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PROCEDURE M: A FRAMEWORK FOR STRATIFIED AREA ESTIMATION

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I. ABSTRACT

This paper describes Procedure M, a systematic approach to processing multispectral scanner data for classification and acreage estimation. A general discussion of the rationale and development of the procedure is given in the context of large-area agricultural applications. Specific examples are given in the form of test results on acreage estimation of spring small grains.

II. INTRODUCTION

The central theme of this paper is that Procedure M is not to be characterized by the particular collection of algorithms of which it is composed at this point in time, since it is thoroughly modular and flexible in the information sources it can utilize, the transformations employed, and the information to be extracted. Rather it should be characterized by its conceptual framework which may be expressed in terms of processing functions. Procedure M is the current, still imperfect, representative of a philosophy of information extraction from remotely sensed data which has been pursued for 15 years.

Neither is Procedure M an exclusively ERIM invention. The gradual development of a processing philosophy has come about by interaction with and contributions from many individuals and groups within the remote sensing community.

In Section III which follows, we first describe the historical background of the development of Procedure M. In Section IV we turn to a description of the procedure, first in generic terms and then in terms of the particular collection of algorithms which constitute the current spring small grains configuration of the procedure. In Section V we present some tests of the procedure. Section VI presents a summary.

III. BACKGROUND

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 an information gathering and forecasting system, both for domestic and foreign agriculture.

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 understanding of the underlying physical phenomena and the techniques of processing the data to obtain the desireable 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 assess the capability of remote sensing to track the spread of the Southern Corn Leaf Blight northward across the U.S. Corn Belt.

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With the launch of the Earth Resources Technology Satellite (now Landsat) in July of 1972, it became possible to consider the application of spaceborne Multispectral Scanner (MSS) data to the task of commodity 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 (EOD) of NASA's 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. Now in the AgRISTARS project, the feasibility of extending LACIE technology to multiple crops and world regions 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] LARS acquired field measurements data for use in developing insights into the temtemporal-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) had developed advanced techniques of photointerpretation, sampling designs, and stratification.

ERIM's contributions were in developing advanced techniques for acreage estimation, including preprocessing techniques to reduce atmospheric and sensor-related effects, clustering and training techniques, unbiased sampling and estimation techniques, and in developing and applying agrophysical understanding through modeling and empirical data analysis. The results of these efforts 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 information system ought to provide estimates of the error distribution of its forecasts. We have attempted to follow this philosphy 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 inplace 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. An example of the use of such data in testing of Procedure M is given in Section V.

IV. DESCRIPTION OF PROCEDURE M

In this section we discuss the general processing functions which form the framework for Procedure M; a particular current implementation of those functions; and similarities and differences from other current techniques.

A. GENERAL PROCESSING FUNCTIONS

Two conceptual areas drive the formation of Procedure M; statistical estimation and physical understanding.

The central concept in all pattern recognition problems is the conditional probability density, $Pr(X|\theta)$, of the observations X, given the state θ. From the point of view of statistical decision theory, one has in hand a set of observations, X, and wishes to classify them into categories or in general to estimate some parameter, θ, which is thought to

have influenced those observations. In addition one has access to a set of joint observations of X and θ, usually called the training data. Pattern recognition or statistical estimation procedures attempt to use the training data to characterize the density function $Pr(X|\theta)$ in sufficient detail for the purposes at hand. The most commonly documented failure of pattern recognition is to attempt to write processing algorithms based on insufficient knowledge of this density function.

If the dimensionality of the observations, X, is large, as it usually is, it is difficult in practice to estimate $Pr(X|\theta)$ from measurements. It is tempting to simplify the problem by ignoring some of the observables. Ignoring them, however, does not change the fact of their importance.

In pattern recognition it is conventional to place the burden of this difficult problem into precursor steps called preprocessing and/or feature extraction. The purposes of preprocessing and feature extraction of remote sensing data have been described as follows:[10]

1. To make the data more comprehensible by adjusting all of them to standard conditions of observation.

2. To eliminate or flag bad or noisy observations in the data.

3. To make the data more comprehensible by extracting physically meaningful features or projecting the data in such a way as to display their physical structure.

4. To compress the data, retaining most of the information and averaging out noise and redundancy.

5. To make the distributions of the derived features fit some convenient model such as the multivariate normal distribution (This step is not used in the current implementation of Procedure M.).

The primary role of physical understanding is in the development of preprocessing and feature extraction techniques which lead to derived features which carry most of the desired information content of the original observations. The central guiding point of view is that one ought to attempt to unravel the information content of signals in the inverse order in which they were generated.

Following the philosphy that one ought to unscramble the signals in inverse order leads to the preprocessing/feature extraction steps described later in Section IV.B.

From a statistical viewpoint, once feature extraction has occurred, one is still faced with a set of extracted features, Y, and some quantity to be estimated, θ, and it is still necessary to characterize the density function, $Pr(Y|\theta)$ with sufficient detail to meet the requirements of the problem at hand. The parameters of the chosen characterization of the density function are usually called signatures. Thus, in early developments of multispectral classification techniques the density functions of various classes were represented by normal density functions, whose means and covariances (signatures) were estimated from the training data. More recently, in Procedure 1, part of the training data were used to establish an estimate of signatures which were used to separate the data into two strata, S_1 and S_2 ("wheat" and "non-wheat"), defined with respect to the observations, Y. The remainder of the training data is then used to make a stratified areal estimate (SAE) following the classical techniques of survey sampling. Implicit is the fact that the estimate of the posterior probability density function $Pr(\theta|X\epsilon S_i)$ is refined by using the remainder of the training data in this way. In this formulation the prior probability distribution of the condition θ is automatically taken into account by sampling, and the procedure is unbiased if the identification labels on the second part of the training data are accurate.

In Procedure M the same concept is carried out using multiple strata, $S_1,\ldots,S_M$, produced in an unsupervised clustering of the data with respect to the feature set Y. Stratified sampling procedures are used to select the sample to be labeled.

Often the comment is made, with respect to physically based feature extraction, that something important may be lost. An appropriate response is that if one suspects that to be the case, then he should carry along in the revised feature set, Y, enough information to reconstruct the original signal, X. Then, if some subset of the Y's do indeed carry most or all of the useful information, this will become evident with use and experience.

B. CURRENT IMPLEMENTATION

In its current configuration Procedure M carries out its functions through the specific algorithms and steps defined in Table 1.

V. DEVELOPMENT AND TESTING OF PROCEDURE M

Several tests of Procedure M under various configurations have been conducted. These tests were carried out to evaluate not only the overall accuracy and efficiency of the procedure, but also the individual performance of each of its components. Described in the following is a test conducted with sample segments located in the Northern Great Plains of the United States.

A. TEST SITE AND DATA SET

Spring small grains, predominantly wheat, barley, and oats, are an important agricultural commodity grown in the Northern Great Plains of the United States. For example, typical annual production there of spring wheat is in the vicinity of one-half billion bushels and represents roughly one-quarter of the of the total U.S. annual production of wheat. Seventeen 5x6-mile sample segments located throughout North Dakota and Western Minnesota were selected to evaluate the performance of Procedure M. These were among the sites for which ground inventories were conducted for use in accuracy assessment and performance evaluation of LACIE Transition-Year procedures.

The data base analyzed consisted of multidate Landsat MSS data and associated digital ground truth collected during the 1978 season by ground observation and interpretation of aerial photography, crop identification labels derived by interpretation of Landsat imagerv. and a number of features computed or derived from these data. The sites selected for analysis were distributed so as to represent a variety of agrononic conditions. The actual proportion of spring small grains present in each site varied from six to sixty percent, in all averaging 35.6%. Field sizes varied substantially and strip cropping was practiced in a number of the test sites. Other notable ground covers included pasture and summer planted crops.

B. EXPERIMENT DESIGN

Key elements of the evaluation that was conducted included (1) characterization of the overall bias of the procedure, (2) characterization of the variance of its estimates, (3) evaluation of the field definition component, and (4) evaluation of the spectral stratification component.

Each of the seventeen sample segments was processed through the procedure, utilizing both ground truth and analyst-derived labels, with a number of different parameter settings. The key parameters included (1) the size of the quasi-field sample group selected from the usual population of 300 to 500 quasi-fields (i.e., 60, 80, 100, or 120), (2) the number of spectral strata identified (1, 20, 40, or 60) and (3) the specific sample group randomly selected (50 different sample group selections were made in each site for each parameter setting). In all, 1,600 crop area estimates were derived for each site.

Once the estimates were computed, a number of statistical analyses were conducted. Both descriptive statistical tools, like frequency tables and scatter plots, and inferential statistical procedures, like ANOVA, regression, and discriminant analysis, were utilized in the evaluation.

C. RESULTS

Evaluation of the performance of the spring small grains configuration of Procedure M will be discussed by addressing the four questions that were of particular interest. The procedure was found to be largely unbiased with respect to the source of sample labels with a reduction in the variance of the stratified area estimate over LACIE Procedure 1 and unstratified estimates. Quasi-field definitions were notably pure with respect to ground truth, and the resultant purity of spectral stratification based on unsupervised clustering applied to the largest quasi-fields particularly benefited by the elimination of the smallest quasi-fields since these contained most mixture pixels. Estimates based on analyst labels revealed that performance primarily depended upon the accuracy of those labels. Modeling of the procedure has analytically quantified this empirical finding. Details of this result can be found in Reference 18.

i. What are the bias (i.e., accuracy) characteristics of the procedure? Over the seventeen test segments, the overall error in the small-grain proportion estimate when ground truth labels were used was 0.08% which was not significantly different than zero. This would, at first glance, indicate that the procedure is unbiased. However a slight bias in a given segment is possible since only larger quasi-fields are sampled. Smaller quasi-fields are omitted since mostly mixture pixels reside in that stratum and the accuracy of labels for such samples is more likely subject to error. Figure 1 illustrates the proportions derived for each segment for forty spectral strata and one hundred quasi-field samples. Sites containing more than

35% spring small grains were slightly overestimated and others underestimated. This trend was found to be related to the average field size of the dominant crop. Though subject to further research, the bias introduced is felt to be slight compared to the potential bias that would be introduced by mislabeling of mixed pixels in the smaller quasi-fields.

ii. What Variation in the Estimates can be Expected as Sampling Parameters are Changed? Using fifty Monte Carlo iterations of the quasi-field sample selection and ground truth labels, procedure variance characteristics were computed. Reductions in the variance of the estimates were noted as a function of spectral stratification and sample size, as illustrated in Figure 2. The ratio of the variance measured for each stratified estimate to that of the unstratified estimate can be used as a variance reduction measure to quantify the improvement of performance. For forty strata and one hundred samples, the variance reduction factor was 0.59 over unstratified sampling This means that by stratification through spectral clustering only 59% as many samples would be required to achieve the same level of performance in terms of variance as in the unstratified case. Comparison of these empirical results to those achieved by the LACIE Procedure 1 indicate a significant gain in efficiency.

iii. Are Quasi-Field Patterns Pure? The principle sampling unit of Procedure M is the quasi-field extracted automatically by a multi-temporal spatial and spectral clustering algorithm called BLOB. It is crucial that the quasi-fields formed are pure relative to the crops of interest. Evaluation of the BLOB algorithm revealed that this basic assumption was well founded. The quasi-fields were found to visually correspond to actual fields. Figure 3 illustrates a typical result of the algorithm. Small fields and the boundaries of larger fields were omitted to clarify the illustration. Figure 4 illustrates a histogram of quasi-field purity. The majority are clustered at the two extremes of the histogram, indicating that the quasi-fields are relatively pure. The average purity of the 6,000 quasi-fields in the seventeen segments was 93% either grain or non-grain, with more than 80% of the quasi-fields at least 80% pure.

iv. Are Spectral Strata Pure? The reduction of variance realized through spectral stratification of the quasi-fields is achieved by forming strata that are purer than average with respect to the crop types of interest. The BCLUSTER algorithm utilized is a simple unsupervised clustering algorithm that is currently used to form strata using spectral means of quasi-fields contained in the stratum to be sampled. BCLUSTER can be controlled to produce any predefined number of strata or 'bclusters'. Figure 5 illustrates the purity of strata for each of three size settings. The percentage of strata that are pure non-grain remains relatively constant independent of the number of strata targeted. This implies a significant level of separability between certain grains and non-grains. However, the percentage of relatively pure grains shows a dramatic increase from 20 to 40 bclusters. The implication is that a large percentage of grains and non-grains are spectrally close, and a finer threshold level is required to produce sufficient strata to separate the two classes.

Comparison of these results to comparable studies using more sophisticated algorithms[19] imples improved stratification with BCLUSTER over ISOCLAS, AMOEBA, and CLASSY. It is conjectured, however, that much of the apparent improvement is due to excluding the stratum of small quasi-fields in the stratification, rather than to improved clustering procedures. The elimination of mixture pixels, which act as a spectral smoothing mechanism, makes pure spectral distribution more apparent. Recent studies have borne out this conjecture.[20]

VI. SUMMARY

Procedure M is an example of stratified area estimation (SAE) technology. SAE incorporates stratified random sampling as the primary means for producing area estimates of classes of interest. It differs from the common multispectrally based estimation technology in which a classifier, like maximum likelihood, is utilized. Rather, a robust statistical sampling framework is coupled with a mechanism to label or identify samples in the stratified context provided by remotely sensed data. In addition, extensive use of state-of-the-art remote sensing processing technology has been utilized for such purposes as dimensionality reduction, atmospheric haze correction, and automatic definition of fields.

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The authors represent a technical development team composed of many other ERIM staff members.

Currently configured for crop area estimation applications, it could readily be adapted to other resource applications. The salient features of Procedure M include:

multicrop - estimates of any number of crops can be produced

multitemporal - any number of Landsat acquisitions can be utilized

multisegment - any number of segment samples, each at least larger than a field, can be utilized

modular - procedure components are interchangeable; as components are improved, they are simply inserted in place of existing ones

statistically stable - the bias and variance of the estimates are determinable and consistent results are produced to the precision of the labeling mechanism

Six stages of Procedure M have been described above. These stages include data preparation, feature extraction, stratification, sample selection, attribute assignment and aggregation (or estimation).

Two configurations of Procedure M currently exist, for spring small grains inventory and for spring wheat inventory. Extensive research, development and testing of the procedure has taken place and its applicability to the general problem of resource inventory is well established. This paper presents experimental results from the spring small grains configuration.

Currently Procedure M is being reconfigured for application to Corn and Soybeans area estimation. In this new configuration special emphasis is being placed on creating a close relationship to analyst interpreters, to provide feedback to the analyst and to retain statistical control of the area estimation procedure.

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Table 1. Algorithms Used in Current Configuration of Procedure M

	Step	Comments	Algorithm or Source
Data Preparation	Calibration	To make data from different sensing instruments comparable.	Landsat 3 to Landsat 2 Transformation
	Screening	To flag bad or noisy data.	SCREEN
	View Angle Correction Atmosphere Correction Solar Angle Correction	To make data from different places and times comparable.	XSTAR
Feature Extraction	Spectral Feature Extraction	To emphasize the physically meaningful components of the spectral reflectance, and compress data volume.	TASCAP (Tasselled Cap Transform)
	Spatial Feature Extraction	For agriculture, to group pixels into fields, average pixel-to-pixel noise and reduce confusion of mixture pixels.	BLOB
	Temporal Feature Extraction	For agriculture, to extract physically meaningful components of the temporal reflectance spectrum, smooth over missing observations and compress data volume.	Trajectory fitting techniques on Greenness values vs. time
	Stratification	To provide basis for unbiased, efficient areal estimation technique based on labels.	BCLUST
	Sample Selection	To insure unbiased low variance estimates.	Midzuno sampling technique
	Attribute Assignment (Labeling)		Analyst labels small grains. Machine trajectory analysis labels wheat vs. barley.
	Estimation of Segment	Stratified areal estimate.	Final output at segment level.

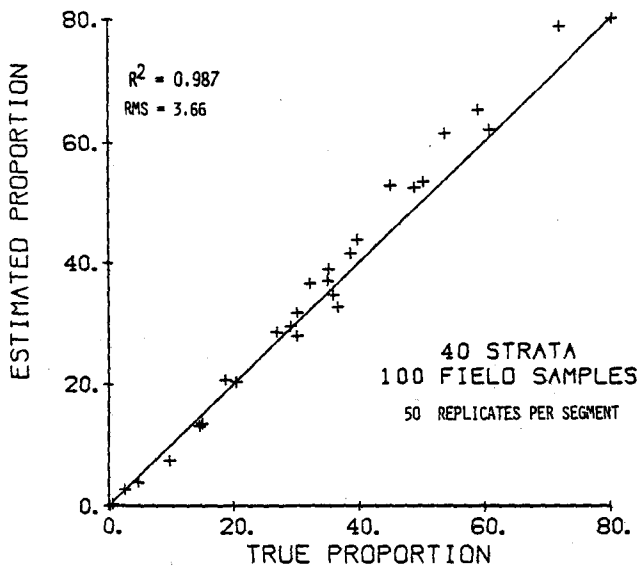

Figure 1. Procedure M Segment Estimates of Total Spring Small Grains

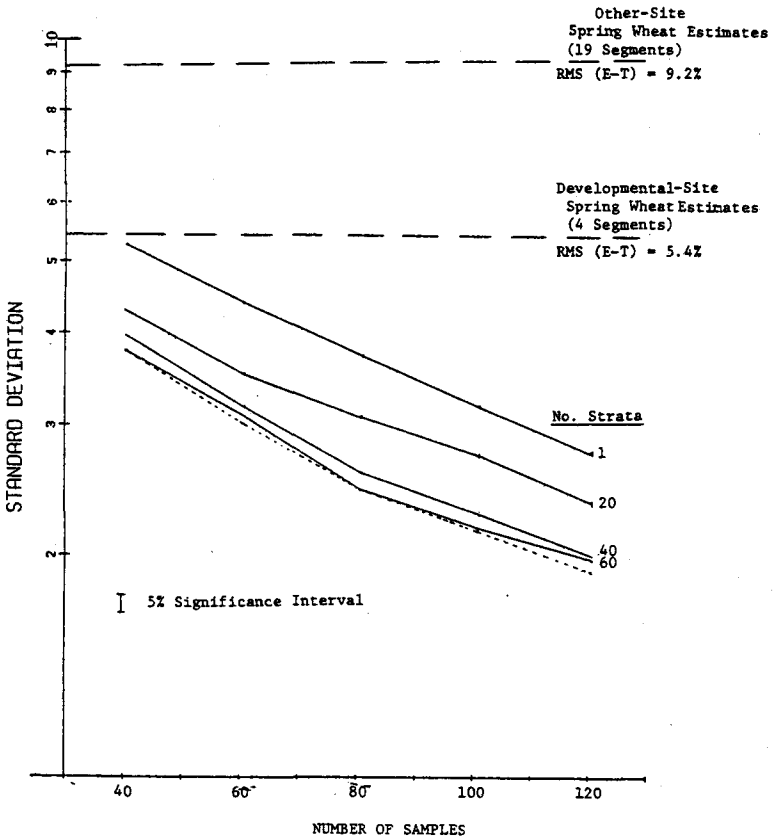

Figure 2. Procedure M Stratified Sampling Variance, Spring Wheat

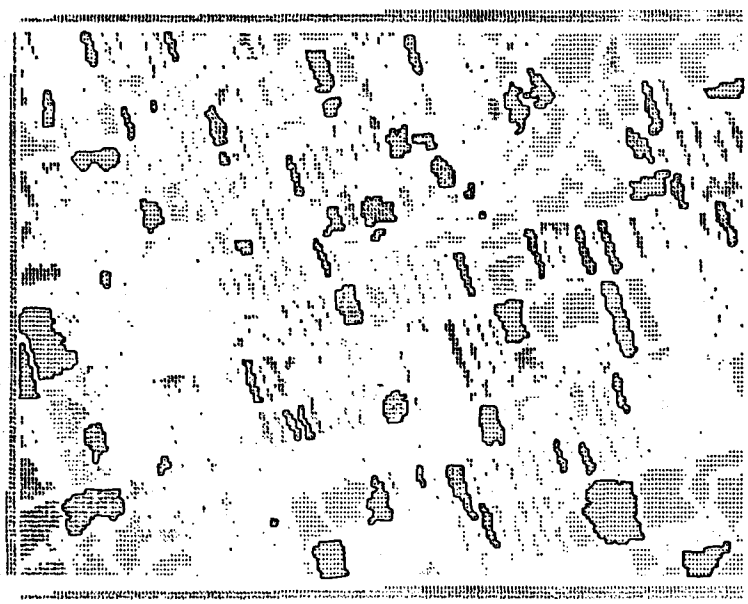

Figure 3. Map of Interiors of Quasi-Fields, Segment 1929

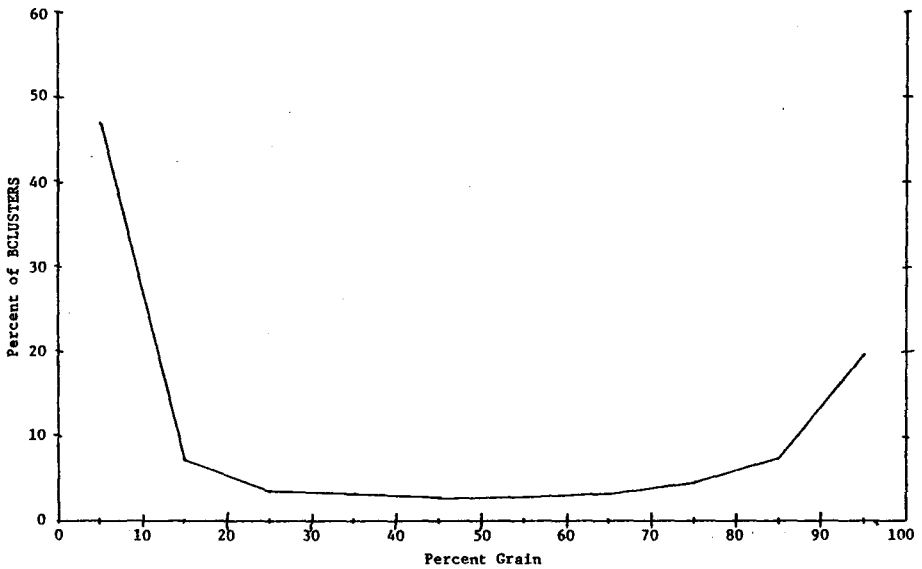

Figure 4. Distribution of Pixels Within BLOBS vs. Percent Grain

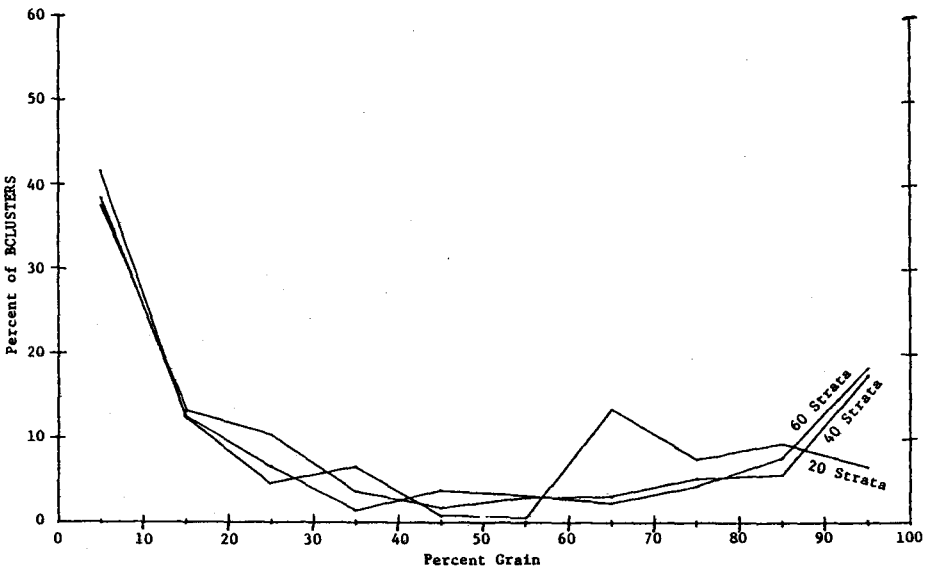

Figure 5. Distribution of the Number of Pixels Within BCLUSTER Grain Percentage Levels

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Mr. Kauth received a B.S. in Physics from Loras College, Dubuque, Iowa in 1958. After graduation worked at the University of Chicago, and since 1963, at Willow Run Laboratories of the University of Michigan (now ERIM). He has worked in atmospheric radiation transfer, pattern recognition and in most of the disciplines associated with design of remote sensing systems for military and civilian applications. He is co-author of the Tasselled Cap concept of Landsat data structure and inventor of the BLOB algorithm.

Dr. Malila has been active since the mid 1960's in the development and testing of techniques for extracting resource information from remotely sensed multispectral scanner data, with emphasis on agricultural applications. His BS and MS education was in Electrical Engineering from Michigan State University and Stanford University, respectively, while his subsequent degree was from the University of Michigan in Forestry with a remote sensing emphasis. He joined the Willow Run Laboratories (now ERIM) in 1960.

Richard C. Cicone

Mr. Cicone received a B.S. in Mathematics from St. John Fisher College, Rochester, New York in 1970 and M.S. in Computer, Information and Control Engineering from University of Michigan, Ann Arbor, Michigan. Since 1976 he has worked as a Research Engineer with ERIM participating in the Supporting Research and Technology (SR&T) program sponsored by the Earth Observation Division of NASA at the Johnson Space Center.