should be felt over a larger region than a single segment. If moisture stress is indeed the cause of the change in development rate, then one would expect to see a geographical clustering or delineation between good and bad segments.

Although such a separation is not apparent in Phase 2 (perhaps only because of the low number and limited distribution of Phase 2 segments in the test set), the separation is readily apparent for the Phase 3 segments, as shown in Figure 3.12. Segments located in the southwestern or western portions of the region, where moisture stress is more likely, yielded poorer labeler results than those in the less arid portions of the region. The same geographical trend is evident in the labeling results for oats. In the northeastern portion of the region (N. Dakota and Minnesota), oats tended to fall into the spring wheat class, while in the southern and western portions (S. Dakota and Montana), oats tended to fall into the other spring small grains class. Finally, LACIE weather summaries reported moisture stress for the general region of the bad segments. Thus we conclude that moisture stress in part of the test region caused an increase in the rate of crop development, which in turn resulted in poor spring wheat labeling accuracy.

Since moisture stress should influence the green development profile, it might be possible to detect such a condition, using the profile, and adjust the decision criterion accordingly. For example, the estimated peak greenness value should indicate the vigor of the field being observed. Similarly, the rate of decrease in greenness from the peak value to the value in the critical day range should be an indicator of the rate of crop development, with a steeper slope indicating a more rapid development rate. Preliminary examination of these and other such indicators is in progress.

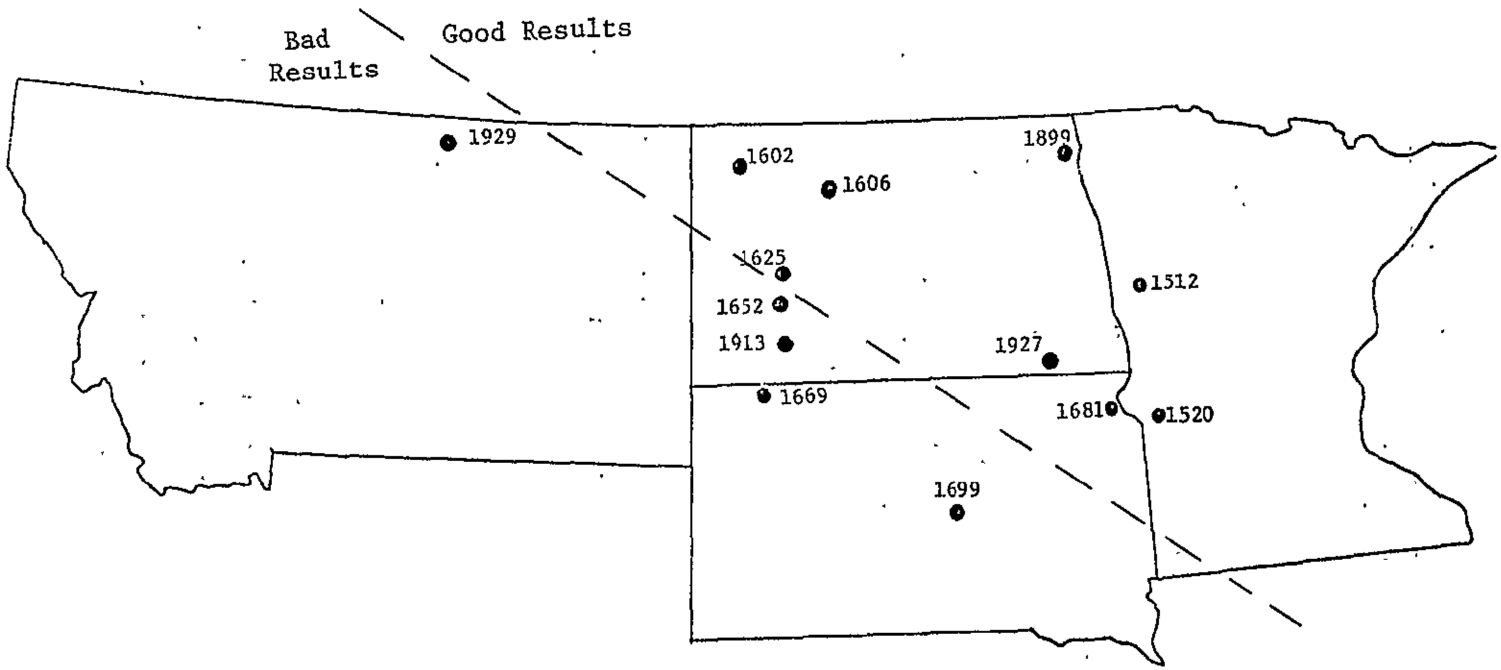

FIGURE 3.12 GEOGRAPHICAL STRATIFICATION OF RESULTS (PHASE 3)

3.2.2 EVALUATION OF SPECTRAL STRATIFICATION

The technique currently employed to establish spectral strata from among the set of quasi-fields formed is called BCLUST. This algorithm is described in Section 2.2.3. Its evaluation is discussed in this section.

BCLUST conducts an unsupervised, multiple-pass clustering of spectral means of quasi-field interiors to produce a fixed number of spectral strata. These strata are formed to direct samples in a manner that, compared to unstratified sampling, would reduce the variance of the estimate made. The success of this procedure is measured by its ability to group quasi-field means into strata that are all grain or all non-grain. Ideally only two strata are needed -- the group of grain clusters, and the group of other clusters. Such a procedure would require drawing only one sample to identify which stratum is which. This, of course, has not been realized.

The variance reduction factor, R_{mn}, was earlier defined and used in describing the efficiency gained in Procedure M due to stratified sampling. This R factor was determined using the measured variation of the procedure. The availability of wall-to-wall ground truth permits the use of a measure that is closely related to the variance reduction factor, called the expected variance reduction factor (R_E factor). The R_E factor can be used to evaluate the degree of separability realizable at any level of stratification. This factor is used to evaluate the performance of BCLUST and of BLOB.

The expected variance reduction factor, R_E, is defined as follows:

$$R_E = \frac{\sum_{i=1}^{m} \left(\frac{n_i}{n}\right) P_i(1 - P_i)}{P(1 - P)}$$

where

n_i the number of pixels in stratum i
n the number of pixels in all strata
m is the number of strata
P_i is the true grain proportion in stratum i
P is the true grain proportion in all strata

If the R_E factor is 0, then the strata are either pure grain or pure other. If R_E = 1 the strata are no purer than the segment as a whole. This latter case is equivalent to unstratified sampling; hence sampling variance is not improved by such stratification. The value $R_E = 0.5$ is approximately equivalent to an 85% average purity among strata.

Figure 3.13 illustrates the R_E factor of the four strata cases employed in the evaluation. The use of 20 strata significantly reduces the R_E factor from unity, with further reductions with the employment of 40 and 60 strata, although the latter two cases track closely. BCLUST strata purity is ultimately limited to the purity of the set of quasi-fields. The associated R_E factors for BLOB are listed in Table 3.12 and plotted as the bottom line in Figure 3.13. In examining the BLOB R_E factor, keep in mind that it is not a linear measure of purity as a function of the grain proportion, p. As p approaches zero, R_E will increase disproportionally due to the defining ratio expression. Hence the R_E factors of the segments at the right hand side of Figure 3.13 are somewhat inflated. The R_E factor of Segment 1652 is large for a different reason that is further discussed in Section 3.1.2.

Figure 3.13 illustrates, as well, that unless limited by available crop separability, additional reduction of this factor can be realized. The employment and evaluation of other stratification strategies is suggested, at least as a basis of comparison.

3.2.3 EVALUATION OF SPATIAL FEATURE DEFINITION

An integral component of Procedure M is the definition of spatial features that we call quasi-fields. Quasi-fields are used as labeling and sampling targets. In addition, scene stratification, described in Section 2.2.3 is based on an unsupervised clustering of the spectral means of quasi-fields. Procedure M for spring wheat employs the BLOB algorithm, described in Section 2.2.4, to structure quasi-fields. A discussion and evaluation of the performance of BLOB in Procedure M is presented in this section.

FIGURE 3.13 BCLUST EXPECTED VARIANCE REDUCTION FACTOR

TABLE 3.12 BLOB PERFORMANCE STATISTICS

Segment	Quasi-Fields Number	Quasi-Fields Number With Interiors	% of Segment Covered	Grain Proportion	R_E Factor Int. Pixels	% Purity Int. Pixels	Exp. Bias
1513	1195	378	78.9	71.60	0.022	99.4	5.99
1515	1074	474	80.0	60.58	0.064	97.6	2.61
1899	1756	415	69.8	58.87	0.043	98.4	5.57
1642	1181	452	81.2	53.45	0.155	95.2	5.73
1663	1760	455	66.5	50.17	0.026	98.8	3.48
1640	1437	488	74.7	48.63	0.114	96.0	4.35
1662	1021	451	83.7	44.89	0.161	94.4	4.39
1633	1163	401	79.9	39.67	0.076	97.2	3.21
1614	1307	445	71.9	38.53	0.253	91.1	2.76
1652	1209	427	76.5	36.49	0.353	85.4	0.51
1602	1820	395	60.2	35.66	0.188	93.9	-0.08
1637	1296	474	79.5	35.04	0.102	96.4	2.54
1681	1248	477	78.6	34.87	0.071	97.2	1.65
1606	1927	455	63.1	31.89	0.107	96.1	3.60
1927	993	442	84.0	29.94	0.099	96.6	1.61
1512	1319	449	72.2	29.83	0.120	96.0	-0.02
1498	1027	470	81.5	28.90	0.136	95.3	1.42
1800	1233	510	79.7	26.76	0.109	96.4	1.58
1699	697	358	89.5	20.08	0.082	97.6	0.13
1520	1466	472	70.8	18.42	0.137	96.1	1.72
1805	1241	461	78.6	14.73	0.333	94.0	-0.89
1913	979	382	77.6	14.29	0.206	96.7	-0.82
1669	414	251	94.9	9.54	0.442	95.7	-0.89
1104	605	320	89.0	4.61	0.101	98.3	-0.24
1811	1574	478	72.4	2.46	0.115	98.7	0.23
1803	866	342	86.2	0.51	0.389	99.0	-0.23
Average		429	77.7%			96.3%	

A quasi-field is a set of spatially contiguous pixels that may or may not correspond to a real farm field. A quasi-field is comprised of interior pixels and edge pixels. An interior pixel is one whose four strong neighbors are in the same quasi-field. Procedure M samples from, and bases its estimate only on, the set of quasi-fields with interior pixels. Fields comprised of only edge pixels thus form a stratum that is not sampled.

On the average 429 quasi-fields with interior pixels were formed by the BLOB algorithm in each of the 26 segments used in the procedural evaluation. This stratum covered 78% of each segment on the average, with 22% not being sampled. Table 3.12 presents information about the performance of BLOB on a segment-by-segment basis. Elaboration follows.

The major criterion to be used in evaluating BLOB performance is whether the quasi-fields formed properly represent the contiguous areas of spring small grain and other classes. Since a subset of quasi-fields formed in a segment are used as labeling targets, it is important to evaluate how these structures are visually presented to the analyst interpreters, and to determine what advantages may arise in labeling quasi-fields rather than dots (as in LACIE Procedure 1).
Figure 3.14 is a typical map of the interior of quasi-fields, produced in Montana Segment 1929. In a region where strip cropping is practiced, field structure is strikingly apparent and road boundaries are visible. Sixty of these quasi-fields have been outlined to illustrate a set of labeling targets that could be presented to an analyst. Nearly all of these quasi-fields are associated with real fields. Mixture pixels are not singled out as targets, though small fields containing only one interior pixel do appear.

Several measures of BLOB performance have been utilized. One measure, the R_E factor, is related to the minimum variance that a subsequent sampling procedure can expect to achieve. The R_E factors for quasi-field interiors are listed in Table 3.12. The R_E factor is related

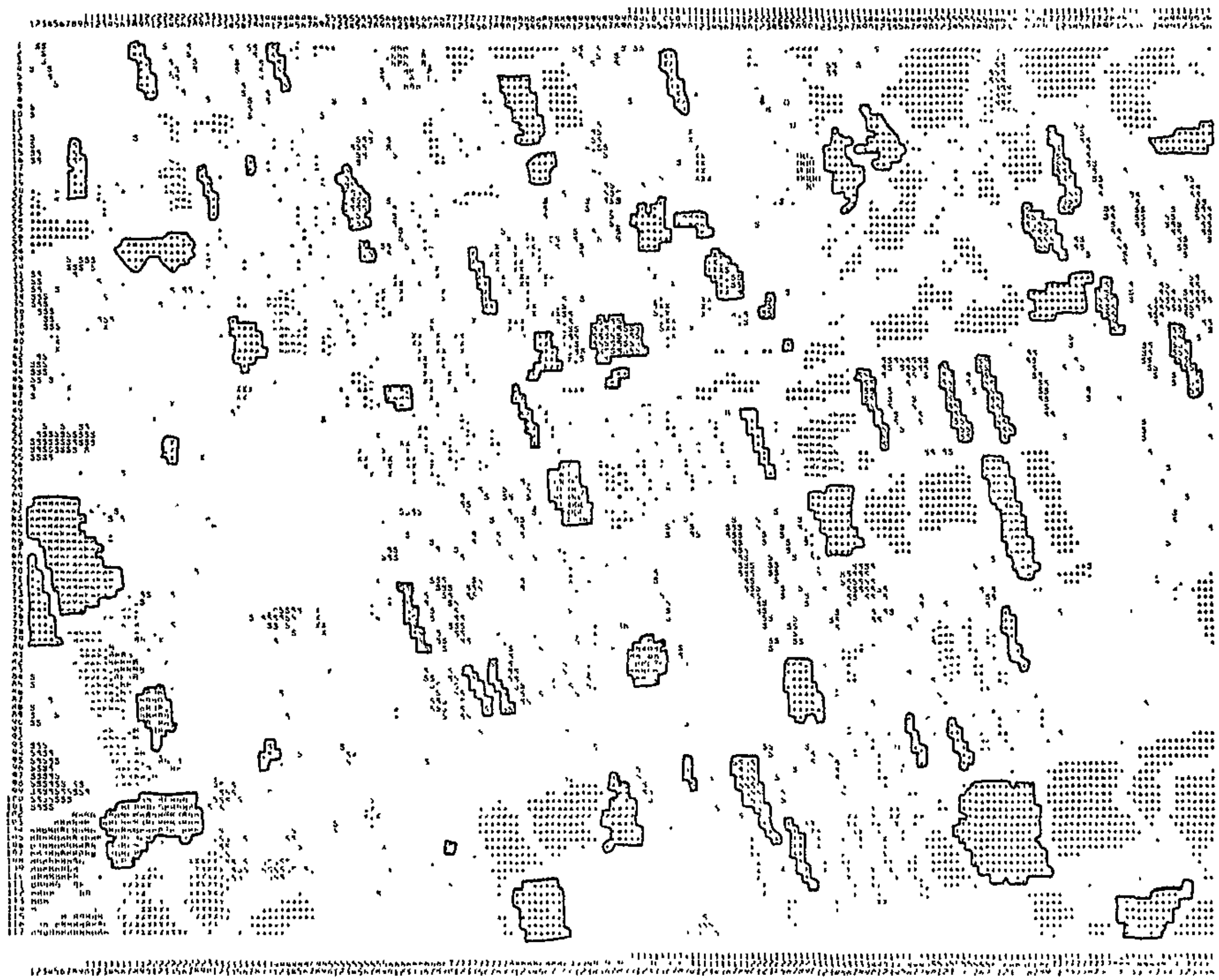

FIGURE 3.14 MAP OF INTERIORS OF QUASI-FIELDS, SEGMENT 1929

to the percent purity measure also listed in Table 3.12. Over all segments, the interiors of quasi-fields formed were found to be 96.3% pure, that is, only 3.7% of the time were they found to be a mixture of spring small grain and other. Figure 3.15 illustrates the purity factor for each segment. Quasi-field edge pixels obviously were more mixed than interior pixels.* Interiors, which would operationally be used as labeling targets, were found to be composed of a single crop class of interest. This makes feasible the assignment of single class, rather than proportional, labels to fields. In addition it is conjectured that the elimination of any need to label mixture pixels makes the task of labeling quasi-fields a feasible one, more so than that of dot labeling.

3.2.4 EVALUATION OF ATMOSPHERIC HAZE CORRECTION

During the development of the spatially varying XSTAR haze correction procedure, attention was focused on computational cost as well as haze correction performance as criteria for evaluating the algorithm. The computational cost was observed to be primarily a function of the block size used to quantize the moving window aspects of the procedure. This relation between computational cost and block size is illustrated in Figure 3.16. We had expected that, while the computational cost would increase as the block size was decreased, the performance should increase with decreasing window size until the moving window became too small to provide a statistically representative haze diagnostic for the procedure. What we observed with respect to performance, however, is shown in Figure 3.17. Although the figure does not indicate performance for windows smaller than 15 lines by 15 pixels (measured between half amplitude points), in general we observed no evidence that the performance

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*Segment 1652 is the only segment whose apparent interior purity was less than 90%. It was found that the ground truth used to label many of the strip fields in the segment did not distinguish between individual grain and other strips, whereas the BLOB algorithm often could separate the two. The evaluation programs assumed that any blob labeled 'Strip' was 50% grain and 50% other, resulting in an artificially lower average purity.

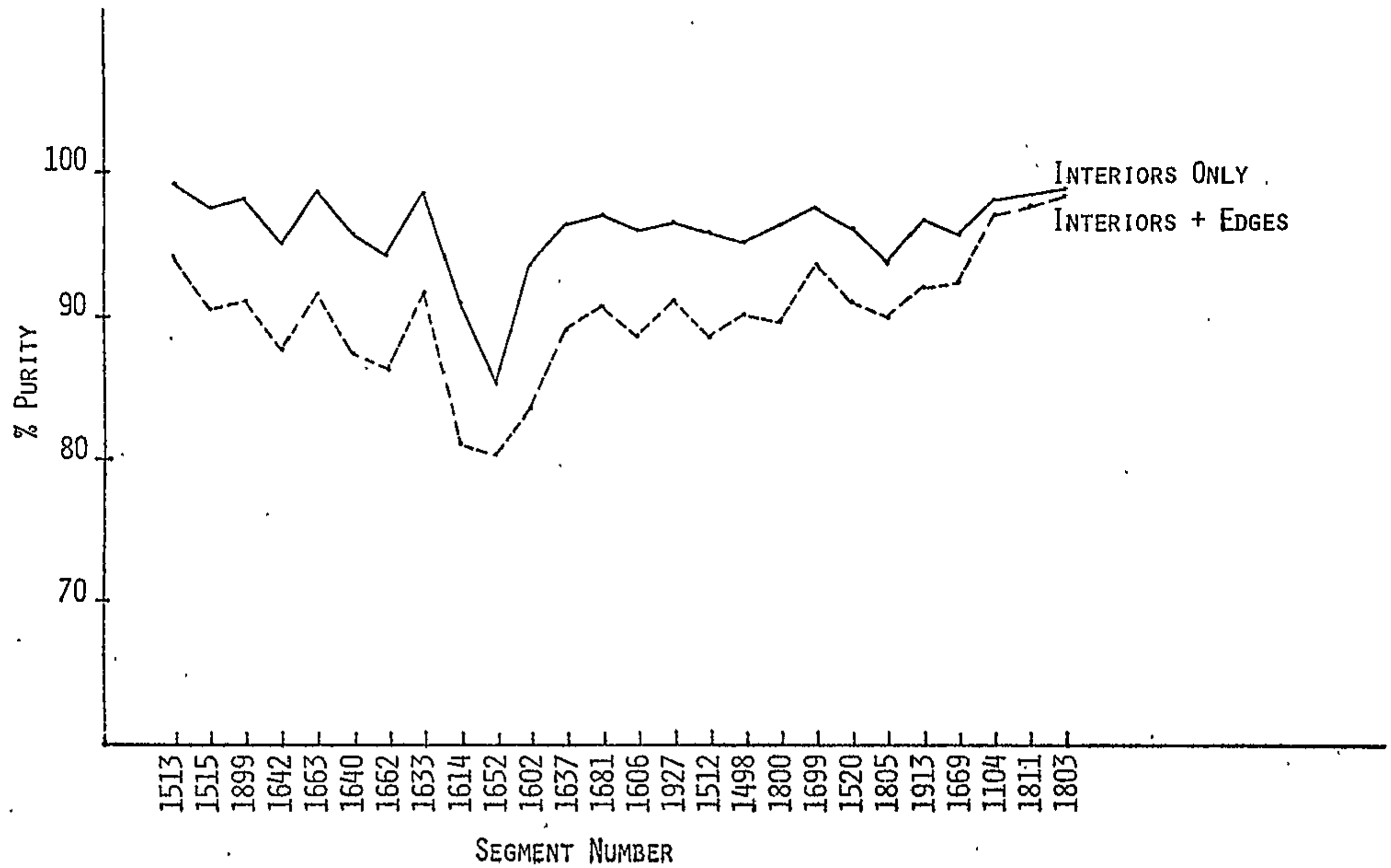

FIGURE 3.15 QUASI-FIELD PURITY (%)

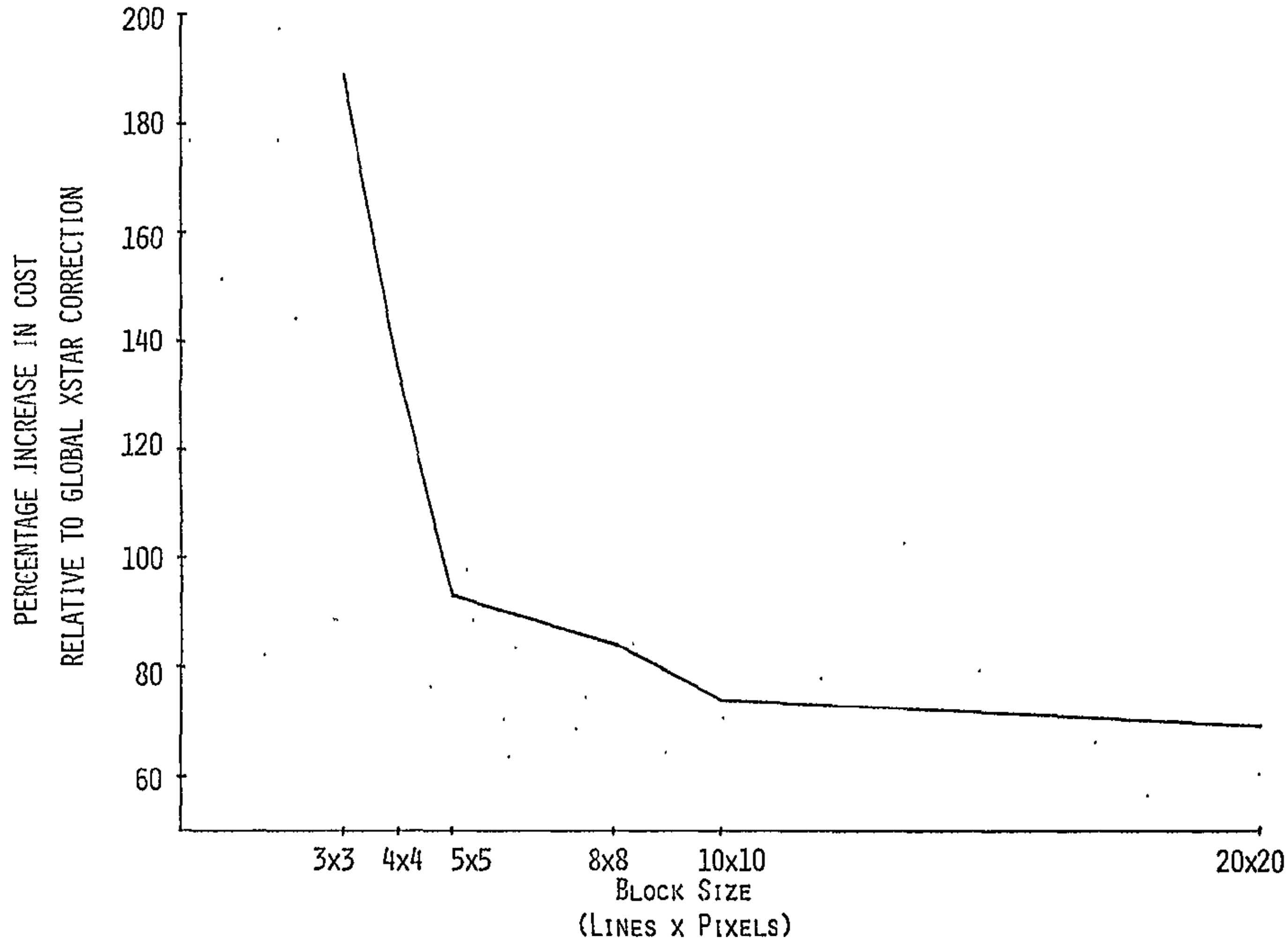

FIGURE 3.16 COST OF SPATIALLY VARYING XSTAR HAZE CORRECTION AS FUNCTION OF BLOCK SIZE USED

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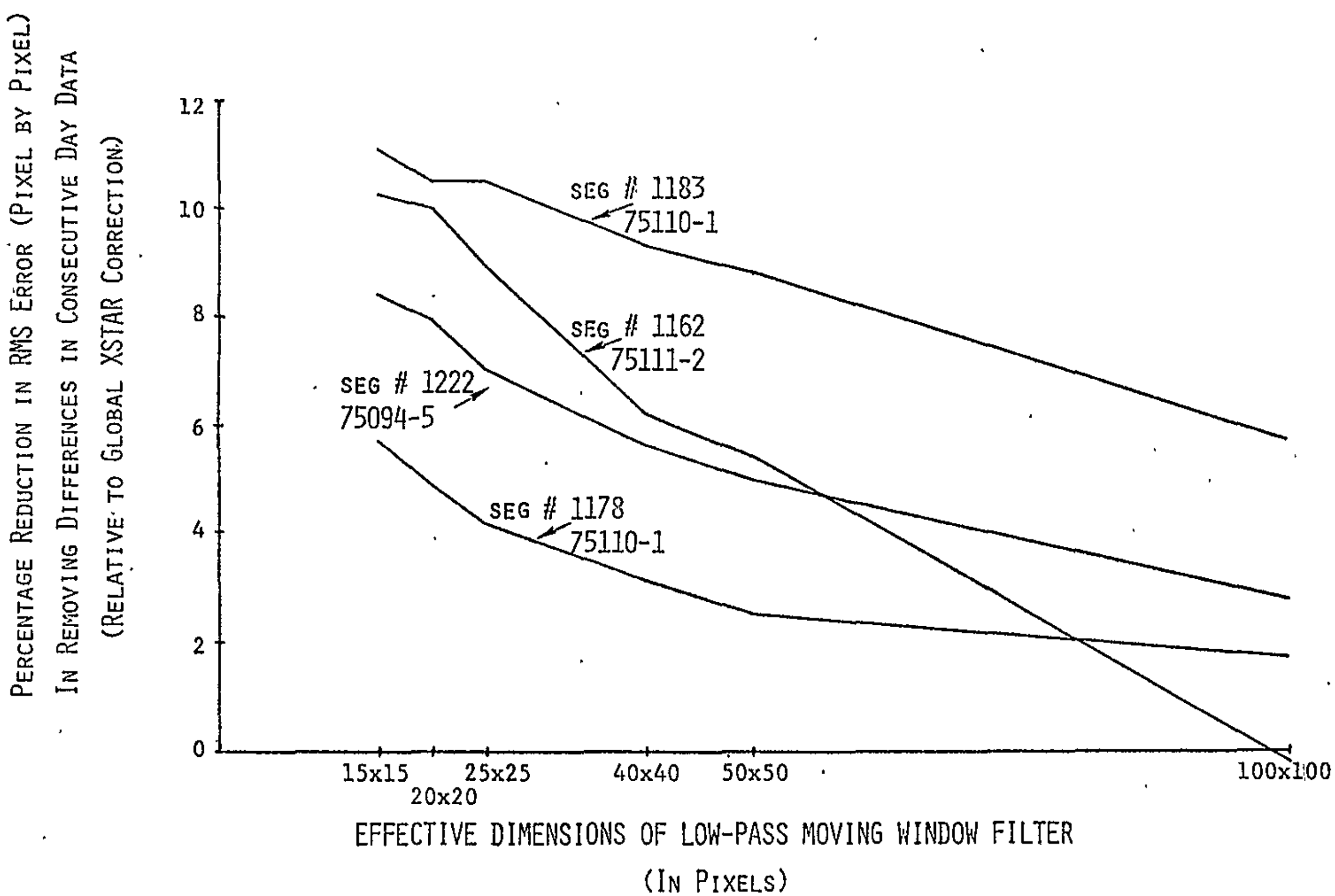


FIGURE 3.17 PERFORMANCE OF SPATIALLY VARYING XSTAR HAZE CORRECTION ON FOUR CONSECUTIVE-DAY DATA SETS WITH VARYING HAZE CONDITIONS

leveled off as the window size decreased below the 15 x 15 size. We decided that the 15 x 15 window size was the smallest practical size for the window, however, because a smaller window would have required a block size smaller than 5 x 5 for proper performance, and the computational cost began to increase dramatically for block sizes smaller than 5 x 5.

Since the spatially varying haze correction procedure applies a different correction to each pixel, performance has been evaluated by measuring the pixel by pixel differences between approximately equivalent scenes (consecutive day Landsat acquisitions) before and after correction. The alternative would have been to use ground reflectance measurements from representative scenes to establish an NE$\Delta\rho$ (Noise Equivalent Change in Reflectance) performance figure; however, present reflectance data are too sparse to provide a proper evaluation of the spatially varying nature of the algorithm. On the other hand, one inherent limitation in using pixel by pixel differences between haze corrected consecutive day scenes as a measure of preprocessing performance is that distortions introduced to both scenes in an equivalent way (e.g., due to misleading haze diagnostics from non-vegetated portions of the scene) are not measured. However, an approximate assessment of these distortions can be made by looking for areas of abnormal contrast in a corrected image. In general the corrected images have been found to exhibit only minor distortions of this sort, while the beneficial aspects of the correction are dramatically apparent in images wherever non-uniform haze is present. Thus, the performance of the spatially varying haze correction has been statistically measured by calculating the root-mean-squared Euclidean distance between registered pixels in consecutive day Landsat data before and after correction. (This performance measure uses only pixels which have passed the screening procedure on both days of a consecutive day acquisition.) Some example results of this type are presented in Table 3.13 for three scenes in which significant spatial haze variations were apparent on one or both days. The RMS error figures in this table include "error" contributions from some effects other than haze

TABLE 3.13 RMS ERROR IN REMOVING DIFFERENCES IN CONSECUTIVE-DAY DATA (IN LANDSAT COUNTS)

	Untransformed (UT)	Global XSTAR		Spatially Varying XSTAR	
	RMS Error	RMS Error	Improvement Over UT	RMS Error	Improvement Over UT
Segment #1619 77175-6	11.7*	10.1*	13.5%	9.1*	21.7%
Segment #1640 77139-40	13.7	11.3	17.7%	9.8	28.8%
Segment #1927 77193-4	16.2	11.5	29.1%	9.3	42.8%

*Non-atmospheric effects set a lower bound of 3 to 6 counts on this RMS error figure, depending on the scene being processed.

variations. These other effects include bidirectional effects in crop appearance (due to an approximate 6^{o} change in view angle from one day to the other), misregistrations of pixels between acquisitions (which were minimized, but could not be completely removed), and quantization effects (due to the digital nature of the data). These other effects set a lower bound of approximately 3 to 6 counts on the RMS error figure, depending on the scene being processed. For scenes with uniform haze conditions, the spatially varying XSTAR performance is equivalent to the global XSTAR performance which has been reported previously [33]. For scenes with non-uniform haze conditions, the spatially varying XSTAR performance is a significant improvement over that of the global procedure, as indicated in Table 3.13. We estimate, based on tests over numerous consecutive day acquisitions [33], that the XSTAR haze correction approximately doubles the amount of data which is amenable to signature extension or multisegment training applications.

4
SUMMARY, CONCLUSIONS, AND RECOMMENDATIONS

4.1 SUMMARY

Procedure M, an objective multicrop area inventory procedure, has been defined. It is a modular system with state-of-the-art components which is readily modified or configured for different applications. In the LACIE context, Procedure M's major differences from LACIE Procedure 1 are: (a) additional preprocessing to correct for atmospheric haze variations and to perform other normalizations and transformations, (b) definition and use of more strata, (c) definition, selection, and labeling of quasi-field interiors in the scene instead of labeling individual pixels, and (d) proportion estimation without maximum likelihood classification. Procedure M evolved from, and incorporates developments and understanding gained from, a series of supporting research and technology tasks that have been pursued at ERIM, as well as other organizations in JSC's SRT community.

Procedure M was configured for spring wheat inventory by including a two-step labeling process. First, an analyst labels each sampled quasi-field as either 'Spring Small Grain' or 'Other'. Then a machine labeler refines the label of the 'Spring Small Grain' samples, assigning either a proportional label between 'Spring Wheat' and 'Other Spring Small Grain' or the label 'Unidentifiable Spring Small Grain'. The machine labeler makes use of a temporal profile of the Greenness component of Landsat data to estimate crop calendar shifts and detects the less rapid maturation or brightening of wheat.

4.2 CONCLUSIONS

Extensive tests of the spring wheat configuration of Procedure M were made using Landsat data from 26 LACIE blind test sites in North Dakota, South Dakota, Minnesota, and Montana -- five from Phase 2 (Summer 1976) and the remainder from Phase 3 (Summer 1977). The tests were designed to assess both the bias and variance of the procedure's performance in estimating crop areas, by use of 50 replicates (estimates using different selections of quasi-fields for labeling) for each test case. In addition to testing the configuration's design of 40 spectral strata and 100 samples for labeling, 19 other combinations of strata and samples were tested.

Accurate two-class (spring small grains vs. other) proportion estimates were achieved in tests using ground truth labels as a substitute for analyst labels. Only a slight absolute bias (<2%) was observed and this was found to be primarily due to not sampling those (small) quasi-fields which are without interior pixels. The use of 40 spectral strata and labeling of 100 quasi-fields provided low-variance proportion estimates (standard deviation, $\sigma = 2.5\%$). The average reduction of variance factor was 0.34 for the procedure. Use of more strata or more samples does not appear to be warranted.

Encouraging but less accurate three-class (spring wheat, other spring small grains, and other) performance was found when results were aggregated over the 23 segments for which proper acquisitions were available. The absolute bias was relatively low (-2.6% for spring wheat and +3.8% for other spring small grains) and the variance attributable to sampling was about the same as for two classes. On the other hand, segment-to-segment variance, largely attributable to labeling errors, was much larger ($\sigma = 9.2\%$). In analyzing these results, systematic spring wheat errors were noted for certain subsets of segments. The fixed decision rule employed by the machine labeler was developed using four Phase 3 sites. Spring wheat errors were greatest for Phase 3 sites to the far West and Southwest of the development sites and for two of the five Phase 2 sites. Nineteen of the twenty-three segments were found to be in a stratum in which it was reasonable to employ the spring wheat discriminant developed on four segments. The absolute error of the spring wheat estimate in this stratum was less than 0.5% with a relative error of 3%.

Moisture stress is a likely cause of many of the spring wheat labeling errors. Moisture stress accelerates the rate of maturation of grains, the characteristic being used in the labeler. Indications of moisture stress were found in collateral data for those Phase 3 areas where performance was poorest, leading to hopes that an improved machine labeler can be developed in the future.

In developing Procedure M we gained understanding and incorporated improvements in other system components besides the labeler. An unbiased procedure for sampling quasi-fields for labeling was developed and improvements were made in our spectral stratification procedure. Increased knowledge of the BLOB algorithm led to the development of a standard parameter set for use in wheat inventory, as well as a method for maintaining field definition in spite of cloud-covered data. Also, haze correction procedures were improved by the development and implementation of a version that applies a spatially varying correction.

4.3 RECOMMENDATIONS

It is recommended that Procedure M tests be expanded to include analyst labeling of quasi-fields, a step that has not yet been tested. In addition, efforts to develop a moisture stress indicator should be undertaken and the mechanism, when developed, should be incorporated into the machine labeler to allow appropriate localized adjustment of the spring wheat decision rule. Continued development of machine labeling techniques for these and other crops is recommended.

It is also recommended that efforts be addressed to possible improvements in other components of Procedure M. The bias caused by not sampling edge pixels and small fields should be analyzed and corrected. Additional improvements in the spectral stratification technique can be expected to further reduce the sampling variance. Finally, the application of Procedure M to additional crops, such as corn and soybeans in segments acquired during the 1978 season, and performance evaluation are recommended.

As was mentioned earlier, JSC's Procedure 1 is an initial implementation of a statistical sampling viewpoint applied to the spectral domain of remotely sensed data. Procedure M carries this development further in several important respects; by the use of state-of-the-art preprocessing, normalization and feature extraction techniques based on a physical interpretation of Landsat MSS data; by extending the spectral stratification concept with multiple strata to produce improved sampling efficiency; by using an unbiased technique of cluster sampling; by providing natural (field-like) labeling targets; and by automatic labeling applied to an especially difficult discrimination problem, spring wheat from other spring small grains. As mentioned above, further development in these various component areas is recommended. In addition, in the longer term, further synthesis of classification and sampling viewpoints, and research toward that goal is recommended. Procedure M is one realization of a flexible, modular, and efficient testbed which can be used to test advanced procedures which will derive from such a synthesis.

APPENDIX A
PROOF OF UNBIASEDNESS OF MIDZUNO SAMPLING TECHNIQUE

The Midzuno sampling technique is described and illustrated by example in Section 2.2.2. This appendix presents both an algebraic proof of its unbiasedness and an empirical demonstration.

A.1 ALGEBRAIC PROOF

We suppose that

- S is a sample of k fields* to be chosen
- B is the number of fields in the stratum
- n_i is the number of pixels in the i^{th} field
- p_i is the proportion of wheat in the i^{th} field
- N is the total number of pixels in the stratum

We will prove that the proportion of wheat in the sample

$$\frac{\sum\limits_{i\varepsilon S} n_i p_i}{\sum\limits_{i\varepsilon S} n_i}$$

is an unbiased estimate of the proportion of wheat in the stratum

$$\frac{\sum\limits_{i\ \varepsilon\ \text{stratum}} n_i p_i}{N}$$

We first show that, as in the example, the technique chooses a sample with probability proportional to the size of the sample (i.e., the number of pixels in the sample).

The sample S of k fields is chosen in one of k distinct ways depending on which field, i, is chosen first. The probability of one of the ways is

*In Procedure M for spring wheat, quasi-fields or blobs are the entities sampled and labeled.

$$\frac{n_i}{N} \times \frac{1}{\binom{B-1}{k-1}}$$

because the first field is chosen with probability n_i/N, proportional to size, and the remaining k-1 fields are chosen with equal probability from among the $\binom{B-1}{k-1}$ such subsets. Thus the subset of k-1 fields that complete S is chosen with probability $1/\binom{B-1}{k-1}$. When the k terms of the sample probability are added up, one term for each way, the result is

$$\frac{\sum\limits_{i \varepsilon S} n_i}{N} \bigg/ \binom{B-1}{k-1} \quad ,$$

and thus the sample probability is proportional to the size of the sample (as measured in pixels).

The sample extimate $\hat{p}$ is

$$\frac{\sum\limits_{i \varepsilon S} n_i p_i}{\sum\limits_{i \varepsilon S} n_i}$$

The expected value of $\hat{p}$ is obtained by multiplying the sample probability by $\hat{p}$ and summing over all possible samples. In symbols

$$\mathcal{E}\hat{p} = \sum_{\substack{\text{all samples} \\ \text{of k fields}}} \frac{\sum\limits_{i \varepsilon S} n_i}{N \binom{B-1}{k-1}} \; \frac{\sum\limits_{i \varepsilon S} n_i p_i}{\sum\limits_{i \varepsilon S} n_i}$$

As in the example, the number of pixels in the sample $\sum\limits_{i \varepsilon S} n_i$ cancels out of numerator and denominator.

We are left with

$$\mathcal{E}\hat{p} = \frac{\displaystyle\sum_{\substack{\text{all samples } S\\ \text{of size } k}} \sum_{i \varepsilon S} n_i p_i}{N \binom{B-1}{k-1}}$$

Any one field, i, will occur in exactly $\binom{B-1}{k-1}$ samples because the other fields in the sample can be chosen in that many ways. A term $n_i p_i$ will occur in the numerator that many times, once for each possible sample in which Field i occurs. Thus the numerator is

$$\binom{B-1}{k-1} \sum_{i=1}^{B} n_i p_i$$

and hence

$$\mathcal{E}\hat{p} = \frac{\sum_{i=1}^{B} n_i p_i}{N} = p \qquad \text{Q.E.D.}$$

A.2 DEMONSTRATION

A FORTRAN program was written to try out the Midzuno technique and compare it with simple random sampling. We defined a stratum with seven quasi-fields as follows:

Number of Pixels	Percent Wheat
5	10
10	20
20	30
40	40
70	60
100	75
150	90

It works out that there is exactly 70% wheat in the stratum. We ran the program choosing subsets of three fields, first with 400 then with 10,000 replications. The results were as follows:

Sample Scheme	Replications	Mean	True	Stand. Dev.	t	Significance
Simple	400	65.6	70.0	16.0	-5.50	0.0000001
Midzuno	400	69.2	70.0	13.2	-1.25	0.21
Midzuno	10,000	69.9	70.0	12.5	-0.95	0.34

Using the conventional 0.05 level for determining whether a bias is significant, we found that the simple sampling scheme was significantly biased and the Midzuno scheme was not.

The simple scheme had a significantly larger variance than the Midzuno scheme as judged by an F test. The variance ratio of 1.45 was significant at the 0.001 level.

APPENDIX B
PARAMETER VALUES OF BCLUST AND BLOB

B.1 BCLUST PARAMETER VALUES

The distance function used in BCLUST (See Section 2.2.3) is defined as

$$\sum_{j=1}^{nchan} w_j^2 (x_j - \bar{x}_{ji})^2$$

where

x is the data vector

$\bar{x}_i$ is the mean vector of Cluster i

nchan is the number of multispectral channels

$w_1, \ldots, w_{nchan}$ is a set of weights

If the distance to the closest cluster is greater than τ, a new cluster is formed with its mean at x.

$w_1, \ldots, w_{nchan}$ and τ are parameters of the algorithm. Each setting of the parameters produces a different result. The question is, which setting to use?

We observe that if $w_1^2, \ldots, w_j^2$ and τ are all multiplied by the same constant, the algorithm is unchanged. We note that if τ is increased, the number of clusters formed decreases (or may stay the same) and vice versa.

Our performance measure for setting parameters is the R factor (See Section 3.1.1) which measures the purity of the clusters. A clustering that purely separates the crops of interest has an R factor of 0, whereas one that produces a constant proportion in all clusters has an R factor of 1. Thus the smaller the R factor, the better the score of the parameter setting.

A complication is that the R factor tends to go down as the number of clusters goes up. Therefore to make the parameter runs comparable, the number of clusters must be held fixed.

The following experiment was run to obtain a reasonably good set of weights $w_1, \ldots, w_{nchan}$. BCLUST was run in a multisegment mode on nine segments in Kansas. Winter wheat was the crop of interest. There were six data channels -- the Tasseled Cap variables Brightness and Greenness in each of the first three biophases.

The starting point of the search of six-dimensional space was a set of weights in inverse proportion to the ranges of the values of the variables. For each setting of the weights, BCLUST was run repeatedly with converging values of τ until just 90 clusters were obtained. Then the R factor for the 90-cluster run was recorded as the score for that set of weights. The search pattern was to follow the path of steepest descent to a setting of the weights with the smallest R factor.

It happened that the optimal setting was formed at the starting point. Any change in weight in any variable or likely combination of variables resulted in a higher R factor. The values of the weights at the optimal setting are given in Table B.1. Physically speaking, these values are no surprise. In Biophase 1, the fields are predominantly bare soil, which has a greater variation in Brightness than green vegetation. Hence a small weight (inversely proportional to the effective range) is placed on Brightness, Phase 1. In Biophases 2 and 3, crop development results in greater variation in the Greenness direction and hence smaller weights than for Greenness, Phase 1.

As for the parameter τ, it is usually determined by the number of clusters wanted. BCLUST has the capability of making repeated runs with appropriate changes in τ until the wanted number of clusters is obtained (with a little leeway).

TABLE B.1 OPTIMAL BCLUST WEIGHTS DETERMINED FOR WINTER WHEAT ESTIMATION IN NINE SEGMENTS IN KANSAS

Tasseled-Cap Channel	Biophase	Weight*
Brightness	1	0.6
Greenness	1	1.3
Brightness	2	0.8
Greenness	2	1.0
Brightness	3	0.7
Greenness	3	1.0

*Weights are in inverse proportion to the effective ranges of the variables.

The number of clusters, in turn, is chosen with regard to sampling considerations. It would be a mistake to have more clusters (strata) than the size of the sample of quasi-fields to be labeled because then some clusters would not be sampled at all, possibly leading to considerable bias. An equal number of clusters and sampled quasi-fields is not too satisfactory either because the large clusters cannot be awarded increased sample size. In general, sampling proportionate to the size of the cluster produces efficient sampling.

So the number of clusters ought to be small enough to allow sampling approximately in proportion to size. If such sampling leaves out some small clusters, then the total of their pixels should be small enough not to introduce significant bias. Within this constraint, the number of clusters should be as large as possible, because the greater the number of clusters, the purer they are with respect to the ground truth.

B.2 PARAMETER VALUES OF BLOB

A form of BLOB's distance function (See Section 2.2.4) that favors rectangular fields is defined as

$$\sum_{j=1}^{nchan} \frac{(x_j - \overline{x}_{ji})^2}{v_j} + \max \left[\frac{(\ell - \overline{\ell}_i)^2}{v_\ell} , \frac{(p - \overline{p}_i)^2}{v_p} \right]$$

where

x is the spectral data vector of a pixel

$\overline{x}_i$ is the spectral mean vector of Quasi-Field i

ℓ and p are the pixel line and point numbers rotated to measure distance north-south and east-west

$\overline{\ell}_i$ and $\overline{p}_i$ are the mean rotated line and point numbers for Quasi-Field i

nchan is the number of spectral channels

$v_1, \ldots, v_{nchan}, v_\ell$ and v_p are weights

If the distance from the pixel to the closest quasi-field is greater than τ, a new quasi-field is formed with its spectral mean at x and its line and point coordinates at ℓ and p.

The pattern of quasi-fields depends upon what values of the parameters $v_1, \ldots, v_{nchan}, v_\ell, v_p$ and τ are set. A set of parameters suitable for the problem of estimating winter wheat in Kansas was determined as follows.

First, the spectral weights $v_1, \ldots, v_{nchan}$ were obtained from the corresponding weights determined for BCLUST by observing that $1/v_j$ plays the same role in the BLOB distance measure that w_j^2 plays in the BCLUST distance measure. So $v_1, \ldots, v_{nchan}$ were set proportional to the optimal values

$$\frac{1}{w_1^2}, \ldots, \frac{1}{w_{nchan}^2}$$

Next, the rotated line and point variances, v_ℓ and v_p, were set in relation to each other so that the line standard deviation $\sqrt{v_\ell}$ and the point standard deviation $\sqrt{v_p}$ represented the same geographical distance. This ratio is not 1:1 because Landsat pixels are not square. Allowing for rotation and squaring, it turns out that $v_p/v_\ell = 1.736$.

The next question was to find a balance between spatial and spectral weights that would produce good quasi-fields. Larger values of v_ℓ and v_p relative to the other v's emphasize the spectral homogeneity of the clusters; smaller values, the spatial. The criterion of goodness was defined as the expected variance reduction factor, R_E,

$$R_E = \frac{\sum_i \frac{n_i}{n} P_i (1 - P_i)}{P (1 - P)}$$

where

P_i is the proportion of wheat in Quasi-Field i

n_i is the number of pixels in Quasi-Field i

P is the overall wheat proportion in the segment

n is the number of pixels in the segment

The purity of the quasi-fields with respect to the ground truth is measured by how small the R_E factor is.

To find a suitable balance, we held the spectral weights constant and compared the R_E factor for three sets of spatial weights, small, medium and large. (We do not restrict ourselves by this strategy because raising all the v's and decreasing τ by the same factor leaves the algorithm unchanged.) The comparison was made for eight segments and is shown in Figure B.1.

The general result is that the R_E factor is quite stable for all three settings. The vertical scale has been stretched to show any trend in the curves. To decide on a parameter setting, we choose one that these gentle trends indicate is optimal.

The worst case, Segment 1165, has a minimum in the middle but most of the segments and the average trend indicate a lower setting. A setting of $v_\ell = 3.46$ and $v_p = 6.0$, midway between the two lower setting, was chosen.

A good setting for the parameter τ is harder to specify. Some considerations in setting τ are that when τ is increased,

1) the quasi-fields are larger.

2) there are fewer quasi-fields.

3) the R_E factor increases (because the larger the quasi-fields, the less pure they are likely to be).

4) there are fewer "small quasi-fields" (those with no interior pixels) which are left out of the stratified sampling.

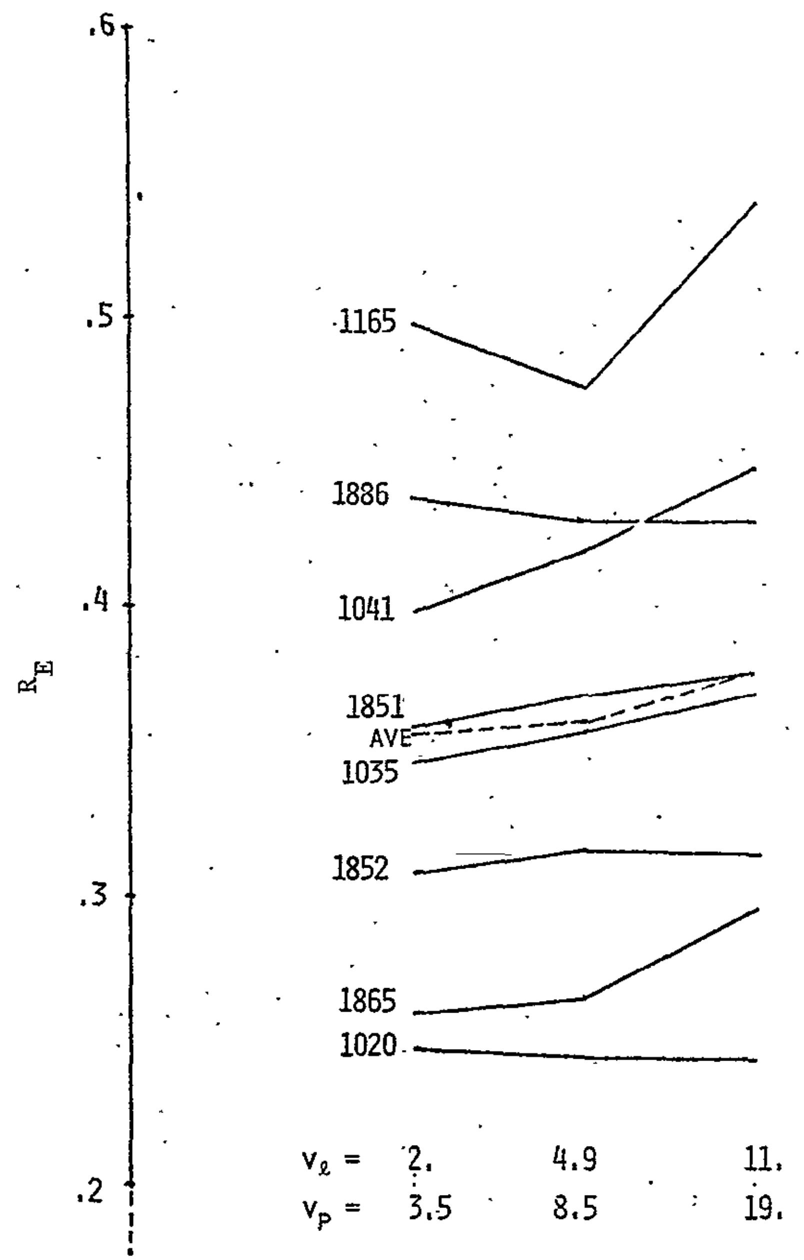


FIGURE B.1 QUASI-FIELD R_E FACTOR FOR THREE SETS OF SPATIAL WEIGHTS AND EIGHT SEGMENTS IN KANSAS

The choice of τ depends on the balance we wish to strike between considerations (3) and (4). On the one hand, we would like the quasi-field interiors to be as pure as possible so that we aren't trying to label a mixture of crops. On the other hand, we don't want to leave out of the sampling many small quasi-fields and thereby incur a substantial bias. A thorough job of choosing τ would require the trial of several values, observation of the percentage of pixels in small fields, measurement of the bias incurred by omitting the small fields (when ground truth is available) and calculation of the R_E factor for quasi-field interiors.

For our study of Kansas segments, we chose a constant value (22.0) of τ that made the number of large quasi-fields roughly equal to the number of fields. This value was associated with the "medium" setting of v_ℓ and v_p. To obtain comparable results for the "small" and "large" settings, we chose τ for each segment that produced about the same number of quasi-fields as were obtained with $\tau = 22.0$ at the medium setting. When a setting halfway between medium and small was chosen, a corresponding τ (23.2) was defined.

The BLOB parameters used in the Kansas and North Dakota tests are given in Table B.2. The BLOB statistics resulting from this choice are given in Table B.3. A comparison of BLOB statistics for two values of τ was made on a North Dakota segment and is shown in Table B.4.

In Table B.3, we observe that the largest bias incurred by leaving out small quasi-fields is found in the segment with the largest percentage (35%) of pixels in small quasi-fields. We also observe that the percent wheat in the small quasi-fields is highly variable -- not at all a representative sample for estimating wheat in the segment. In Kansas, the small quasi-fields overestimated wheat but in North Dakota, the reverse is true, as shown by Segment 1663 (Table B.4) and by several other North Dakota segments.

TABLE B.2 BLOB PARAMETERS USED IN KANSAS AND NORTH DAKOTA TESTS

Tasseled-Cap Channel	Biophase	v_j
Brightness	1	25.0
Greenness	1	5.3
Brightness	2	14.0
Greenness	2	9.0
Brightness	3	18.4
Greenness	3	9.0
Brightness	4	21.2
Greenness	4	8.1

Number of Channels Used	v_ℓ	v_p	τ
2	10.38	18.0	7.73
4	5.19	9.0	15.47
6	3.46	6.0	23.2
8	2.59	4.5	30.9

TABLE B.3 KANSAS BLOB STATISTICS

Segment	% Wheat	% Wheat: Large Quasi-Fields	% Wheat: Small Quasi-Fields	% Pixels: Small Quasi-Fields	R Factor: Quasi-Field Interiors
1020	26.1	24.0	43.2	11	0.04
1035	17.7	17.5	18.3	23	0.19
1041	14.4	14.3	15.3	13	0.21
1163	9.3	8.0	13.7	24	0.28
1165	7.1	6.2	8.9	31	0.20
1167	10.1	7.0	15.7	35	0.18
1851	22.8	20.4	33.6	18	0.16
1852	23.4	24.6	15.6	14	0.14
1860	26.1	26.2	25.1	15	0.15
1861	34.9	34.4	42.5	7	0.09
1865	28.5	26.6	34.5	24	0.09
1886	29.7	29.9	28.4	15	0.17
1887	11.4	10.2	17.8	16	0.17
Average	20.18	19.17	24.05	19	0.16
Average Bias		-1.0	3.9		
Average Absolute Error		1.1	5.5		

TABLE B.4 COMPARISON OF BLOB STATISTICS FOR SEGMENT 1663, N. D., USING TWO VALUES OF τ

Time Period Used	Usual τ	Bigger τ
2 and 3		
τ	15.47	22.1
No. of big quasi-fields	463	381
% pixels in big quasi-fields	81.4	90.4
% wheat bias using big quasi-fields	2.3	1.1
R factor for quasi-field interiors	0.108	0.137
% purity for quasi-field interiors	92.6	91.9
2, 3 and 4		
τ	23.2	33.2
No. of big quasi-fields	501	434
% pixels in big quasi-fields	78.7	87.5
% wheat bias using big quasi-fields	2.2	1.2
R factor for quasi-field interiors	0.076	0.109
% purity for quasi-field interiors	93.7	93.1
1, 2, 3 and 4		
τ	30.9	44.2
No. of big quasi-fields	502	452
% pixels in big quasi-fields	74.0	85.2
% wheat bias using big quasi-fields	2.4	1.3
R factor for quasi-field interiors	0.045	0.067
% purity for quasi-field interiors	94.1	93.8

Table B.4 illustrates the dilemma of choosing a value of τ. The τ used in our tests is in the "usual τ" column and values of τ half again as large in the "bigger τ" column. In terms of reduction of variance (R factor) the usual τ is superior. But the bigger τ, with its halving of the number of pixels in small quasi-fields, cuts the bias in half. The question is, which is worse, a slight increase in bias or a slight decrease in purity? We don't have a definite answer to this question.

Another perspective on purity is provided by the "% purity" figure. This is defined by

$$\frac{\sum n_i p_i}{\sum n_i}$$

where

P_i is the proportion of the majority crop in the interiors of Quasi-Field i

n_i is the number of pixels in Quasi-Field i
The sum is taken over all large Quasi-Fields i in the segment

If all quasi-field interiors were pure, the % purity score would be 100. If there are only two categories, wheat and non-wheat, the % purity score cannot fall below P or 1-P, whichever is larger. The difference in purity scores is very slight.

The 1% average absolute bias in the Kansas results would seem acceptably small by most standards indicating that a sound value of τ was used. This judgment is based on the assumption that the bias would be overshadowed by other larger errors in the system. Whether this bias can be safely reduced by raising τ depends on how the labeling accuracy varies with the purity of the quasi-field interiors, a relationship that has not been measured, though further investigation of this is warranted.

APPENDIX C
PROCEDURE M FLOW CHARTS

This appendix describes the major program flow of Procedure M. Software flow charts are presented in Table C.1 and program descriptions in Table C.2.

The procedure is coded primarily in XTRAN, an extended Fortran compiler developed at ERIM. ERIM's QLINE data processing system provides the software operating environment. Currently, the software is configured for use on an AMDAHL 470/V6 operating under the Michigan Terminal System (MTS).

TABLE C.1 SOFTWARE FLOW CHARTS

Phase 1: Data Preparation and Screening

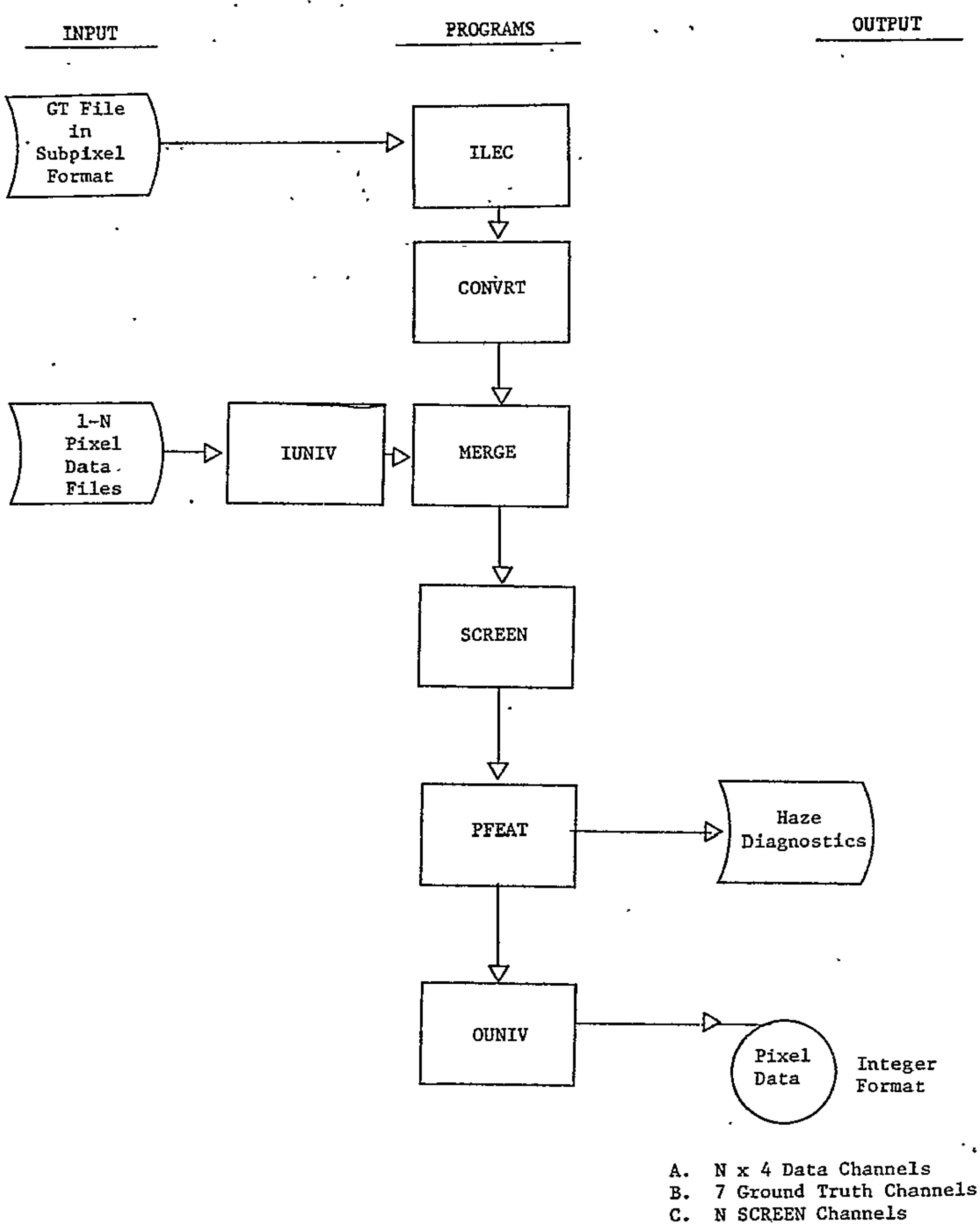
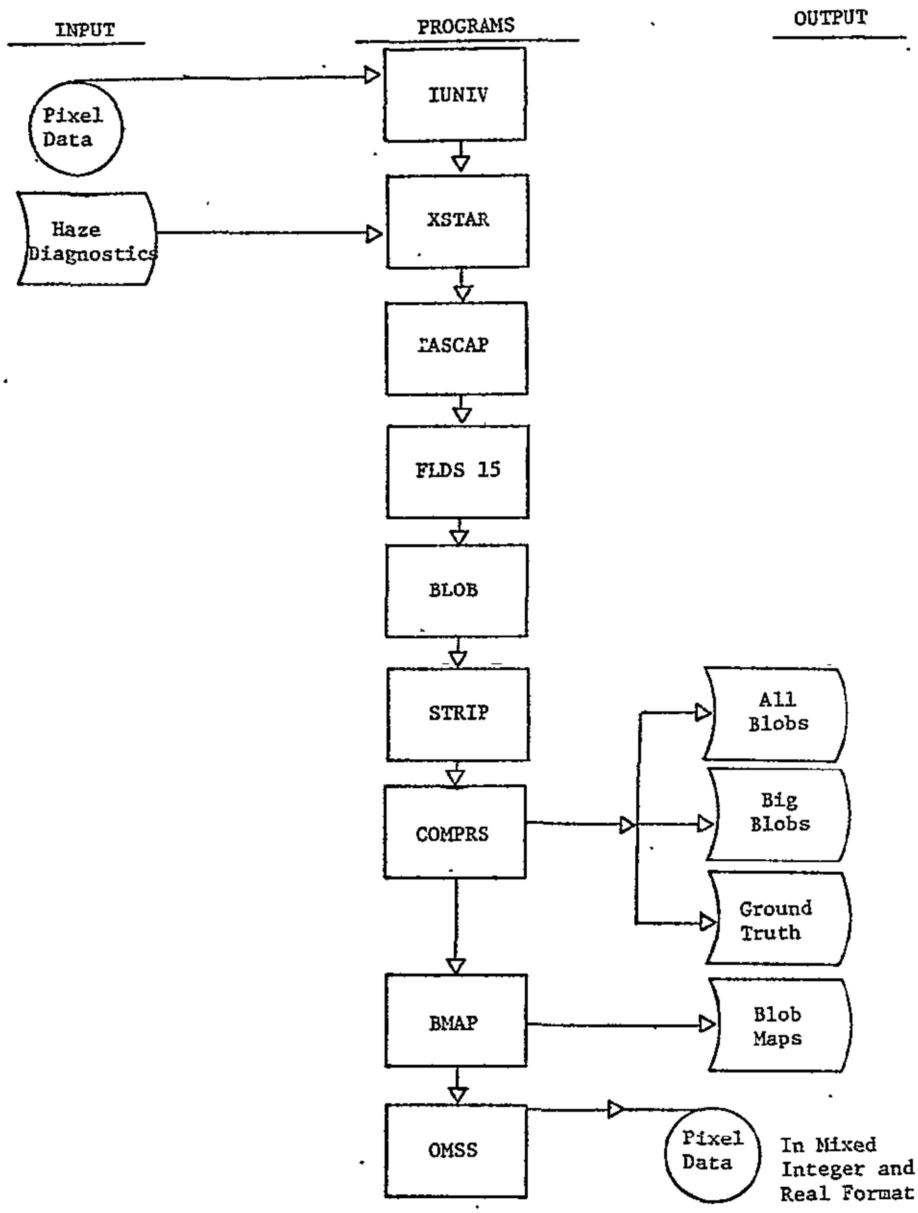


TABLE C.1 SOFTWARE FLOW CHARTS (Cont'd)

Phase 2: External Effects Correction and Quasi-Field Definition



A. N x 4 TASCAPPED Data
B. 7 Ground Truth Channels
C. N SCREEN Channels
D. 2 BLOB Channels
E. 1 STRIP Channel

TABLE C.1 SOFTWARE FLOW CHARTS (Cont'd)

Phase 3: Strata Definition

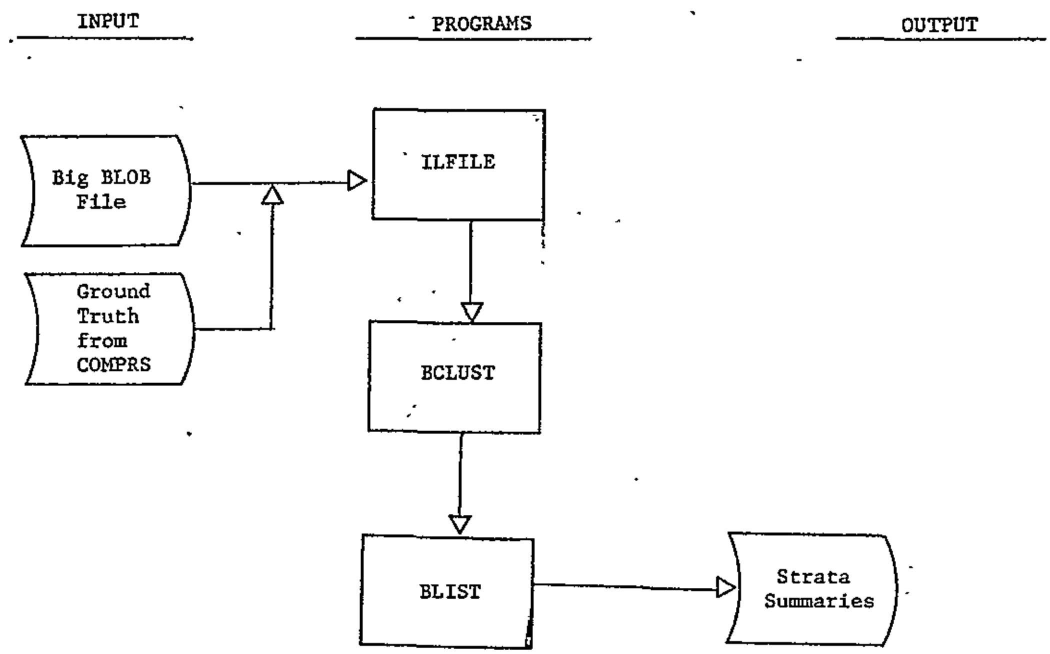
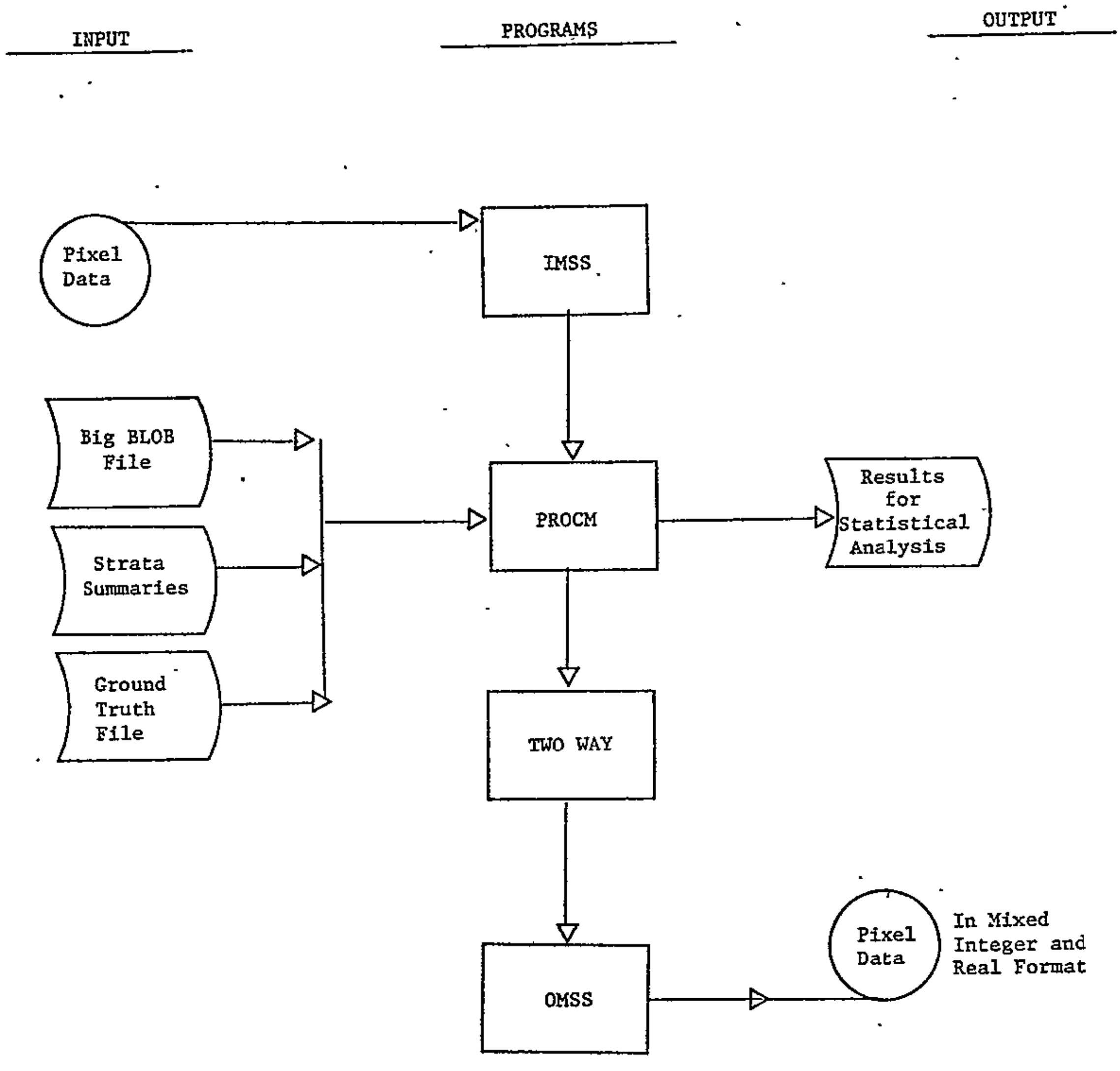


TABLE C.1 SOFTWARE FLOW CHARTS (Cont'd)

Phase 4: Labeling and Estimation



A. N x 4 Data Channels
B. 7 GT Channels
C. N SCREEN Channels
D. 2 BLOB Channels
E. 1 STRIP Channel
F. 1 SHIFT Channel
G. 1 Classification Channel

TABLE C.2 DESCRIPTION OF MODULES AND SUBROUTINES USED IN PROCEDURE M

CONVRT	-	Converts Lockheed sub-pixel ground truth codes to pixel format. Input is Lockheed, one channel, six sub-pixel ground truth. Output is 7 channels of ground truth with ERIM codes. Channel number 1 is ground truth code for whole pixel. If all six sub-pixels have the same code, then the whole pixel is given that code. If not, a zero is assigned to that pixel. Channels 2 - 7 are the 6 sub-pixel codes.
MERGE	-	Merges data, i.e., pixel data with ground truth, as needed for machine processing. Output is all needed data in one file.
SCREEN	-	Flag bad data, clouds, shadows, etc. Input is merged data file. Output is same file with added screen channels, one added channel per acquisition of data.
PFEAT	-	Calculate spatially varying haze diagnostics which are needed for haze correction algorithm (XSTAR). Input is merged data file with screen channels. Output is a separate file containing haze diagnostics.
XSTAR	-	To apply a spatially varying haze correction to Landsat data. Input is merged data file with screen channels and the output file from PFEAT. Output is merged data file with pixel values corrected for haze.
TASCAP	-	Performs a Tasselled Cap Transformation on Landsat 2 data. Input is merged data file. Output is merged data file with transformed data values.
FLDS15	-	To correct ground truth labels coded for 15 visited fields. Input is merged data files. Output is same files with some ground truth codes corrected.
BLOB	-	To group pixels into clusters that are spectrally, homogeneous, and spatially contiguous. Input is merged data file. Ouput is same file with 2 BLOB channels added. These channels contain the blob number that each pixel is assigned.
STRIP	-	Strips off all boundary pixels around each blob. Input is data file with BLOB channels. Output is same file with strip channel added. Each exterior pixel is flagged with a 1 in the strip channel.

TABLE C.2 DESCRIPTION OF MODULES AND SUBROUTINES USED IN PROCEDURE M (Cont'd)

COMPRS - To compute signatures of MSS data where polygons (blobs) are encoded in extra channels (e.g., blob number). Input is data file with blob and strip channels. Output consists of 3 files; (a) Means of all blobs, (b) Means of blobs with at least one interior pixel called Big Blobs, (c) Ground truth tables.

BCLUST - To group blobs into spectrally similar strata. Input, Big blob file, and ground truth tables from COMPRS. Output is cluster means and other associated information.

BLIST - To provide information for selecting training blobs and calculate crop percentage estimates. Input is file from BCLUST, Output cluster (STRATA) summaries.

PROCM - Carries out labelling and proportion estimation as a part of a small grains estimation procedure. PROCM call 9 subroutines, 4 of which (PBREAD, ALLOC, BLBSEL, ESTIM) are in a package called AUTO. The following is a brief description of each subroutines:

- ALLOC - Allocates training blobs.
- BLBSEL - Selects training blobs.
- CLASIF - Carries out spring wheat vs other small grains classification.
- ESTIM - Computes proportion estimate.
- GTREAD - Creates blob labels from ground truth tables.
- PBREAD - Reads in necessary information for allocation, selection, and estimation routines.
- SHFBLB - Carries out field shift on blob means.
- SHFPIX - Carries out pixel-by-pixel shift.
- TIME - MTS subroutine to provide date and time information.

Input is merged data file with Blob and strip channels, plus Big Blob and ground truth files from COMPRS, and STRATA summary from BLIST. Output is file for statistical analysis and the data file with 2 added channels: (a) Shift channel, (b) Classification channel.

TWOWAY - To produce a twoway table for comparison of the occurrence of specified values in to tape channels. Input is data file with added channels from PROCM. Output is the table.

TABLE C.2 DESCRIPTION OF MODULES AND SUBROUTINES USED IN PROCEDURE M (Cont'd)

MISCELLANEOUS SUBROUTINES

TRUTH	-	To produce ground truth tables from Lockheed or ERIM ground truth tables. Called by "COMPRS".
GTREAD	-	To read ground truth produced by "TRUTH". Called by "PROCM" and "BSTUFF".
GTSNIF	-	To read header record of ground truth tables and pass information through common.
BSTUFF	-	Stand alone routine to provide diagnostic information about blobs.
MXMPY	-	To multiply matrices.
MOVER	-	To move data from one array to another.
UNTASS	-	Perform inverse Tasselled Cap Transformation. Called by "XSTAR" and "PFEAT".
GAMMA	-	To calculate gamma for "XSTAR".
XCOEFF	-	To calculate multiplicative and additive coefficients for "XSTAR".
SATCOR	-	To return diagonal matrix and additive vector for transforming Landsat data to Landsat 2 LACIE segment calibration. Called by "SCREEN".
SUNCOR	-	Perform cosine sun angle correction on 4 x 4 multiplicative transformation matrix. Called by "SCREEN".
TASSEL	-	Perform tasselled cap rotation 4 x 4 multiplicative transformation matrix. Called by "SCREEN".
UNCOR	-	To undo cosine sun angle correction performed by "SUNCOR". Called by "PFEAT".
PCILE	-	Computes percentile points of histograms. Used for computing certain scene parameters in PFEAT, such as the mean of the green arm, the mean of soils, etc.

TABLE C.2 DESCRIPTION OF MODULES AND SUBROUTINES USED IN PROCEDURE M (Cont'd)

MISCELLANEOUS SUBROUTINES

URAND	-	System subroutine to produce random numbers.
RANKP	-	Computes for a vector the rank of each number in the vector. It is used to order a listing of clusters in BCLUST according to size.
VPROD	-	Computes the inner product of two vectors. Use in BCLUST.
RANSUB	-	Generates a random subset of the integers 1, ..., N. Used to get a random sample of blobs in BLBSEL. (The first blob is chosen with probability proportional to size. The others are chosen with equal probability by calling RANSUB.)
ZERO	-	To zero arrays, written in IBM 370 Assembler language.

TABLE C.2 DESCRIPTION OF MODULES AND SUBROUTINES USED IN PROCEDURE M (Cont'd)

I/O FORMAT SERVICE ROUTINES (FSR's)

IUNIV	-	Input routine to read universal formatted tapes or files.
ILEC	-	Modification of IUNIV, used to read Lockheed ground truth data tapes.
OUNIV	-	Output routine, writes universal output to tapes or files.
IMSS	-	Input routine to read multispectral formatted data files.
OMSS	-	Output routine to write multispectral formatted data files.
ILFILE	-	Input routine to read COMPRS output files.

APPENDIX D

DATA BASE FOR TESTING AND EVALUATING PROCEDURE M

Twenty-three Phase 3 and five Phase 2 LACIE blind sites were initially selected for the testing of Procedure M. Acquisitions for each blind site were chosen to best represent the growing season of spring small grains. The acquisitions for each site were merged into 28 channels of data according to the list in Table D.1.

The ground truth for each site was merged on a pixel-by-pixel basis with the acquisition data, forming the next seven channels. The ground truth codes were converted from the subpixel ground truth codes produced by LEC to an alternative code and format. Each set of six subpixels was inter-compared; if all codes were the same, the appropriate value was placed in Channel 29, otherwise a zero was inserted to indicate that the pixel was not pure. Channels 30 through 35 contain ground truth codes for each subpixel. One channel per acquisition was added (Channels 36-42) to flag data that were rejected by the SCREEN algorithm.

Of the acquisitions available, those listed in Table D.2 were used for clustering and stratifying the data. Segment partitions that were evaluated in Section 2 are listed in Table D.3.

TABLE D.1 SEGMENTS SELECTED AND PREPARED FOR ANALYSIS

PHASE 3

Site (State)	Channels 1-4	5-8	9-12	13-16	17-20	21-24	25-28
1104 (Mont)	128	146	164	182	199	zero*	236
1498 (SD)	120	zero	157	174	193	210	zero
1512 (Minn)	120	zero	156	174	193	zero	zero
1513 (Minn)†	zero	140	157	175	193	zero	zero
1515 (Minn)	zero	zero	157	175	193	zero	zero
1520 (Minn)	120	zero	156	174	192	zero	zero
1602 (ND)	125	143	zero	179	197	216	zero
1606 (ND)	125	143	zero	179	197	zero	zero
1625 (ND)	125	143	zero	179	197	zero	233
1640 (ND)	121	140	zero	175	193	211	229
1652 (ND)	125	143	zero	179	197	zero	233
1663 (ND)	121	139	157	175	193	211	229
1669 (SD)	125	143	161	179	197	215	zero
1681 (SD)	120	139	156	174	192	210	zero
1681 (SD)**	120	139	157	175	193	210	zero
1699 (SD)	zero	140	158	176	194	zero	230
1800 (SD)	120	zero	156	174	192	210	zero
1803 (SD)	123	142	159	178	195	213	zero
1805 (SD)	zero	zero	158	176	193	211	zero
1811 (SD)	120	138	157	174	192	210	zero
1899 (ND)	122	140	157	175	193	zero	zero
1913 (ND)	125	143	161	179	197	215	233
1927 (ND)	122	140	158	176	194	zero	230
1927 (ND)**	121	140	157	175	193	zero	230
1929 (Mont)†	129	147	zero	184	201	220	zero

PHASE 2

Site (State)	Channels 1-4	5-8	9-12	13-16	17-20	21-24	25-28
1614 (ND)	129	zero*	zero	183	201	219	zero
1633 (ND)	128	147	zero	182	201	zero	237
1637 (ND)	129	147	zero	182	201	219	237
1642 (ND)	127	145	163	182	199	zero	236
1662 (ND)	127	145	163	zero	199	217	236

*Zero indicates that no acquisition was available, and four channels of zeros were merged to keep the files uniform.

**For two segments, consecutive-day coverage permitted the merging of two substantially different sets of acquisitions.

†Two sites were eliminated from analysis due to inadequate ground truth codes designated for strip fields which dominated the scene.

TABLE D.2 ACQUISITIONS USED FOR SPATIAL FEATURE DEFINITION AND STRATIFICATION

PHASE 3 SITES

Site	Acquisition Dates			
1104	146	182	199	236
1498	120	182	193	210
1512	156	174	193	
1513	157	175	193	
1515	157	175	193	
1520	120	174	192	
1602	143	179	197	216
1606	143	179	197	
1625	143	179	197	233
1640	140	175	193	211
1652	143	179	197	233
1663	139	175	193	211
1669	143	179	197	215
1681	139	174	192	210
1681	139	175	193	210
1699	140	176	194	230
1800	120	174	192	210
1803	123	159	178	195
1805	158	176	193	211
1811	138	174	192	210
1899	140	157	175	193
1913	143	179	197	215
1927	140	176	194	230
1927	140	175	193	230
1929	147	184	201	220

PHASE 2 SITES

Site	Acquisition Dates			
1614	129	183	201	219
1633	147	182	201	237
1637	147	182	201	219
1642	145	163	199	236
1662	145	163	199	217

TABLE D.3 SEGMENT PARTITIONS

Phase 3	Phase 2	Developmental	Problem Segments	Red River
1669	1614	1498	1637	1498
1681	1633	1515	1652	1512
1699	1637	1640	1662	1515
1800	1642	1663	1913	1520
1803	1662			1640
1805				1663
1811				1681
1913				1927
1927				
1513				
1606				
1899				
1104				
1498				
1512				
1515				
1520				
1602				
1640				
1652				
1663				

APPENDIX E

SEGMENT-BY-SEGMENT LABELER RESULTS

PHASE 3 SEGMENTS WITH GOOD LABELING ACCURACY (> 50%)

SEGMENT	SPRING WHEAT NUMBER	SPRING WHEAT % RIGHT	BARLEY NUMBER	BARLEY % RIGHT	BOTH NUMBER	BOTH % RIGHT	OATS NUMBER	OATS % RIGHT
1512	429	72.5	448	68.5	877	70.5	244	22.1
1520	392	72.4	35	88.6	427	73.8	170	30.6
1602	660	82.0	46	50.0	706	79.9	50	68.0
1606	113	72.6	22	27.3	135	65.2	20	20.0
1625	294	76.5	12	91.7	306	77.1	12	50.0
1681	1049	56.9	206	97.6	1255	63.6	1007	64.7
1899	162	72.2	499	81.4	661	79.1	0	0.0
1927	1112	75.2	380	88.7	1492	78.6	223	21.1

PHASE 2 SEGMENTS WITH GOOD LABELING ACCURACY (> 50%)

SEGMENT	SPRING WHEAT NUMBER	SPRING WHEAT % RIGHT	BARLEY NUMBER	BARLEY % RIGHT	BOTH NUMBER	BOTH % RIGHT	OATS NUMBER	OATS % RIGHT
1614	861	52.0	266	90.2	1127	61.0	104	59.6
1633	1284	60.7	87	88.5	1371	62.5	1289	39.5
1642	1074	58.7	365	51.8	1439	56.9	1159	39.6

PHASE 3 SEGMENTS WITH POOR LABELING ACCURACY (< 50%)

SEGMENT	SPRING WHEAT NUMBER	SPRING WHEAT % RIGHT	BARLEY NUMBER	BARLEY % RIGHT	BOTH NUMBER	BOTH % RIGHT	OATS NUMBER	OATS % RIGHT
1652	255	16.9	8	37.5	263	17.5	0	0.0
1669	156	1.3	38	100.0	194	20.6	36	97.2
1699	623	7.7	300	99.0	923	37.4	561	99.5
1913	424	10.1	17	100.0	441	13.6	82	96.3
1929	517	0.2	302	100.0	819	37.0	57	82.5

PHASE 2 SEGMENTS WITH POOR LABELING ACCURACY (< 50%)

SEGMENT	SPRING WHEAT NUMBER	SPRING WHEAT % RIGHT	BARLEY NUMBER	BARLEY % RIGHT	BOTH NUMBER	BOTH % RIGHT	OATS NUMBER	OATS % RIGHT
1637	1895	24.4	46	91.3	1941	26.0	1940	75.8
1662	2902	38.3	290	71.4	3192	41.3	298	86.6

SEGMENTS USED TO DEVELOP MACHINE LABELING CRITERION

	SPRING WHEAT		BARLEY		BOTH		OATS	
SEGMENT	NUMBER	% RIGHT	NUMBER	% RIGHT	NUMBER	% RIGHT	NUMBER	% RIGHT
1498	619	66.1	204	76.0	823	68.5	902	66.7
1515	1278	82.9	933	84.2	2211	83.5	49	18.4
1640	2022	84.9	863	71.0	2885	80.8	0	0.0
1663	1263	94.3	549	71.4	1812	87.4	207	39.6

SEGMENTS NOT USED IN LABELER PERFORMANCE ANALYSIS

	SPRING WHEAT		BARLEY		BOTH		OATS	
SEGMENT	NUMBER	% RIGHT	NUMBER	% RIGHT	NUMBER	% RIGHT	NUMBER	% RIGHT
1104	0	0.0	155	100.0	155	100.0	161	100.0
1513	1	100.0	15	100.0	16	100.0	0	0.0
1800	18	27.8	376	97.1	394	93.9	1360	95.6
1803	0	0.0	0	0.0	0	0.0	0	0.0
1805	12	8.3	9	100.0	21	47.6	589	85.1
1811	1	100.0	0	0.0	1	100.0	108	18.5

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