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# STATISTICAL ALGORITHMS AND COMPUTER PROGRAMS FOR ANALYSIS OF MULTI-SPECTRAL OBSERVATIONS

FINAL REPORT

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Prepared for:

**NATIONAL AERONAUTICS AND SPACE ADMINISTRATION  
GEORGE C. MARSHALL SPACE FLIGHT CENTER  
Aero-Astrodynamic Laboratory**

UNDER CONTRACT NO. NAS8-25182

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by

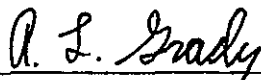
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**NATIONAL AERONAUTICS AND SPACE ADMINISTRATION  
GEORGE C. MARSHALL SPACE FLIGHT CENTER  
AERO-ASTRODYNAMICS LABORATORY**

*Under Contract NAS8-25182*

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## FOREWORD

This study was undertaken by Northrop-Huntsville, for the NASA/MSFC Huntsville, Alabama, under Contract No. NAS8-25182. The program was under the direction of MSFC's Flight Data Statistics Office with Dr. F. R. Krause as the project monitor.

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## Section I INTRODUCTION

As more sophisticated space vehicles and orbiting space stations are developed, onboard data processing and conditioning becomes an imperative system design consideration. The outputs from hundreds or thousands of various sensors in advanced mission payloads are fast exceeding the capacity of available and near-real-time communication systems. In particular, the airborne sensors for earth resources and advanced surveillance have larger amounts of data output as requirements increase for greater area coverage and resolution.

Remote sensing of the earth's resources and environment from airborne and satellite-borne sensors is becoming one of the most significant and immediate applications of the developed space technology to the whole world. The entire spectrum of remote sensing technology will cover sensor design, ground truth study, atmospheric physics, data handling, and data analysis. This study is concerned with data analysis only.

The purpose of data analysis in remote sensing problems is to assess or identify some desired characteristics of the sensor's targets through analysis of multispectral (or multimage) data collected by the sensors. These characteristics may be surface temperature, humidity of the ground, salinity of the ocean, or classifications among different crops and soils. Different applications mainly require different sensors designed to operate at different ranges of the electromagnetic spectrum, while the methods of data analysis are quite similar in principle. Therefore, it is not necessary to specify any particular applications in order to discuss the data analysis techniques.

Since these techniques are to be used for identifying desired characteristics from some given data measurement, they are really within the region of pattern recognition problems. These problems have a long history of developments especially in the field of experimental psychology, neurophysiology of the visual system, and automatic machine character recognition.

Handling and processing of the vast amount of data, which are usually random processes, will require compression of the data to smaller quantities of more meaningful parameters. These parameters should characterize the physical phenomena recorded by the various sensors and usually include the mean value, first few orders of central moment, correlation functions, spectral density functions, probability density function, and associated error functions with respect to each evaluated parameter. To handle many sensor outputs simultaneously would require multi-channel data processing. Further, to perform the data processing in a continuous and near-real-time basis, on-line sequential techniques are necessary.

Statistical methods for the analysis of aircraft survey data are being developed by the University of Michigan, Purdue University, and the University of Kansas. All these methods require human intervention to select homogeneous training areas on the ground. Spectroscopic reference signatures are then computed for each training set and all other resolution elements are classified by matching them with all the reference signatures. The University of Michigan uses the correlation computation for the match, i.e., by computing the correlation coefficients between the sample spectrum and the various reference spectra (ref. 1). Purdue University uses more complex Bayesian statistical decision methods for classification (ref. 2). The University of Kansas uses even more complex clustering techniques which employ both measurement space and spatial clustering (ref. 3).

Our classification differs from the above techniques in using methods of change analysis for the classification of resolution elements. Human interventions for the selection of training areas and reference spectra are not needed. The strip map of an electromechanical scanner is subdivided into inventory areas whose resolution elements are homogeneous.

Statistical methods for data flow compression and signature enhancement are being developed to improve the utilization of remote earth observations from aircrafts and spacecrafts. The objectives of our present research program are to extend the automatic data flow compression and signature enhancement that has previously been developed for earth based sensors to flight systems.

Section II presents analytical consideration and mathematical algorithms for automatic analysis of multispectral data. Section III describes in detail the computer programs developed based on mathematical algorithms presented above. The application of these computer programs to some actual remote sensing data by the University of Michigan multispectral scanner from a aircraft over some agricultural fields is presented in Section IV. Finally, the summary and conclusions are given in Section V.

## Section II

### ANALYTICAL CONSIDERATIONS AND ALGORITHMS

#### 2.1 INTRODUCTION

Analytical considerations and the corresponding classification algorithms for multispectral data sequences are presented in this section. In order to have a better understanding of the overall problem involved, a survey of pattern recognition problems will be given first. This will be followed by (a) statistical analysis of feature characteristics, (b) statistical test for inventory boundary, (c) boundary enhancement by area smoothing and differentiation, and (d) similarity criteria between different populations. An overall functional block diagram of the data analysis is shown in Figure 2-1.

#### 2.2 PATTERN RECOGNITION PROBLEMS - A BRIEF SURVEY

Pattern recognition techniques are methods for making decisions based on statistical testing. The purpose is to identify a specified pattern from a set of given input measurement or to classify a given input to one of several prescribed categories. The input measurement is usually composed of a set of  $N$  numbers of ordered entries (or components)  $X_i$  ( $i = 1, 2, \dots, N$ ), which may be considered as a feature vector  $\bar{X}$  in  $N$  - dimensional feature space. The pattern recognition technique is to be used to classify  $\bar{X}$  to one of  $M$  categories  $C_j$ ,  $j = 1, 2, \dots, M$ , based on some criterion of similarity between the input feature and the given patterns.

The first important step in any pattern recognition problem is to know the characteristics of the feature vector from a sufficiently large ensemble of presentative samples of every possible category  $C_j$ . The necessity of this step is obvious, since, without knowing the characteristic or invariants associated with every pattern category, there is simply no rational basis for identifying them. Some variations in the characteristics of the feature vector always exist and some uncontrollable factors further introduce errors in the measurement of the feature vector. Hence, the logical way to analyze the feature characteristics is by statistical methods. This will require evaluating the

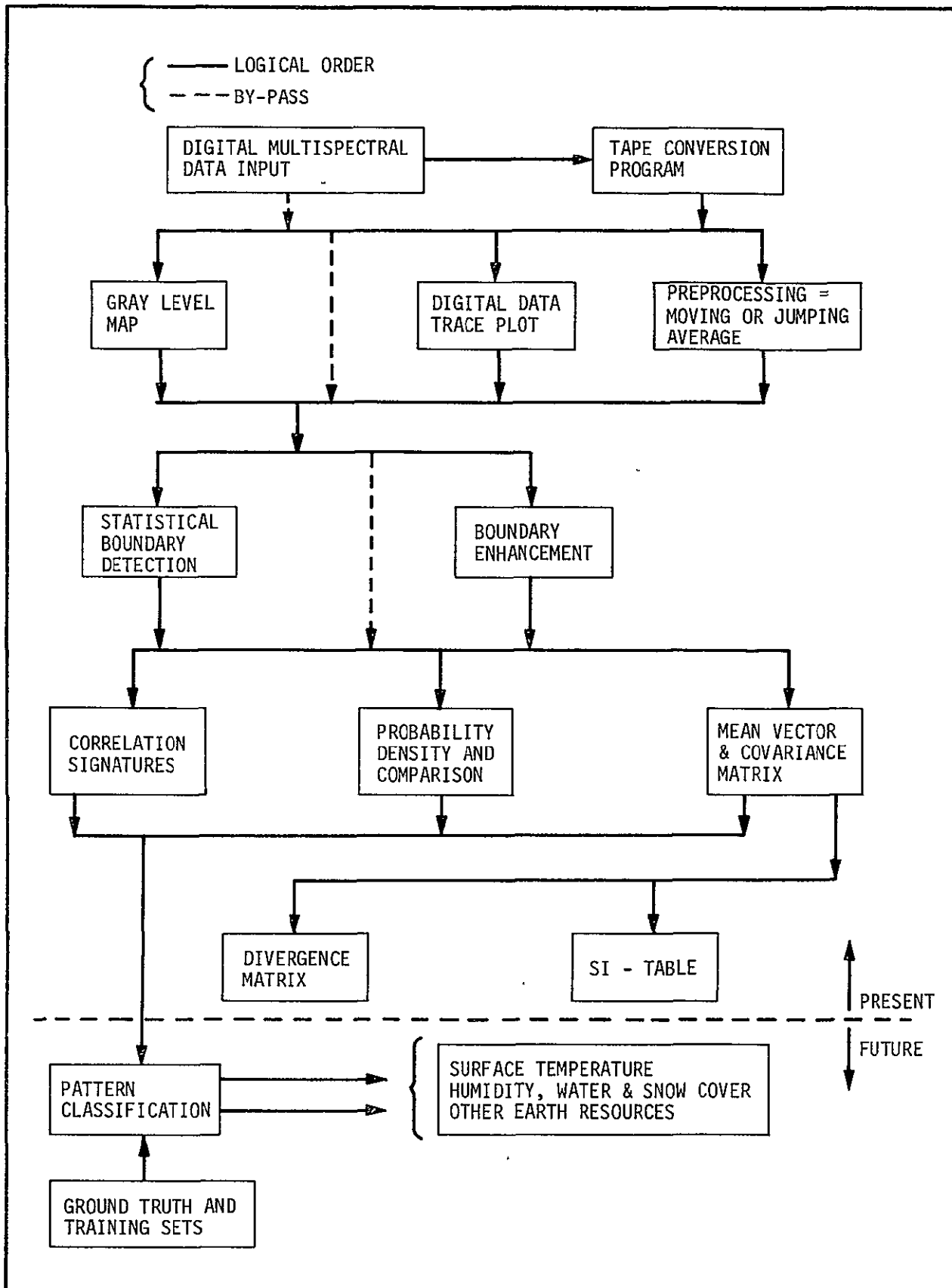


Figure 2-1. BLOCK DIAGRAM OF DATA FLOW

mean, rms, probability density of each component, covariance matrix among any two pair of components, etc., from the set of representative samples (usually, called a training set). From these parameters and quantities evaluated, some statistical models may be formulated. These models, expressed in functional form, may replace those often lengthy and volumous numerical values of the feature characteristics. Some particular statistical models such as Gaussian distribution permit simplification in the latter steps involved in the pattern recognition.

The statistical theory states that if every component of a given feature vector is equally important, then the probability of success for recognizing a certain pattern will increase with the number of the components employed. If every component is not equally important, then the probability of success will depend not only on the number of components employed, but also on their relative importance. Further, a complete statistical description of an ensemble of samples require very large numbers of components to be measured from each sample. It is both impractical and undesirable to do so. This consideration brings out the second important step in pattern recognition, namely, the problem of feature selection. A rationale for feature selection may be stated as follows: "Given the desired accuracy, we want to find the optimum group (or groups) of a predetermined number of components from the feature space so that the probability of error or misrecognition be a minimum." Actually, the optimum feature selection depends on the error criterion chosen, feature characteristics, and algorithms for classification.

Assume one has been given the optimum set of measurement vectors, the next step in pattern recognition is to devise some rule by which to classify any given feature measurement into one of several pattern categories. So this is the classification problem. One of the simplest classification methods is to compare the relative distance between the point (in feature space) to be classified to every representative mean point of available pattern categories. The category with the shortest distance to the point under consideration will be assigned as the recognized pattern. Such a simple classification method is, however, quite limited. For example, there may be a situation where making a wrong classification on some pattern categories is more costly than others.

Under such a situation, we want to weigh differently on different pattern categories according to their relative importance. Many more sophisticated classification methods have been developed based on testing hypotheses in statistical inference theory. One of the most powerful methods is the maximum likelihood ratio test.

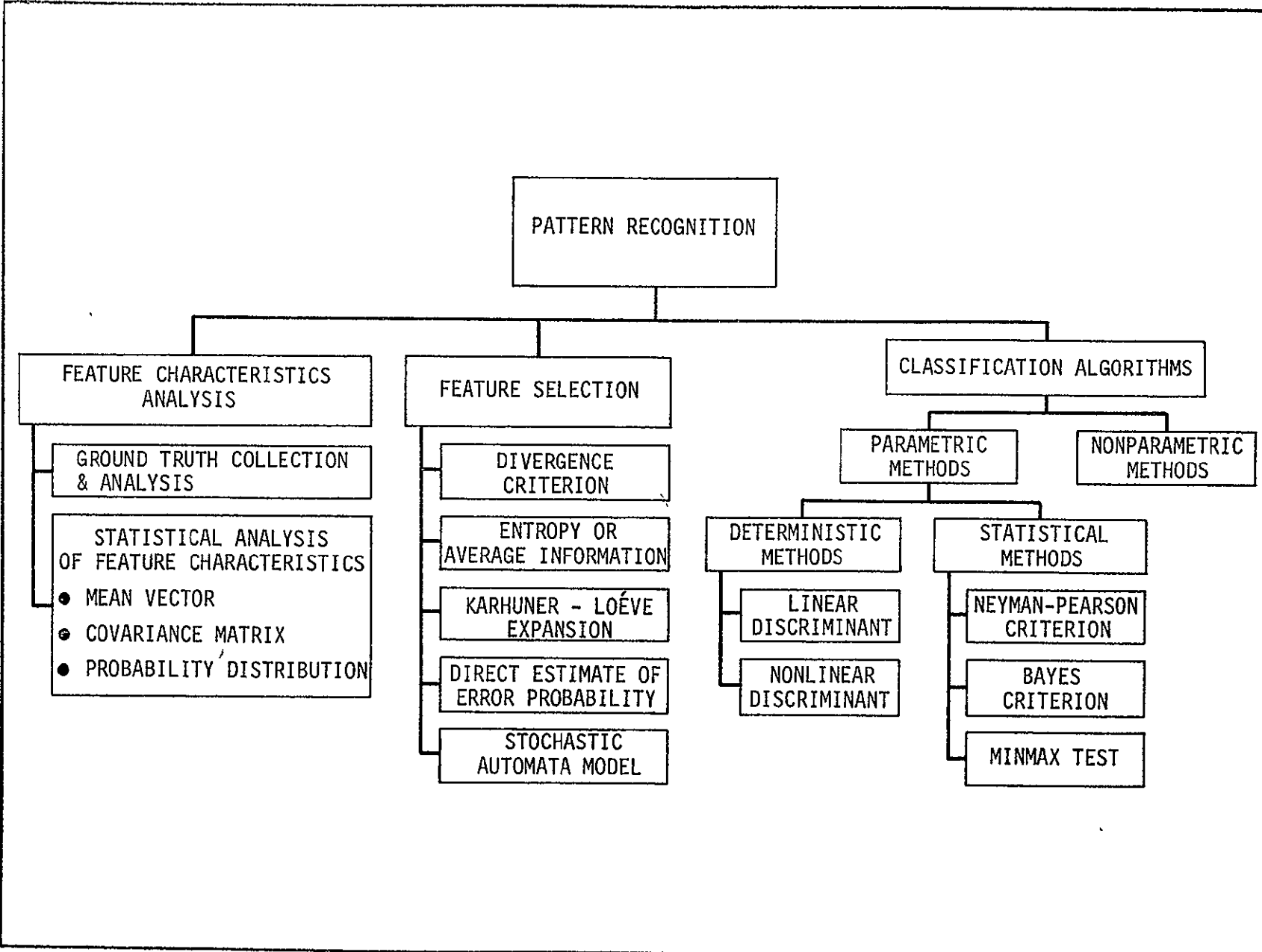
In summary, a pattern recognition system consists of three interrelated aspects: feature characteristics analysis, feature selection, and classification algorithms. Each of these aspects will be described in more detail in the following sections including corresponding pertinent bibliographies. A hierarchy of the pattern recognition program is shown in Figure 2-2.

### 2.2.1 Feature Characteristics Analysis

Because the feature measurement taken in natural situations always involve some influence by the environment, and because some variations also exist in most pattern categories, the logical way to assess the characteristics of the feature vector will be the statistical analysis. More specifically, since the feature vector is of multiple components, a multivariate analysis will be needed. There are many different statistical methods to describe the feature characteristics in the feature space such as joint probability density, correlation function, spectral density, and characteristic function (which is the Fourier transform of the probability density), just to name a few. In general practice and for simplicity, however, it usually takes some combination of these different types of statistical descriptions in their respective lowest order. In other words, one will usually evaluate at least the following quantities from the representative set of available samples:

- Mean vector, which is the ordered mean values of the feature components denoted by  $\bar{\mu} = (\mu_1, \mu_2, \dots, \mu_N)$ .
- Correlation matrix, which is a matrix of mean products of any two pair of feature components, denoted by  $R_{ij}$ .
- Covariance matrix, which is a matrix of mean products of any two pair of feature components subtracted by their respective mean values, denoted by  $C_{ij}$ .
- Univariate histogram, which is the probability density of a single feature component.





2-5

Figure 2-2. A HIERARCHY OF PATTERN RECOGNITION PROBLEM

From the above evaluated parameters and functions some analytical models or approximation of the feature space of the pattern categories may be induced.

When the multivariate Gaussian distribution is made, the ensuing analysis on feature selection and classification algorithms can be greatly simplified. This is also the reason why so many approaches developed for pattern recognition system employ this particular distribution (or model).

### 2.2.2 Feature Selection

Not every component of the feature vector (or the set of measurement) are equally important for classification. Obviously, those components peculiar to pattern categories are of primary importance. It is also desirable to use as few components as possible to achieve the prefixed accuracy of successful recognition. These two facts suggest the need for an objective study of selecting the feature components. The feature selection is closely related to the performance of pattern classification.

Generally speaking, the more feature components used, the higher the probability of successful recognition. So, the problem of feature selection might be more rigorously stated as follows: out of a given physically accessible or available set of feature components, to select an optimum subset of a prescribed number of feature components such that the probability of successful recognition is maximized. By this definition, the feature selection problem must be analyzed with respect to a particular decision process for pattern recognition. However, this logical approach for feature selection is very complicated. Therefore, several existing methods for the feature selection adopt different approaches based on various measures of effectiveness in the choice of components.

One approach is to employ a measure of distance between any two (arbitrary) probability density of pattern categories (ref. 4). This measure is called "divergence", which is defined as the difference between two expected values of the likelihood ratios. The second approach uses the idea of entropy or average information (ref. 5) as criterion for feature selection. This approach calculates a statistic obtained over a large sample set to yield a measure of goodness for the feature component, which can be considered as the mutual

information of the feature and the pattern classes. The third approach employs Karhunen - Loève expansion which does not require the a priori knowledge of the probability density of the feature vector. The essence of the expansion is to project the original feature vector onto a less-dimensional vector space spanned by a set of deterministic orthonormal coordinate functions. The expansion has the following optimum properties: (1) it minimizes the mean-square error for the truncated series of the expansion and (2) it minimizes the entropy function defined over the variance of the random coefficient in the expansion (ref. 5).

### 2.2.3 Classification Algorithms

The classification scheme in pattern recognition is to divide the feature space into some prescribed number of subspaces, each of which will be designated for one of the pattern categories. Different classification schemes differ mainly in the criteria used to establish these subspaces. The separating boundaries between these subspaces are called decision surfaces which can be defined by a set of functions. These functions are called "discriminant functions" and are so chosen that one and only one of them will give the larger value compared to the others for all samples in a particular pattern class (i.e., a subspace). That is, for a given feature vector to be classified, a finite number of discriminant functions are to be evaluated with this feature vector. The function which yields the largest value will assign the input feature vector to the pattern category for which this function is designated. This scheme may be expressed as follows: Any given feature vector  $\bar{X}$  is classified as a pattern class  $C_i$  ( $i=1, 2, \dots, M$ ), if

$$g_i(\bar{X}) > g_j(\bar{X}) \text{ for all } i \neq j,$$

where  $g_i$  ( $i=1, 2, \dots, M$ ) are the discriminant functions for class  $C_i$ .

The classification methods may be divided into two main groups; namely, the parametric method and the nonparametric method. The parametric method is more appropriate for classification when each pattern category can be characterized by a set of parameters obtained from the feature characteristics analysis of the training set. The nonparametric method is more appropriate when no simple realistic assumption can be made on the characteristics of the pattern classes. These two methods are discussed in more detail in the following paragraphs.

The parametric method may be further divided into two distinct groups; deterministic and statistical methods. The discrimination functions in the deterministic methods can be either linear or nonlinear in the input feature vector. The linear discriminant functions separate the feature space by hyperplanes, while the nonlinear discriminant functions divide the feature space into curvilinear hypersurfaces. The simplest linear deterministic method is the so-called correlation method (also called template matching). This method evaluates the scalar product of the input feature vector with a set of reference feature vectors, each of which represents a particular pattern class. The feature vector will then be assigned to the particular pattern class that yields the largest scalar product. Another linear deterministic method is the minimum-distance method which uses the shortest distance between the input feature vector to the set of reference pattern vectors as the criterion.

The three common statistical classification methods are Neyman-Pearson criterion, Bayes criterion, and minimax test. The Neyman-Pearson criterion is the simplest of all and demands the least a priori information. The Bayes criterion is to minimize the average cost of misrecognition, when the priori probability of occurrences of pattern classes are known, and when the average cost is a linear function of the absolute error probabilities. The minimax test is a Bayes test except that the former minimizes the maximum of the conditional cost of misrecognition. All three of these tests are optimum under the respective criteria and also use the likelihood ratio of the conditional probability densities of the pattern classes. These methods hold for any arbitrary distribution functions; however, great simplifications may be made if the distribution is Gaussian.

Finally, we shall describe the nonparametric methods for pattern classification. By these methods, no parameter from the training set is evaluated a priori, rather the discriminant function (in the linear case) will assume the form of

$$g_j(\bar{X}) = \bar{W}_j \cdot \bar{X} = \sum_{i=1}^N W_{ji} X_i$$

( $j=1, 2, \dots, M$  and  $i=1, 2, \dots, N$ ),

where  $\bar{W}_j$  ( $W_{j1}, W_{j2}, \dots, W_{jN}$ ) are the weighting functions for the  $j^{\text{th}}$  pattern class. These weighting functions are to be determined by a systematic error-correction scheme from the training set. The error-correction scheme may be written as

$$\bar{W}'_j = \bar{W}_j + c\bar{X}$$

This states that each new weighting function is simply the sum of the old one plus a fixed fraction  $c$  of the input feature vector. It has been proven theoretically that within the finite number of error corrections, a suitable weighting function can be obtained, provided that the training set is separable by hyperplanes.

In summary, the advantage of the nonparametric method is that no assumption is needed on the feature space. However, they are applicable to those cases where pattern classes may be separable by hyperplanes, while the parametric method is not restricted by the separability requirement.

#### 2.2.4 Pertinent Bibliography For Pattern Recognition

Some pertinent bibliography on the pattern recognition technique together with remote sensing of the earth's resources and environment will be given in Appendix A. This bibliography is classified into five categories.

- Remote sensing of the earth's resources and environment
- Pattern recognition in general
- Feature characteristics analysis
- Feature selection
- Classification algorithms.

This bibliography is not intended to be extensive, rather it is considered to be more informative for the reader.

### 2.3 STATISTICAL TEST FOR INVENTORY BOUNDARIES

#### 2.3.1 Introduction

Any statistical evaluation of multispectral observation requires a population of resolution elements that are statistically alike. Such a population

occupies a certain area of the strip map, which shall be called an inventory area. In many cases such inventory areas are continuous in space. Typical examples of such continuous inventory areas are clouds, snow fields, agricultural fields, forests, etc. The boundary of the inventory area shall be called inventory boundary which thus separate populations of homogeneous resolution elements. However, all statistical properties will change whenever an inventory boundary is crossed. Conversely, the change of statistical properties along a scan line indicates that an inventory boundary has been crossed.

The above considerations provide a basis for the development of sequential and completely automatic methods for the selection of the inventory boundary. Our previous tests for environmental variations (refs. 6 and 7) recognize the change of statistical parameters with record length. Furthermore, the position of an inventory boundary indicates a change of reflectance or thermal emission which is not tied to any particular application. Statistical methods which utilize inventory areas are thus applicable to crop surveys, yield surveys, and land use investigations. Automatic detection of inventory boundaries could thus support statistical data flow compression and signature enhancement methods that may be used for many disciplinary applications.

### 2.3.2 Formulation of the Algorithm

The computer selection of inventory boundaries follows from a direct application of accumulative error curves (refs. 6 and 7). Consider a sequence of resolution areas,  $i = 1, 2, \dots, m$ , along a scan. Each of these resolution areas is assumed to be statistically independent. Any average  $(\bar{\quad})_i$  from a single resolution area then represents a statistical experiment. If all resolution areas belong to the same inventory area, then the accumulative average over these areas

$$(\bar{\quad})_m = \frac{1}{m} \sum_{i=1}^m (\bar{\quad})_i \quad (2-1)$$

should become more accurate as  $m$  increases. The statistical error of such an accumulative average should thus become smaller with increasing  $m$ .

The test for inventory boundaries is now derived by monitoring the decrease of the actual error with accumulative number  $m$ , by comparing this actual error curve with the most probable error curve.

The actual (or sampled) error of an accumulative mean,  $\Delta (\overline{\overline{\quad}})_m$ , can be computed from the deviation of the individual experiment  $(\overline{\quad})_i$  relative to the accumulative average over all experiments.

$$\Delta (\overline{\overline{\quad}})_m^2 = \frac{1}{m(m-1)} \sum_{i=1}^m \left[ (\overline{\quad})_i - (\overline{\overline{\quad}})_m \right]^2 \quad (2-2)$$

This actual error can also be used to construct a random variable; i.e, Chi-square variable with  $(m-1)$  degree of freedom. That is

$$\chi^2 (m-1) = \frac{m(m-1) \Delta^2 (\overline{\overline{\quad}})_m}{\sigma^2} \quad (2-3)$$

The value of  $\sigma^2$  is constant as long as the resolution areas,  $i = 1, 2 \dots m$ , are statistically independent and belong to the same population. Under these considerations, the probability distribution of the variable  $\chi^2$  is also known. The most probable  $\chi^2 (m-1)$  value is given by

$$\chi^2 (m-1) \Big|_{\text{most prob.}} = m-3 \quad \text{for } m \geq 4 \quad (2-4)$$

This most probable value indicates the existence of a most probable error

$$\delta_m^2 = \frac{\delta^2}{m(m-1)} \chi^2 (m-1) \Big|_{\text{most prob.}} = \frac{m-3}{m(m-1)} \sigma^2 \quad (2-5)$$

The value of the unknown variance  $\sigma^2$  can now be estimated by fitting the shape of the most probable error curve,  $\delta_m$ , to the actual error curve  $\Delta (\overline{\overline{\quad}})_m$ . This curve fit is chosen such that the relative mean square variation between these two curves become a minimum. Let  $M$  denote the last accumulative number. The above curve fit may thus be expressed by

$$\frac{\partial}{\partial \sigma} \sum_{m=4}^M \left\{ \frac{\Delta (\overline{\overline{\quad}})_m - \delta_m}{\delta_m} \right\}^2 = 0 \quad (2-6)$$

Substituting  $\delta_m$  from the previous equation and differentiating yields

$$\sigma^2 = \frac{\sum_{m=4}^M \frac{m(m-1)}{m-3} \Delta \left(\overline{\quad}\right)_m^2}{\sum_{m=4}^M \sqrt{\frac{m(m-1)}{m-3}} \Delta \left(\overline{\quad}\right)_m} \quad (2-7)$$

The actual error  $\Delta \left(\overline{\quad}\right)_m$  should oscillate around the most probable error curve. The range of oscillations is given by the confidence factor of the Chi-square  $\chi^2$  distribution.

$$\frac{\chi_{1-p}^2 (m-1)}{\sqrt{m-1}} \frac{\sigma}{\sqrt{m}} \leq \Delta \left(\overline{\quad}\right)_m \leq \frac{\chi_p^2 (m-1)}{\sqrt{m-1}} \frac{\sigma}{\sqrt{m}} \quad (2-8)$$

The values of  $\chi_p^2 (m-1) / \sqrt{m-1}$  and  $\chi_{1-p}^2 (m-1) / \sqrt{m-1}$  are listed in Table 2-1.

The above derivation is only for single channel data. It is natural to extend the test for inventory boundary to a combination of several channels. This extension is achieved by replacing the random variable (defined by equation (2-6)) for a single channel by the generalized random variable of combining L number of channels.

$$\chi^2 (m-1) \Big|_L = \frac{m(m-1)}{L} \sum_{\lambda=1}^L \frac{\Delta^2 \left(\overline{\quad}\right)_{m,\lambda}}{\sigma_\lambda^2} \quad (2-9)$$

Selected Channels

Inventory boundaries for a combination of L channels are then derived by testing the following confidence interval.

$$\frac{\chi_{1-p}^2 (m-1)}{\sqrt{m-1}} \leq \left\{ \frac{1}{L} \sum_{x=1}^L \frac{\Delta^2 \left(\overline{\quad}\right)_{m,\lambda}}{\sigma_\lambda^2 / m} \right\}^{1/2} \leq \frac{\chi_p^2 (m-1)}{\sqrt{m-1}} \quad (2-10)$$

Selected channels

The derivation of this extended test is exactly analogous to the derivation for the single channel.



Table 2-1. CONFIDENCE FACTORS FOR INVENTORY BOUNDARIES

M	$x_p(m-1)/\sqrt{m-1}$					
	p=0.005	p=0.01	p=0.10	p=0.90	p=0.99	p=0.995
3	1.985	1.821	1.17	.01	0.032	0.000
4	1.880	1.752	1.24	.08	0.082	0.058
5	1.789	1.681	1.25	.12	0.170	0.134
6	1.726	1.631	1.25	.46	0.244	0.203
7	1.668	1.586	1.24	.52	0.304	0.262
8	1.626	1.549	1.23	.56	0.353	0.311
9	1.593	1.521	1.22	.60	0.394	0.352
10	1.563	1.494	1.22	.62	0.428	0.386
11	1.536	1.473	1.21	.65	0.457	0.416
13	1.494	1.435	1.20	.68	0.504	0.465
15	1.459	1.407	1.19	.71	0.542	0.505
17	1.432	1.383	1.18	.73	0.572	0.536
19	1.408	1.362	1.17	.75	0.597	0.563
21	1.389	1.345	1.17	.77	0.618	0.585
26	1.351	1.311	1.15	.79	0.660	0.629
31	1.320	1.286	1.13	.81	0.690	0.661
62	1.253	1.214	1.10	.87	0.768	0.755
m → ∞	1	1	1	1	1	1

The above formulation is discussed for a one-dimensional data sequence. Actually, it is applicable equally well for 2-dimensional data sequences such as data from a strip map. The above algorithm may be employed to detect the inventory boundaries in two directions, simultaneously.

## 2.4 BOUNDARY ENHANCEMENT ALGORITHM

Another method for inventory boundary detection - boundary enhancement method - will now be presented. Basically, the idea of the boundary enhancement is to precondition the two-dimensional array of original data by converting the difference between adjacent samples into the corresponding absolute value or by taking the square of the difference. Since, at the boundary between any two homogeneous regions, one expects larger differences in the data difference, the method of the boundary enhancement will accentuate the existing boundary.

Let the 2-dimensional multispectral data sequence be denoted by  $x(i,j,k)$ , where  $i$  and  $j$  represent the scan line and the sample number along a scan line, respectively, while  $k$  stands for the channel number for each data sample.

Further let

$$\begin{aligned} i &= 1, 2, \dots, M \\ j &= 1, 2, \dots, J \\ k &= 1, 2, \dots, K \end{aligned}$$

The 2-dimensional moving average, which serves as a smoothing operator, is defined by

$$y(i,j,k) = \frac{1}{(2N+1)^2} \sum_{i'=-N}^N \sum_{j'=-N}^N x(i+i', j+j', k)$$

where a  $(2N+1) \times (2N+1)$  array of given data samples have been averaged. This operation is illustrated in Figure 2-3.

Two types of the boundary enhancement have been used. The first type is based on taking the square of the difference of adjacent samples after the 2-dimensional averages. Specifically, it is defined as

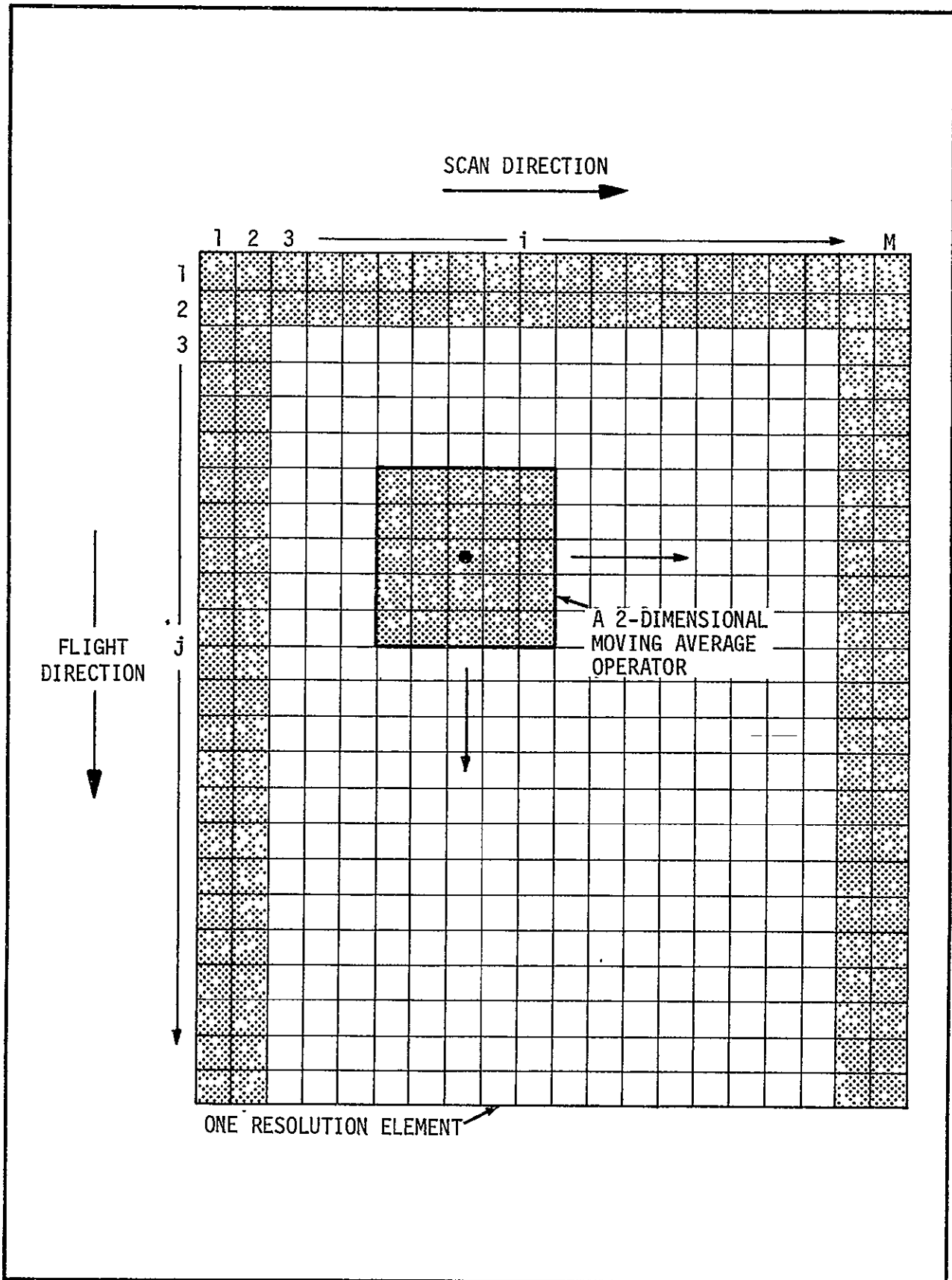


Figure 2-3. ILLUSTRATION OF 2-DIMENSIONAL MOVING AVERAGE OVER TARGET SCENES

$$\begin{aligned}
 Z_1(i,j,k) &= [y(i,j,k) - y(i,j-d,k)]^2 \\
 &+ [y(i,j,k) - y(i,j+d,k)]^2 \\
 &+ [y(i,j,k) - y(i-d,j,k)]^2 \\
 &+ [y(i,j,k) - y(i+d,j,k)]^2
 \end{aligned}$$

The second type is the same as the first type except replacing the squaring operation by taking the absolute value of difference. That is

$$\begin{aligned}
 Z_2(i,j,k) &= |y(i,j,k) - y(i,j-d,k)| \\
 &+ |y(i,j,k) - y(i,j+d,k)| \\
 &+ |y(i,j,k) - y(i-d,j,k)| \\
 &+ |y(i,j,k) - y(i+d,j,k)|
 \end{aligned}$$

where  $d$  denotes the number of samples skipped in calculating the finite difference and it can be any positive integer. This operation is illustrated in Figure 2-4.

The new sample sequence  $Z_1(i,j,k)$  or  $Z_2(i,j,k)$  is enhanced data in the sense that their values have been magnified if they happen to locate close to inventory boundaries as illustrated in Figure 2-5.

In order to find a systematic and automatic selection of the inventory boundaries based on these enhanced data, the mean value  $\bar{Z}_{1,2}(k)$ , mean square value  $\bar{Z}_{1,2}^2(k)$ , and the standard deviation  $\bar{S}_{1,2}(k)$  must be calculated for each channel over the entire 2-dimensional sample sequence as follows.

$$\bar{Z}_{1,2}(k) = \frac{1}{MJ} \sum_{i=1}^M \sum_{j=1}^J Z_{1,2}(i,j,k)$$

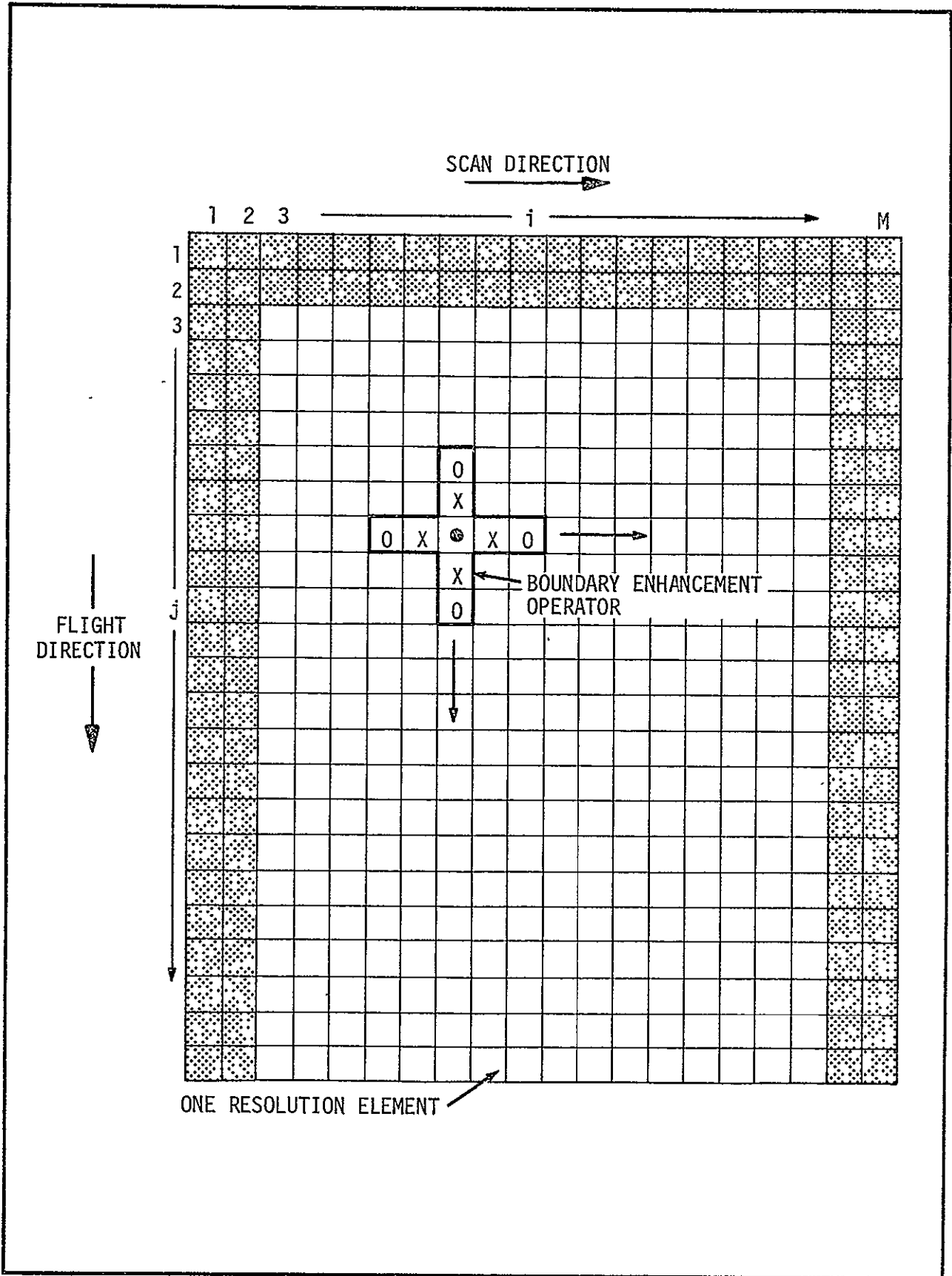


Figure 2-4. ILLUSTRATION OF ENHANCING DATA AROUND INVENTORY BOUNDARIES

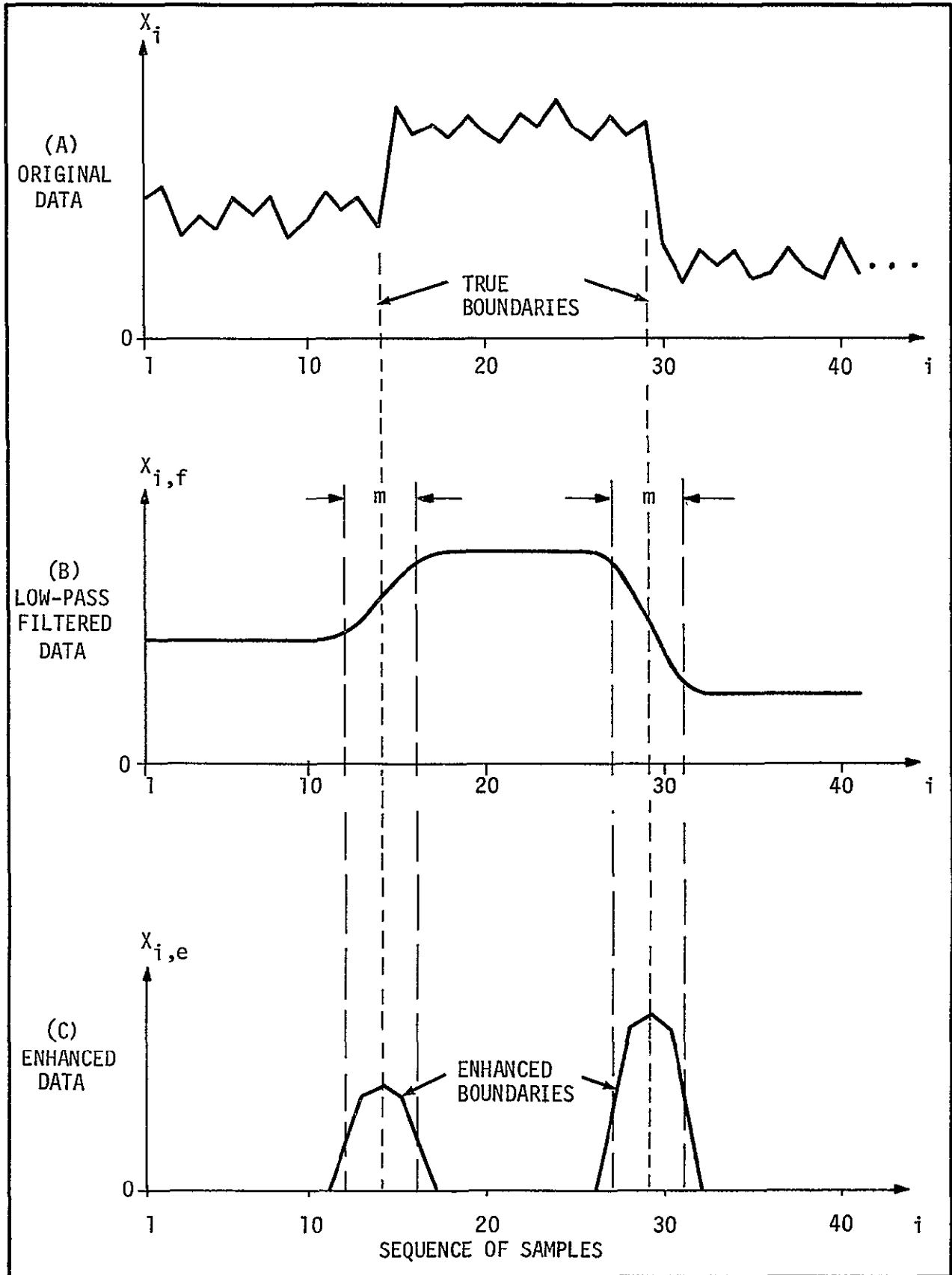


Figure 2-5. ILLUSTRATION OF INVENTORY BOUNDARY ENHANCEMENT

$$\bar{Z}_{1,2}^2(k) = \frac{1}{MJ} \sum_{I=1}^M \sum_{j=1}^J Z_{1,2}^2(i,j,k)$$

$$\bar{S}_{1,2}^2(k) = \bar{Z}_{1,2}^2(k) - (\bar{Z}_{1,2}(k))^2$$

The threshold value, T, for determining the inventory boundary is then defined by

$$T(k) = \bar{Z}_{1,2}(k) + a \bar{S}_{1,2}(k)$$

where a is some arbitrary constant. If the enhanced data sample

$$Z(i,j,k) \geq T(k)$$

for at least one channel, then that sample will be considered to locate on or close to the inventory boundary. On the other hand, if  $Z(i,j,k) < T(k)$  for all k, then the sample is not considered on the inventory boundary.

In the above discussion, the 2-dimensional moving average and boundary enhancement have been treated as two independent operations. That is, any given data will be processed by the moving average first and then use the output data to be processed by the boundary enhancement. Actually, these two operations may be combined into one. Further, in many applications one needs only to use d=1 or 2. The algorithm to accomplish these required operations simultaneously is given below.

$$Z_1(i,j,k) = W_1^2(i,j,k) + W_2^2(i,j,k) \\ + W_3^2(i,j,k) + W_4^2(i,j,k)$$

and

$$Z_2(i,j,k) = |W_1(i,j,k)| + |W_2(i,j,k)| \\ + |W_3(i,j,k)| + |W_4(i,j,k)|$$

Here, the expressions in the right hand side of the equations for d=1 and d=2, respectively, are defined as follows.

For d=1:

$$W_{31}(i,j,k) = - \sum_{j'=-N}^N x(i-N-1, j+j', k)$$

$$W_{41}(i,j,k) = \sum_{j'=-N}^N x(i-N, j+j', k)$$

$$W_1(i,j,k) = \sum_{i'=-N}^N [-x(i+i', j-N-1, k) + x(i+i', j+N, k)]$$

$$W_2(i,j,k) = \sum_{i'=-N}^N [x(i+i', j-N, k) - x(i+i', j+N+1, k)]$$

$$W_{32}(i,j,k) = \sum_{j'=-N}^N x(i+N, j+j', k)$$

$$W_{42}(i,j,k) = - \sum_{j'=-N}^N x(i+N+1, j+j', k)$$

$$W_3(i,j,k) = W_{31}(i,j,k) + W_{32}(i,j,k)$$

$$W_4(i,j,k) = W_{41}(i,j,k) + W_{42}(i,j,k)$$

For d=2:

$$W_{31}(i,j,k) = - \sum_{j'=-N}^N x(i-N-2, j+j', k)$$

$$W_{32}(i,j,k) = - \sum_{j'=-N}^N x(i-N-1, j+j', k)$$

$$W_{41}(i,j,k) = \sum_{j'=-N}^N x(i-N-1, j+j', k)$$

$$W_{42}(i,j,k) = \sum_{j'=-N}^N x(i-N, j+j', k)$$



$$W_1(i,j,k) = \sum_{i'=-N}^N [-x(i+i',j-N-2,k) - x(i+i',j-N-1,k) \\ + x(i+i',j+N,k) + x(i+i',j+N+1,k)]$$

$$W_2(i,j,k) = \sum_{i'=-N}^N [x(i+i',j-N-1,k) + x(i+i',j-N,k) \\ - x(i+i',j+N+1,k) - x(i+i',j+N+2,k)]$$

$$W_{33}(i,j,k) = \sum_{j'=-N}^N x(i+N,j+j',k)$$

$$W_{34}(i,j,k) = \sum_{j'=-N}^N x(i+N+1, j+j',k)$$

$$W_{43}(i,j,k) = - \sum_{j'=-N}^N x(i+N+1, j+j',k)$$

$$W_{44}(i,j,k) = - \sum_{j'=-N}^N x(i+N+2, j+j',k)$$

$$W_3(i,j,k) = W_{31}(i,j,k) + W_{32}(i,j,k)$$

$$+ W_{33}(i,j,k) + W_{34}(i,j,k)$$

$$W_4(i,j,k) = W_{41}(i,j,k) + W_{42}(i,j,k)$$

$$+ W_{43}(i,j,k) + W_{44}(i,j,k)$$

Care has been taken in arranging the above equations such that the input data  $x(i,j,k)$  can be read in from magnetic tape in the most sequential manner with respect to data storage in tape for any channel  $k$ .

## 2.5 STATISTICAL CHARACTERISTICS OF AN INVENTORY AREA

Two methods for detecting the inventory boundaries in any given target area have been presented in subsections 2.3 and 2.4. Thus, the area was divided into some inventory areas, each of which represents a homogeneous population. How to describe statistically the properties or characteristics associated with each inventory area will be discussed in the following paragraphs.

In a two-dimensional inventory area, the multispectral data are expressed as  $x(i,j,k)$ . Here, the scan line  $i$  may run from  $I_s$  to  $I_e$ , and for each particular  $i$ , the sample number  $j$  may run from  $J_s(i)$  to  $J_e(i)$ , and  $k$  represents the channel number (or components) for each sample.

The mean vector for an inventory area is then defined by

$$\bar{M}(k) = \frac{1}{N} \sum_{i=I_s}^{I_e} \sum_{j=J_s(i)}^{J_e(i)} x(i,j,k)$$

where  $N$  is the total number of samples within the inventory area.

The correlation matrix of the inventory area is defined by

$$\bar{R}(k_1, k_2) = \frac{1}{N} \sum_{i=I_s}^{I_e} \sum_{j=J_s(i)}^{J_e(i)} x(i,j,k_1) x(i,j,k_2)$$

The covariance matrix of the inventory area is defined by

$$\begin{aligned} \bar{C}(k_1, k_2) &= \frac{1}{N} \sum_{i=I_s}^{I_e} \sum_{j=J_s(i)}^{J_e(i)} [x(i,j,k_1) - \bar{M}(k_1)] [x(i,j,k_2) - \bar{M}(k_2)] \\ &= \bar{R}(k_1, k_2) - \bar{M}(k_1) \bar{M}(k_2) \end{aligned}$$

The normalized correlation matrix is defined by

$$\bar{R}_n(k_1, k_2) = \frac{\bar{R}(k_1, k_2)}{\sqrt{\bar{R}(k_1, k_1) \bar{R}(k_2, k_2)}}$$

The normalized covariance matrix is defined by

$$\bar{C}_n(k_1, k_2) = \frac{\bar{C}(k_1, k_2)}{\sqrt{\bar{C}(k_1, k_1) \bar{C}(k_2, k_2)}}$$

Finally, the univariate (first-order) probability density function is defined by

$$p[x_1 \leq x(k) \leq x_2] = \frac{1}{N} \left\{ \begin{array}{l} \text{Number of samples whose value in } k^{\text{th}} \\ \text{channel lies between } x_1 \text{ and } x_2 \end{array} \right\}$$

More conveniently, if  $x_1$  and  $x_2$  will be given in exact multiple of prescribed increment  $\Delta x$ , then the above probability density function may be written as

$$\begin{aligned} p_i(x(k)) &= p[(i - \frac{1}{2})\Delta x \leq x(k) \leq (i + \frac{1}{2})\Delta x] \\ &= \frac{1}{N} \left\{ \begin{array}{l} \text{Number of samples whose value in } k^{\text{th}} \text{ channel lies} \\ \text{between } (i - 1/2)\Delta x \text{ and } (i + 1/2)\Delta x. \end{array} \right\} \end{aligned}$$

Clearly, the above quantities defined for the inventory area are just a few of the simplest and more significant statistical features that one may choose.

In many applications, the multivariate Gaussian distribution is a quite realistic approximation for the multispectral data, as is also predicted by the Central Limit theorem of the probability theory. One of the desirable features of this distribution is because the distribution is completely determined by the mean vector and covariance matrix only. Since this distribution occupies such a central important position in the pattern classification problem, it is given below.

$$p(x(k)) = \frac{1}{(2\pi)^{K/2} |\bar{C}(k_1, k_2)|} \exp \left\{ \frac{-|\bar{C}(k_1, k_2)|}{2} \sum_{k_1=1}^K \sum_{k_2=1}^K |\bar{C}^*(k_1, k_2)| [x(k_1) - M(k_1)][x(k_2) - M(k_2)] \right\}$$

where  $|\bar{C}(k_1, k_2)|$  is the determinant of the matrix  $\bar{C}(k_1, k_2)$  while  $|\bar{C}^*(k_1, k_2)|$  is the cofactor of  $\bar{C}(k_1, k_2)$ .

Another form of the expression is

$$p(x(k)) = \frac{1}{(2\pi)^{K/2} |\bar{C}(k_1, k_2)|} \exp \left\{ -\frac{1}{2} [x(k) - \bar{M}(k)]' \bar{C}^{-1}(k_1, k_2) \cdot [x(k) - \bar{M}(k)] \right\}$$

where the prime represents the transpose and  $\bar{C}^{-1}(k_1, k_2)$  is the inverse of  $\bar{C}(k_1, k_2)$ . Also

$$\bar{C}^{-1}(k_1, k_2) = \frac{(-1)^{k_1+k_2}}{|\bar{C}(k_1, k_2)|} |\bar{C}^*(k_1, k_2)|$$

## 2.6 SIMILARITY CRITERIA BETWEEN INVENTORY AREAS

So far, we have formulated methods for determining inventory areas and presented a statistical description for each inventory area. The next question that arises is how to determine the similarity or dissimilarity among those inventory areas that do not have any common inventory boundary. In other words, we want to know whether two inventory areas far apart belong to the same population or not based on their statistical characteristics described in the last subsection.

There are many criteria one can choose to establish the similarity between two inventory areas that are characterized by the given statistical descriptions, such as mean vectors and covariance matrices. One of the most appropriate criteria available is the so-called "divergence" measure, which can be considered to be a dimensionless "distance" between two arbitrary multivariate probability density functions  $p_i(x(k))$  and  $p_j(x(k))$ , for  $i^{\text{th}}$  and  $j^{\text{th}}$  inventory areas, respectively. Since the mean vector and covariance matrix can be calculated from the probability density function, this "divergence" measure does take into consideration all the information from the inventory areas of interest. This measure is defined as follows (ref. 4)

$$D(i, j) = E \left[ \log \left( \frac{p_i(x(k))}{p_j(x(k))} \right) \Big|_i \right] \\ - E \left[ \log \left( \frac{p_i(x(k))}{p_j(x(k))} \right) \Big|_j \right]$$

Thus, it is the difference between two expected values of the logarithms of the likelihood ratios of a random input sample vector  $x(k)$ , ( $k=1, 2, \dots, K$ ). In other words, the divergence is a measure of the difficulty for discriminating between the two given probability density functions. The divergence possesses all the properties of "distance" or "norm" as well as several others:

- $D(i,i) = 0$
- $D(i,j) \geq 0$  for  $i \neq j$ .
- $D(i,j) = D(j,i)$
- If every component of the sample vector is statistically independent, then the divergence is equal to the sum of the divergences for each component, individually, i.e.

$$D(i,j) = \sum_{k=1}^K D_k(i,j)$$

- If one more component is added to the original sample vectors, then the divergence for the  $(K+1)$  - dimensional sample space will never decrease, i.e.

$$D(i,j | x(k)) \leq D(i,j | x(k), x(k+1)).$$

We shall now consider several special cases of the divergence measure. If the probability density functions are Gaussian with the mean vector  $\bar{M}_i(k)$  and  $\bar{M}_j(k)$ , and covariance matrices  $\bar{C}_i(k_1, k_2)$  and  $\bar{C}_j(k_1, k_2)$ , then the divergence becomes

$$\begin{aligned}
 D(i,j) = & \frac{1}{2} \operatorname{tr} \left\{ [\bar{C}_i(k_1, k_2) - \bar{C}_j(k_1, k_2)] \right. \\
 & \left. x[\bar{C}_j^{-1}(k_1, k_2) - \bar{C}_i^{-1}(k_1, k_2)] \right\} \\
 & + \frac{1}{2} \operatorname{tr} \left\{ [\bar{C}_i^{-1}(k_1, k_2) + \bar{C}_j^{-1}(k_1, k_2)] \right. \\
 & \left. x[\bar{M}_i(k_1) - \bar{M}_j(k_2)] [\bar{M}_i(k_2) - \bar{M}_j(k_2)]' \right\}
 \end{aligned} \tag{2-11}$$

where  $\operatorname{tr}$  denotes the trace, the exponent  $-1$  denotes the inverse, and the prime the transpose.

Further, if the covariance matrices are the same,  $\bar{C}_i = \bar{C}_j = \bar{C}(k_1, k_2)$ , the above expression reduces to

$$\begin{aligned}
 D(i,j) &= \text{tr} \left\{ \bar{C}^{-1}(k_1, k_2) [\bar{M}_i(k_1) - \bar{M}_j(k_1)] \right. \\
 &\quad \left. \times [\bar{M}_i(k_2) - \bar{M}_j(k_2)]' \right\} \\
 &= [\bar{M}_i(k_1) - \bar{M}_j(k_2)]' \bar{C}^{-1}(k_1, k_2) [\bar{M}_i(k_2) - \bar{M}_j(k_2)]
 \end{aligned} \tag{2-12}$$

If the components are statistically independent, then equation (2-11) can be reduced to

$$\begin{aligned}
 D(i,j) &= \frac{1}{2} \sum_{k=1}^K \left\{ [\sigma_i^2(k) - \sigma_j^2(k)]^2 + [\sigma_i^2(k) + \sigma_j^2(k)] \right. \\
 &\quad \left. \times [\bar{M}_i(k) - \bar{M}_j(k)]^2 \right\} / [\sigma_i^2(k) \sigma_j^2(k)]
 \end{aligned} \tag{2-13}$$

where  $\sigma_i^2(k)$  is the covariance vector which is the diagonal of the original covariance matrix for  $i^{\text{th}}$  inventory area.

Further, if the covariance vectors are equal, i.e.,  $\sigma_i^2(k) = \sigma_j^2(k) = \sigma^2(k)$ , then the above expression reduces to

$$D(i,j) = \sum_{k=1}^K \frac{[\bar{M}_i(k) - \bar{M}_j(k)]^2}{\sigma^2(k)} \tag{2-14}$$

On the other hand, if the mean vectors are equal, then

$$D(i,j) = \frac{1}{2} \sum_{k=1}^K \frac{[\sigma_i^2(k) - \sigma_j^2(k)]^2}{\sigma_i^2(k) \sigma_j^2(k)} \tag{2-15}$$

Finally, the ordinary Euclidean distance between two vectors is obtained from expression (2-14) by letting  $\sigma^2(k) = 1$ , or from expression (2-12) by letting  $\bar{C}(k_1, k_2)$  equal to the identity matrix.

$$D(i,j) = \sum_{k=1}^K [\bar{M}_i(k) - \bar{M}_j(k)]^2$$

From the above various special cases, it can be seen that the divergence measure is to very general criterion for similarity.

## Section III

### COMPUTER PROGRAMS DESCRIPTION

#### 3.1 INTRODUCTION

Computer programs based on the algorithms discussed in the last section have been developed for processing and analysis of multispectral data. The purposes of these programs, their input and output formats, and the program listing will be presented in this section. A list of these programs is as follows:

- Tape Conversion Program
- Alphanumeric Plot Program
- Statistical Inventory Boundary Program
- Boundary Enhancement Program
- Mean, Correlation, and Covariance Program
- Piecewise Correlation and Covariance Program
- Probability Histogram Program
- Divergence Matrix Program
- Si-Table Program

#### 3.2 TAPE CONVERSION PROGRAM

This program is devised for converting a standard FORTRAN and/or binary tape to the standard format of input data tapes to the following programs:

- Boundary Enhancement Program
- Alphanumeric Plot Program
- Statistical Averages Program
- Piecewise Correlation and Covariance Program
- Statistical Inventory Boundary Programs
- Mean, Correlation, and Covariance Program
- Probability Histogram Program.

The outputs of the program is a FORTRAN binary or BCD tape with a control parameter (fixed-point binary or BCD) and data sets of some specified number

of channels (floating point binary or BCD). The data set is a 3-dimensional array, DATA (i,j,k), with i designating the scan line number, j the same number along each scan, and k the channel number. The control number is set to be 1 at the end of each scan line, 2 at the end of each specified field, and 3 at the end of each data set.

It is optional in this program to read a header identification record at the start of each data set and also optional to write this on the output tape in either BCD or FORTRAN binary of some specified length.

Because of the characteristic of most experimental data sets to contain erroneous data samples from some undetermined origin, it becomes desirable to replace these erroneous data samples with some data samples that best characterize the data set. The capability to replace these erroneous data samples is optional in the program.

The control parameters in this program are inputted as NAMELIST parameters. The documentation on the usage of this system package is in IBM Manual C28-6390-2. There are two major sets of NAMELIST calls in this program NAMDAT and NAMFIL. The following is the definition of the input parameters used in NAMDAT and NAMFIL.

NAMDAT

- NFILE - Number of files of data to process from the input tape.
- NWHICH - Number of the selected files to be processed.
- LTN - Logical tape number of the input tape to be reformatted.
- LTN1 - Logical tape number of data reformatted by the program.
- LTN2 - Logical tape number of output header identification record.
- NSCANS - Number of scan lines to be processed in this field.
- IDWORD - Number of words in the input tapes header identification record.
- LLL - Data sample to start with from input data record in generating the output tape.
- NBEAMS - Number of channels of data.
- IHEAD - Option to read or write a header identification record. IHEAD not equal zero executed.



- IBCDH - Option to read header identification record in BCD. IBCDH  $\neq$  0 header record read as BCD information. IBCDH = 0 read as Binary.
- IHMRT - Option to write header identification record on output tape. IHMRT  $\neq$  0, record written.
- ISKBIN - Option to determine if any files are to be skipped on input tape to get to data file. ISKBIN = 0, no files to be skipped.
- IBCDW - Option to write output data tape in BCD. IBCDW  $\neq$  0, tape written in BCD. IBCDW = 0, tape written in Binary.
- IDROP - Option to replace selected data samples in data set. IDROP  $\neq$  0, data samples replaced.

NAMFIL

- XMEAN - Variables used to replace erroneous samples in first region of field.
- XMEAN1 - Variables used to replace erroneous samples in second region of field.
- XMEAN2 - Variables used to replace dropouts in third region of field.
- ISAM - Specifies location of regions in the data set to be replaced by means.
- XMIN - Minimum value of each region for a field.
- XMAX - Maximum value of each region for a field.

Figure 3-1 is a flowchart of the program and the following is a listing of the program.

**3.3 ALPHANUMERIC PLOT PROGRAM**

The program is devised for printing a two-dimensional alphanumeric plot for grey-level display or classification results. The input tape can be BCD or binary. The other input parameters are the upper and lower class limits and desired alphanumeric symbols for each class.

Definition of Input Data:

CARD 1 (A1)

IALPHA - Alpha-numeric characters for printout

LLP - Border designation.

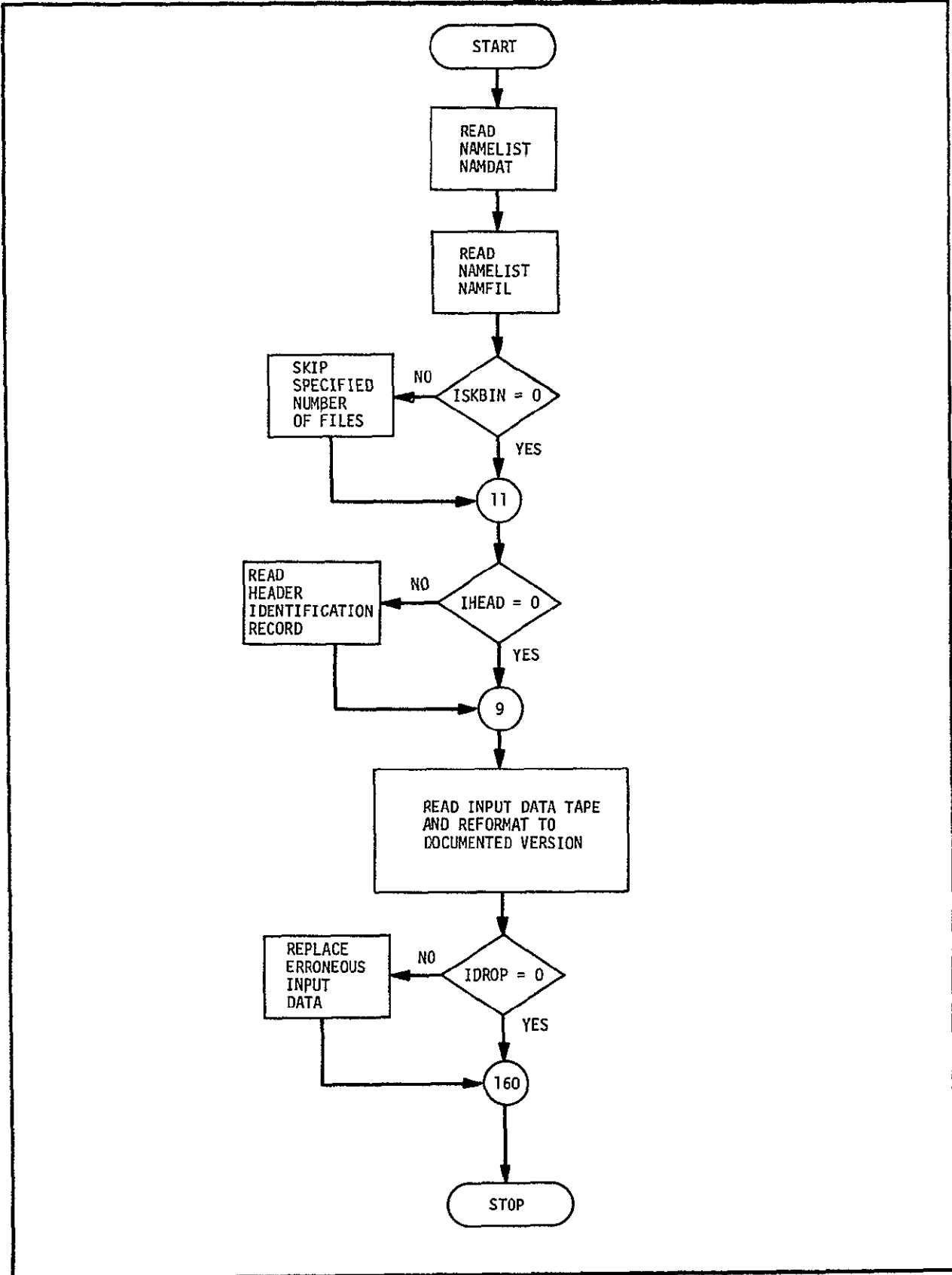


Figure 3-1. FLOWCHART FOR TAPE CONVERSION PROGRAM

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```

C      TAPE      CONVERSION      PROGRAM
      DIMENSION  ISAM(6)
      DIMENSION  XMEAN(12),XMEAN1(12),XMEAN2(12)
      DIMENSION  DATA(12)
      DIMENSION  DAT(5000),NWHICH(4)
      DIMENSION  RCDID(20)
      DIMENSION  DUM(12)
      NAMELIST /NAMDAT/ NFILE,NWHICH,LTN,LTN1,LTN2,NSCANS,IDWØRD,
1LLL,KKK,NCT,NBEAMS,IHEAD,IBCD,IFLD,ISUB,NA,NAB,NB,IBCDH,
2IMRD,IMRT,IHMRT,ISKBIN,IBCDØ,IBCDW,IDRØP
      NAMELIST /NAMFIL /XMEAN,XMEAN1,XMEAN2,ISAM,XMIN,XMAX
      IZERØ=0
      IØNE=1
      ITWØ=2
      ITHREE=3
      NDUM=0
      DØ 4 J=1,12
4      DUM=0.0
      READ (5,NAMDAT)
      WRITE(6,NAMDAT)
      REWIND LTN
      REWIND LTN1
      DØ 998 IAA=1,NFILE
      READ(5,NAMFIL)
      WRITE(6,NAMFIL)
C      SEARCH      FØR      FILE      TØ      PRØCESS
      IF (ISKBIN.EQ.0) GØ TØ 11
      REWIND LTN
      IAB=NWHICH(IAA)-1
      IF(IAB)11,11,12
12     CØNTINUE
      DØ 10 IAC=1,IAB
      CALL SKFBIN(9,1,RD)
10     CØNTINUE
11     CØNTINUE
C      READ RECORD ØNE
C      READ      HEADER      IDENTIFICATION      RECORD
      IF(IHEAD) 14,9,14
14     CØNTINUE
      IF(IBCDH.NE.0) GØ TØ 5
      READ (LTN) (RCDID(I),I=1,IDWØRD)
      IF(IFLD.EQ.0) GØ TØ 6
      NCT=0
      CALL FLD (NCT,NA,NAB,NB,RCDID(ISUB))
      GØ TØ 6
5      CØNTINUE
      READ (LTN,1006) (RCDID(I),I=1,IDWØRD)
6      CØNTINUE
      IF(IFLD.NE.0) GØ TØ 21
      RCDID(ISUB)=0.0
      RCDID(ISUB)=NCT
21     CØNTINUE
      IF (IHMRT) 22,23,22
22     CØNTINUE
      WRITE(LTN2) (RCDID(MM),MM=1,IDWØRD)

```

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```

23  CØNTINUE
    WRITE(6,1003) (RCDID(K),K=1,IDWØRD)
9   CØNTINUE

C   READ          INPUT          DATA
    NWW=NCT*NBEAMS
    DØ 1 I=1,NSCANS
    IF(IBCØR .NE.0) GØ TØ 8
    CALL REDTPC(LTN,IMRD,IERR,NW,NWW,DAT)
    GØ TØ (50,51,50,50,51),IERR
51  WRITE(6,1004) I
    GØ TØ 999
50  CØNTINUE
8   CØNTINUE
    LL=LLL
    KK=KKK
13  CØNTINUE
C   REFØRMAT      INPUT          DATA
    DØ 2 J=1,NCT
    IF(IBCØR .EQ.0) GØ TØ 15
    READ (LTN1,1005) IZ,(DATA(III),III=1,NBEAMS)
    NNN=1
    DØ 31 NN=LL,KK
    DAT(NN)=DATA(NNN)
    NNN=NNN+1
31  CØNTINUE
15  CØNTINUE
C   REPLACE      ERRØNEØS      DATA      SAMPLES
    IF(IDRØP.EQ.0) GØ TØ 160
    IF (DAT(LL).LT.XMAX.AND.DAT(LL).GT.XMIN) GØ TØ 160
    IF (J.GE.ISAM(1).AND.J.LE.ISAM(2)) GØ TØ 15C
    IF (J.GE.ISAM(3).AND.J.LE.ISAM(4)) GØ TØ 152
    IF (J.GE.ISAM(5).AND.J.LE.ISAM(6)) GØ TØ 154
    GØ TØ 160
150 IZ=LL
    DØ 151 K=1,KKK
    DAT(IZ)=XMEAN(K)
151 IZ=IZ+1
    GØ TØ 160
152 IZ=LL
    DØ 153 K=1,KKK
    DAT(IZ)=XMEAN1(K)
153 IZ=IZ+1
    GØ TØ 160
154 IZ=LL
    DØ 155 K=1,KKK
    DAT(IZ)=XMEAN2(K)
155 IZ=IZ+1
160 CØNTINUE
    IF(IBCØW .EQ.0) GØ TØ 61
    WRITE(LTN2,1000) IZERØ,(DATA(K),K=LL,KK)
    GØ TØ 64
61  CØNTINUE
    WRITE (LTN2) IZERØ,(DATA(K),K=LL,KK)

```

```
64  CØNTINUE
    LL=KK+1
    KK=LL+NBEAMS-1
    2  CØNTINUE
      IF(I.EQ.NSCANS) GØ TØ 3
      IF(IBCØW.EQ.0) GØ TØ 65
      WRITE(LTN2,1000)  IØNE,(DUMMY(K),K=1,NBEAMS)
      GØ TØ 1
65  CØNTINUE
    WRITE(LTN2)          IØNE,(DUMMY(K),K=1,NBEAMS)
    1  CØNTINUE

    3  CØNTINUE
      IF(IBCØW.EQ.0) GØ TØ 63
      WRITE(LTN2,1000)  ITWØ,(DUMMY(K),K=1,NBEAMS)
      GØ TØ 998
63  CØNTINUE
    WRITE(LTN2)          ITWØ,(DUMMY(K),K=1,NBEAMS)
    998 CØNTINUE
      IF(IBCØW.EQ.0) GØ TØ 67
      WRITE(LTN2,1000)  ITHREØ,(DUMMY(K),K=1,NBEAMS)
      GØ TØ 999
67  CØNTINUE
    WRITE(LTN2)          ITHREØ,(DUMMY(K),K=1,NBEAMS)
    999 CØNTINUE
      END FILE LTN2
      REWIND LTN
      REWIND LTN1
      REWIND LTN2
    200 FØRMAT(20I4)
    1000 FØRMAT(11,8X,12F6.3)
    1001 FØRMAT(11)
    1002 FØRMAT(1H1//2X,24HINPUT REÇØRDS BAD - STØP)
    1003 FØRMAT(1X,12A6,16,5X,2F8.4)
    1004 FØRMAT(2X,14)
    1005 FØRMAT(11,8X,12F5.3)
    1006 FØRMAT(20A6)
    1007 FØRMAT(11,8X,12F8.3)
    1008 FØRMAT(1X,2110)
      STØP
      END
```

```
$NAMDAT
NFILE=4
NWHICH=2,8,19,12
LTN=9
LTN1=9
ISKBIN=1
IBCØR=0
IBCØW=1
IDRØP=1
LTN2=11
NSCANS=27
IDWØRD=15
```

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```
LLL=1
KKK=12
NCT=167
NBEAMS=12
IHEAD=1
IBCD=0
IFLD=0
ISUB=13
NA=19
NAB=17
NB=1
IBCDH=0
IMRD=1
IMRT=1
IHMRT=0
$END
$NAMFIL
XMEAN=1.10358,1.6092,1.13319,1.02380,1.04938,0.99541,0.77604,1.03585,
0.50232,0.63149,0.81489,0.63113
XMEAN1=0.92628,1.36367,1.00306,0.95745,0.90845,0.76673,0.63609,1.03973,
0.59239,0.59394,0.39618,0.30986
XMEAN2=1.27359,1.70424,1.14378,1.02141,0.94322,0.82919,0.62134,0.83949,
0.40804,0.46054,0.58812,0.43592
ISAM=1,63,63,118,118,167
XMIN=0.0
XMAX=3.0
$END
$NAMFIL
XMEAN=1.50995,2.15190,1.52394,1.34540,1.29378,1.15872,0.92575,1.24317,
0.63664,0.68725,0.76504,0.60184
XMEAN1=0.97784,1.47237,1.08407,1.01881,0.97609,0.84300,0.70877,1.13348,
0.63643,0.64560,0.44608,0.36001
XMEAN2=1.13874,1.86139,1.27976,1.13856,1.03394,0.86392,0.68685,0.96813,
0.49192,0.52221,0.49081,0.38598
ISAM=1,42,42,111,111,167
XMIN=0.0
XMAX=3.0
$END
$NAMFIL
XMEAN=1.31144,1.85966,1.28023,1.13480,1.10562,1.00866,0.76919,1.02518,
0.49790,0.56153,0.72571,0.54945
XMEAN1=0.98687,1.46594,0.97921,0.85527,0.84487,0.84443,0.60006,0.75333,
0.33964,0.57555,1.18249,0.89077
XMEAN2=1.29660,1.74870,1.17140,1.05421,0.97544,0.85978,0.64281,0.89028,
0.42091,0.49407,0.61681,0.46276
ISAM=1,39,39,108,108,167
XMIN=0.0
XMAX=3.0
$END
$NAMFIL
XMEAN=1.00572,1.47489,1.03701,0.96775,0.91567,0.80819,0.63198,0.99724,
0.53699,0.56149,0.48457,0.36704
XMEAN1=1.16048,1.58077,1.05821,0.94602,0.87191,0.76703,0.54934,0.78006,
0.37171,0.42442,0.53810,0.39657
ISAM=1,111,111,167,167,167
XMIN=0.0
XMAX=3.0
$END
```

CARD 2 (2F10.0)

XSKSC - Number of scan lines to skip (i.e. every other, 2, 4, etc.)

XSKFL - Number of samples to skip in scan line

CARD 3 (7I4)

ITERM - Set to 1 for new case.

JCNT - Skip numbering across scan line.

NFLSKC - Option to skip data files on input tape.

NFLSFL - Option to skip data sample in scan line.

NFLSKN - Option to skip scan lines.

IAP -- = 0 to initialize numbering of data samples across scan line.

IPRNT -- = 0 for data from boundary enhancement program.  
= 1 for raw data tapes.

CARD 4 (4I4)

N - Number of classes or intervals used.

NPTS - Number of data samples in scan line.

NCH - Number of channels used.

MSTOP - Total data samples used in scan line.

CARD 5 (F6.0)

XLOW<sub>i</sub> - Lower limit for each channel. i = 1, NCH

CARD 6 (F6.0)

XUPP - Upper limit for each channel.

CARD 7 - Card NCH (A1)

IWAVE - Wave length in microns for each channel.

CARD NCH+1 (I5)

ICH - Channels used.

CARD NCH+2 - CARD N (F10.0)

XINCR - Increment size/channel for each N(card 4)

The output format is shown in Figure 3-2.

The flowchart is given in Figure 3-3 which is followed by a program listing.





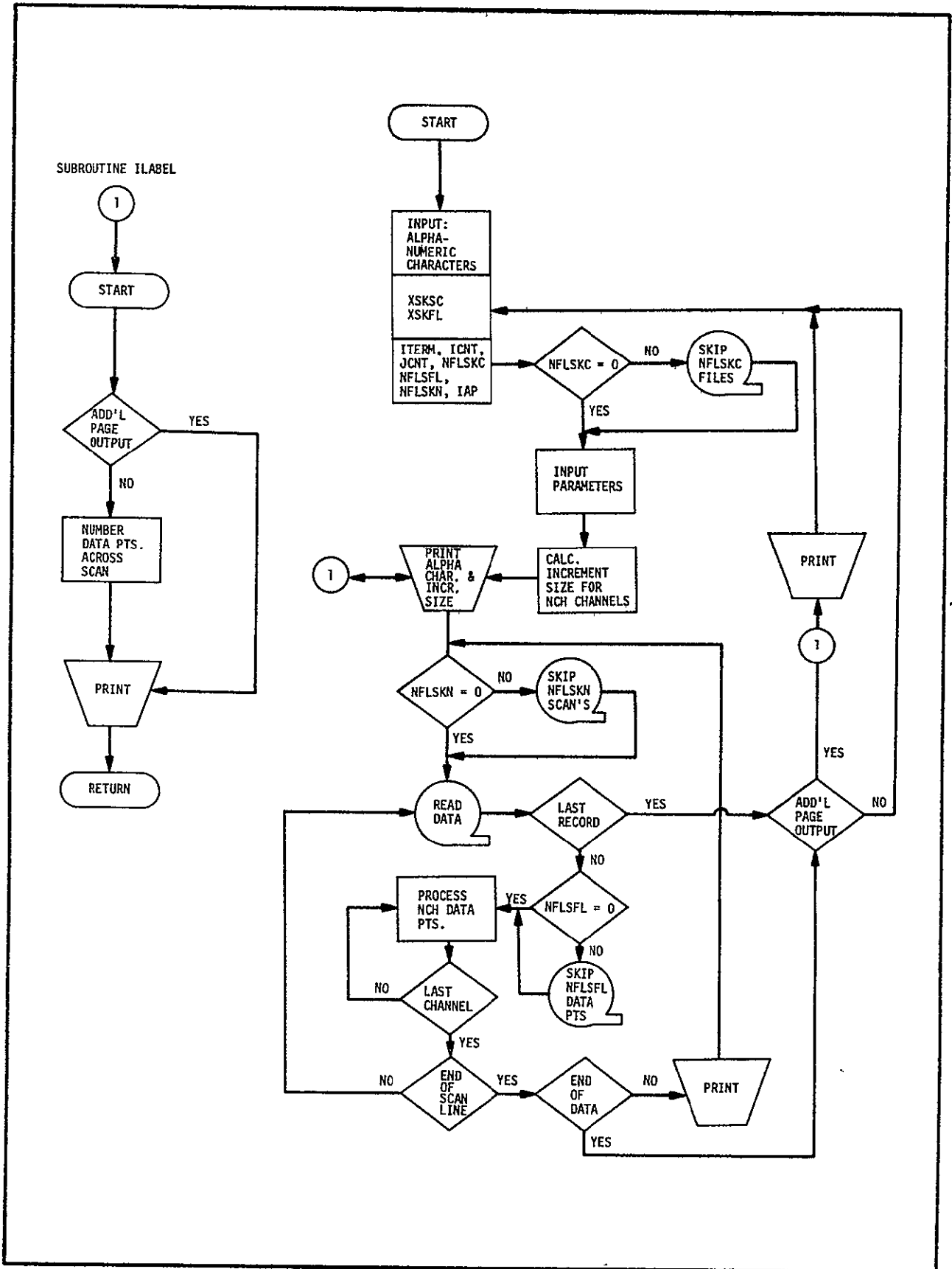


Figure 3-3. FLOWCHART OF ALPHANUMERIC PLOT PROGRAM

```

C
C ALPHANUMERIC PLOT PROGRAM
C
DIMENSION IALPHA[13,20],XLOW[13],XUPP[13],XXLOW[13],DATA[170]
DIMENSION IARRAY[170],XDUM[13],IALP[170],JARAY[108,60]
DIMENSION IDATA[15],XINCR[13,20],ICH[13],XDWN[13],IWAVE[13,13]
IN=5
IN1=9
IOUT=6
DO 299 L=1,13
READ(IN,99) (IALPHA[L,I],I=1,20),LLP
299 CONTINUE
300 CONTINUE
READ(IN,114) XSKSC,XSKFL
READ(IN,100) ITERM,JCNT,NFLSKC,NFLSFL,NFLSKN,IAP,IPRNT
IF(NFLSKC,EQ,0) GO TO 1001
C
C NFLSKC GREATER THAN 0 -- SKIP FILES
C
DO 1000 I=1,NFLSKC
CALL SKFBIN(IN1,1,RD)
1000 CONTINUE
1001 CONTINUE
READ(IN,100) N,NPTS,NCH,MSTOP
READ(IN,116) (XLOW[I],I=1,NCH)
READ(IN,116) (XUPP[I],I=1,NCH)
DO 1002 L=1,NCH
READ(IN,99) (IWAVE[L,I],I=1,13)
1002 CONTINUE
READ(IN,115) (ICH[I],I=1,NCH)
NUMB=N
DO 600 L=1,NCH
READ(IN,114) (XINCR[L,I],I=1,NUMB)
DO 600 J=1,NUMB
XINCR[L,J]=XUPP[L]/XINCR[L,J]
XXLOW[L]=XLOW[L]
600 CONTINUE
XN=N
IFL SKN=0
ISCAN=0
L=0
NCALL=1
INDEX=0
NSTART=1
NSTOP=MSTOP
JPASS=1
WRITE(IOUT,110)
WRITE(IOUT,102)
WRITE(IOUT,106)
WRITE(IOUT,111)
MSKFL=XSKFL
MPTS=NPTS/MSKFL+2
DO 1 I=1,MPTS
IALP[I]=LLP
1 CONTINUE

```

```

      KK=N+1
C
C      CALCULATE AND PRINT INTERVALS FOR EACH CHANNEL
C
      DO 309 L=1,NCH
      IF[ICH[L],EQ,0] GO TO 309
      WRITE[IOUT,103] ICH[L]
      DO 2 I=1,KK
      IF[I,EQ,1] GO TO 9
      IF[I,EQ,2] GO TO 3
      4 WRITE[IOUT,105] IALPHA[L,I],XDWN[L],XUPP[L]
      GO TO 31
      9 WRITE[IOUT,112] [IWAVE[L,K],K=1,13],IALPHA[L,I],XLOW[L]
      GO TO 32
      3 WRITE[IOUT,105] IALPHA[L,I],XLOW[L],XUPP[L]
      31 CONTINUE
      XDWN[L]=XLOW[L]+XINCR[L,I-1]
      32 CONTINUE
      XUPP[L]=XLOW[L]+XINCR[L,I]
      2 CONTINUE
      ZUPP=XLOW[L]+XINCR[L,NUMB]
      WRITE[IOUT,105] IALPHA[L,N+2],ZUPP
      WRITE[IOUT,106]
      309 CONTINUE
      IF[IPRNT,GT,0] GO TO 315
      WRITE[IOUT,110]
      WRITE[IOUT,102]
      WRITE[IOUT,111]
      WRITE[IOUT,118]
      DO 310 L=1,NCH
      IF[ICH[L],EQ,0] GO TO 310
      WRITE[IOUT,119] ICH[L],[IWAVE[L,K],K=1,13]
      310 CONTINUE
      LZ=KK+1
      LL=1
      WRITE[IOUT,106]
      WRITE[IOUT,120] [IALPHA[LL,I],I=1,LZ]
      WRITE[IOUT,106]
      315 CONTINUE
      NSTRT1=1
      NSTOP1=NPTS
      CALL I LABEL[MSTOP,NCALL,NPTS,JCNT,IOUT]
      WRITE[IOUT,106]
      WRITE[IOUT,108] [IALP[I],I=1,MPTS]
C
C      INUM COUNTS SCAN LINES
C
      INUM=0
      5 CONTINUE
C
C      SKIP SCAN LINES
C
      401 IFLSKN=IFLSKN+1
      INUM=INUM+1
      IF[NFLSKN,EQ,0] GO TO 205

```

```

SS=IFLSKN
SM=SS/XSKSC
MS=SS/XSKSC
SS=MS
SM=SM-SS
IF[SM,EQ,0,0] GO TO 205
DO 400 I=NSTART,NSTOP
READ[IN1] ICHEK,[DATA[J],J=1,NCH]
IF[ICHEK,EQ,3] GO TO 210
400 CONTINUE
READ[IN1] ICHEK,[DATA[J],J=1,NCH]
IF[ICHEK,EQ,3] GO TO 210
GO TO 401
205 CONTINUE
KK=NUMB+1
M=0

C
C START PROCESSING ONE SCAN LINE
C
DO 90 I=NSTART,NSTOP
READ[IN1] ICHEK,[DATA[J],J=1,NCH]
7 IF[ICHEK,EQ,3] GO TO 210
IF[NFLSFL,EQ,0] GO TO 403
SS=I
SM=SS/XSKFL
MS=SS/XSKFL
SS=MS
SM=SM-SS
IF[SM,NE,0,0] GO TO 90
403 CONTINUE
M=M+1
NNX=0

C
C CLASSIFY DATA SAMPLES
C
DO 500 J=1,KK
NNX=NNX+1
DO 501 L=1,NCH
IF[ICH[L],EQ,0] GO TO 501
IF[DATA[L],GT,XXLOW[L]+XINCR[L,NUMB]] GO TO 504
IF[J,GT,1] GO TO 502
IF[DATA[L],GT,XXLOW[L]] GO TO 500
GO TO 505
502 IF[DATA[L],GT,XXLOW[L]+XINCR[L,J-1]] GO TO 500
505 IARRAY[M]=IALPHA[L,NNX]
501 IF[L,EQ,NCH] GO TO 90
500 CONTINUE
GO TO 90
504 IARRAY[M]=IALPHA[L,NUMB+2]
90 CONTINUE
MSKFL=XSKFL
MPTS=NPTS/MSKFL

C
C PRINT RESULTS FOR EACH SCAN LINE
C MAXIMUM OF 110 PTS /LINE

```

```

C
96  WRITE(IOUT,104) INUM,(IARAY(K),K=1,MPTS),IALP(1)
    READ(IN1)  IDUM,(DATA(J),J=1,NCH)
    IF(IDUM,GE,3) GO TO 211
    IF(NPTS,GE,MSTOP) GO TO 5
204  L=0
    INDEX=INDEX+1
    NSTOP2=NPTS+1
    DO 206 KK=NSTOP2,MSTOP
    L=L+1
    JARAY(INDEX,L)=IARAY(KK)
206  CONTINUE
    GO TO 5
210  CONTINUE
211  NCALL=2
    IMMP=MPTS+2
    WRITE(IOUT,108) (IALP(I),I=1,IMMP)
    IF(NPTS,GE,MSTOP) GO TO 216
212  CONTINUE
    WRITE(IOUT,110)
    CALL ILABEL(MSTOP,NCALL,NPTS,JCNT,IOUT)
    NSTOP1=MSTOP-NPTS
    DO 215 L=1,INDEX
    WRITE(IOUT,113) (JARAY(L,LL),LL=1,NSTOP1)
215  CONTINUE
216  REWIND IN1
    IF(ITERM,GT,0) GO TO 300
98  WRITE(IOUT,110)
99  FORMAT(25A1)
100  FORMAT(16I4)
101  FORMAT(I1,I4,4X,12F5.3)
102  FORMAT(14X,46HINVENTORY BOUNDARY MAP BY BOUNDARY ENHANCEMENT//)
103  FORMAT(2X,8HCHANNEL I2,36X,22HSYMBOL          INTERVAL /)
104  FORMAT(6X,3,1X,1H*,112A1)
105  FORMAT(50X,A1,8X,F7.4,3H - ,F7.4)
106  FORMAT(1X/)
108  FORMAT(10X,115A1)
109  FORMAT(12F10.0,12A1)
110  FORMAT(1H1/)
111  FORMAT(2X,83HCROPS  C5=17,5-22,5-5,5-8,          ALTITUDE 2000 FT.
1      DATE RECORDED 6/30/66 //)
112  FORMAT(2X,22HWAVE LENGTH [MICRONS] ,13A1,13X,A1,8X,F5.2,
13H - ,F5.2)
113  FORMAT(11X,112A1)
114  FORMAT(8F10.0)
115  FORMAT(13I5)
116  FORMAT(13F6.0)
118  FORMAT(20X,7HCHANNEL,15X,11HWAVE LENGTH/)
119  FORMAT(22X,I2,14X,13A1)
120  FORMAT(2X,7HSYMBOLS,5X,A1,18H = LESS THAN MEAN,5X,A1,16H = MEAN-M
1EAN+1SD,5X,A1,20H = MEAN+1SD-MEAN+2SD//
218X,A1,20H = MEAN+2SD-MEAN+3SD,5X,A1,
325H = GREATER THAN MEAN+3SD)
    STOP
    END

```

```

SUBROUTINE ILABEL(N,ICALL,NSTOP,NCNT,KOUT)
C
C      SUBROUTINE NUMBERS ACROSS SCAN LINE
C      FOR LABELIND AND IDENTIFICATION
C      INUM = HUNDREDS
C      JNUM = TENS
C      KNUM = UNITS
C
C      DIMENSION INUM(150),JNUM(150),KNUM(150)
C      IF(ICALL.GT.1) GO TO 500
C      M=NCNT
C      K=NCNT
C      L=0
C      DO 1 I=NCNT,N,NCNT
C      L=L+1
C      INUM[L]=I/100
C      IF(M.EQ.100) M=0
C      IF(M.GT.100) M=M-100
C      JNUM[L]=M/10
C      M=M+NCNT
C      IF(K.EQ.10) K=0
C      IF(K.GT.10) K=K-10
C      KNUM[L]=K
C      K=K+NCNT
C      1 CONTINUE
C      ISTOP=NSTOP/NCNT
C      WRITE(KOUT,110) [INUM[I],I=1,ISTOP]
C      WRITE(KOUT,110) [JNUM[I],I=1,ISTOP]
C      WRITE(KOUT,110) [KNUM[I],I=1,ISTOP]
C      110 FORMAT(11X,120I1)
C      GO TO 200
C      500 K=NSTOP+1
C      K=K/NCNT
C      M=N/NCNT
C      WRITE(KOUT,110) [INUM[I],I=K,M]
C      WRITE(KOUT,110) [JNUM[I],I=K,M]
C      WRITE(KOUT,110) [KNUM[I],I=K,M]
C      200 RETURN
C      END

```

### 3.4 STATISTICAL INVENTORY BOUNDARY PROGRAM

The inventory boundary program has been developed to automatically construct a map of inventory boundaries for sequential multispectral scanner data. Inventory boundaries are calculated simultaneously in both the scan line (horizontal) and sample number (vertical) directions. The mathematical formulations are given in subsection 2.3.

#### DEFINITION OF INPUT DATA:

##### CARD 1

- DOT - Symbol used where no boundaries exist. Usually a period (.).
- DASH - Symbol used for boundary in the flight line (vertical) direction.
- EYE - Symbol used for boundary in the scan line (horizontal) direction.
- PLUS - Symbol used where a horizontal and a vertical boundary coincide.

##### CARD 2

- L1 - Lower percentage value ( $\alpha_L$ ) for first  $\chi^2$  table.
- U1 - Upper percentage value ( $\alpha_u$ ) for first  $\chi^2$  table.
- L2 - Lower percentage value ( $\alpha_L$ ) for second  $\chi^2$  table.
- U2 - Upper percentage value ( $\alpha_u$ ) for second  $\chi^2$  table.
- I AVG - Number of samples to skip before comparing ERCK to confidence limits.
- MACH - Indicates machine and type of input to be used. MACH = 0 indicates card input on the IBM 7044 or IBM 7094. MACH = 32 indicates tape input on unit 3 (logical unit 54) of the CDC 3200. MACH = 44 indicates type input on unit 5 (logical unit 1) of the IBM 7044. MACH = 94 indicates tape input on Unit B-5 (logical unit 9) on the IBM 7094.

##### CARD 3

- XSTOP - Number of values in first  $\chi^2$  table.

##### CARD SET 1

- CHIL1(m) -  $\frac{\chi^{\alpha_L}}{\sqrt{m}}$  values for first set of tables (13 values per table).

##### CARD 4

- XSTOP - Number of values in second  $\chi^2$  table.

##### CARD SET 2

- CHIUI(m) -  $\frac{\chi^{\alpha_u}}{\sqrt{m}}$  values for first set of tables (13 values per table).

CARD 5

XSTOP - Number of values in third  $\chi^2$  table.

CARD SET 3

CHIL2(m) -  $\frac{\chi_{\alpha L}}{\sqrt{m}}$  values for second set of tables (13 values per table).

CARD 6

XSTOP - Number of values in fourth  $\chi^2$  table.

CARD SET 4

CHIU2(m) -  $\frac{\chi_{\alpha U}}{\sqrt{m}}$  values for second  $\chi^2$  table (13 values per table).

CARD 7

SCALE - Scale value for input data.

CARD 8

CONF - Indicates which set of  $\chi^2$  tables to use.

CONF1 - Percent of confidence within confidence intervals.

CARD 9

ALPHA1 - ID card (Normally used for field discription).

CARD 10

ALPHA2 - ID card (Normally used for test discription).

CARD 11

CHAN(I) - Channels to be averaged over and number of channels. For each channel N to be used, N must be punched in the  $n^{th}$  position on the card. The number "13" must be punched in all other positions except for the thirteenth position which must contain the number of channels used.

DATA 12

NOTE - If data is on cards they can be followed by the "CHAN(I)" card and reloaded for as many channel combinations as required. If data is on tape then the "CHAN(I)" cards can be stacked together for different channel combinations.

OUTPUT:

The program output is given in Figure 3-4 and is self explanatory.

The input card deck is shown in Figure 3-5. The flowchart of the program is given in Figure 3-6, which is followed by a complete listing of the program.



FIELD DESCRIPTION-	C5-17	C5-22	C5-5	C5-8
ALTITUDE- 2000 FT.	DATE RECORDED-		6/30/66	

CHANNEL	WAVE LENGTH (MICRONS)
1	0.40 - 0.44
2	0.44 - 0.46
3	0.46 - 0.48
4	0.48 - 0.50
5	0.50 - 0.52
6	0.52 - 0.55
7	0.55 - 0.58
8	0.58 - 0.62
9	0.62 - 0.66
10	0.66 - 0.72
11	0.72 - 0.80
12	0.80 - 1.00

NOT REPRODUCIBLE

99 PERCENT CONFIDENCE LIMITS

SYMBOLS= V - VERTICAL BOUNDARY H - HORIZONTAL BOUNDARY  
X - BOTH VERTICAL AND HORIZONTAL BOUNDARY

SAMPLE NUMBER

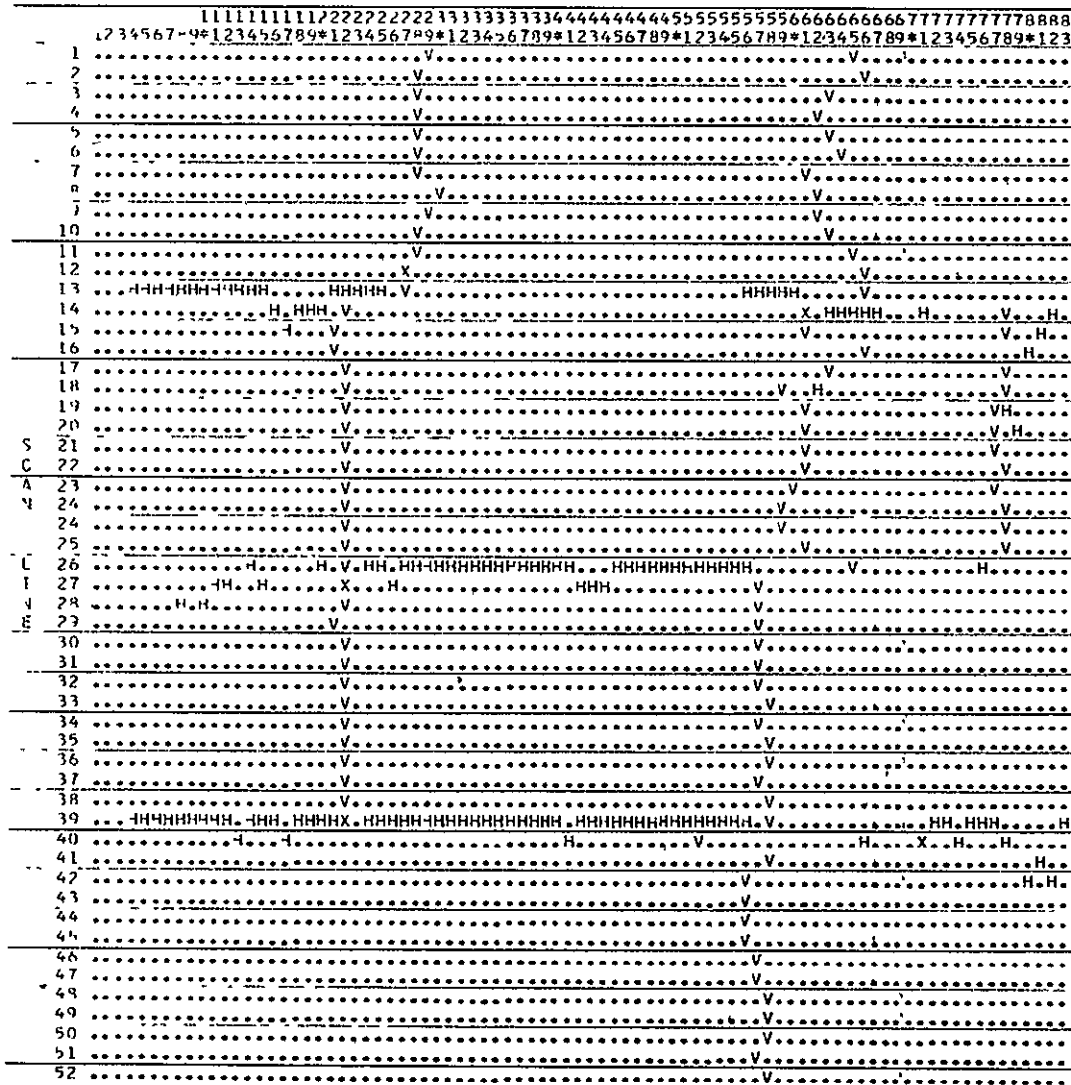


Figure 3-4. MAP OF INVENTORY BOUNDARIES

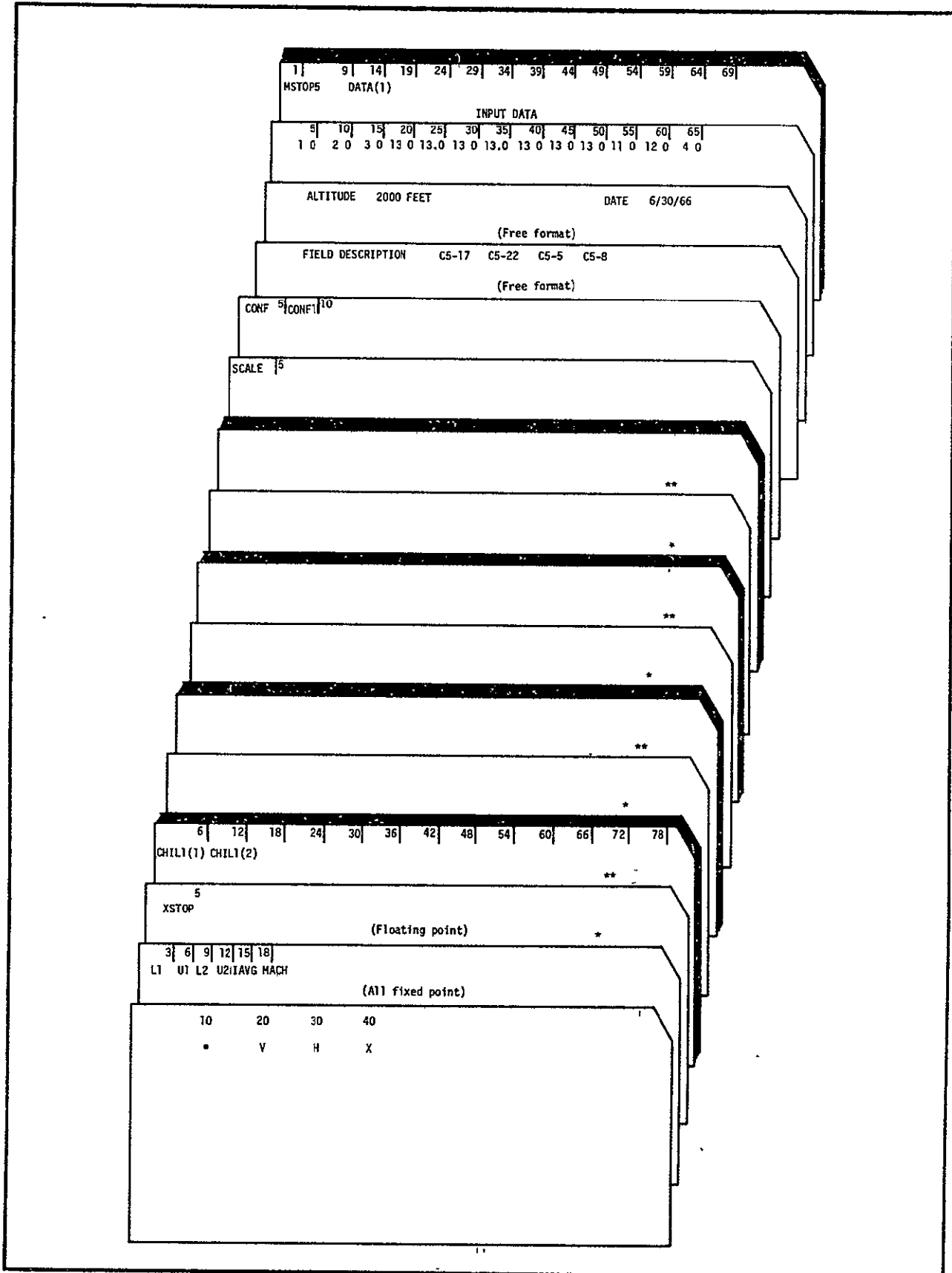


Figure 3-5. INPUT CARDS FOR INVENTORY BOUNDARY PROGRAM

3-21

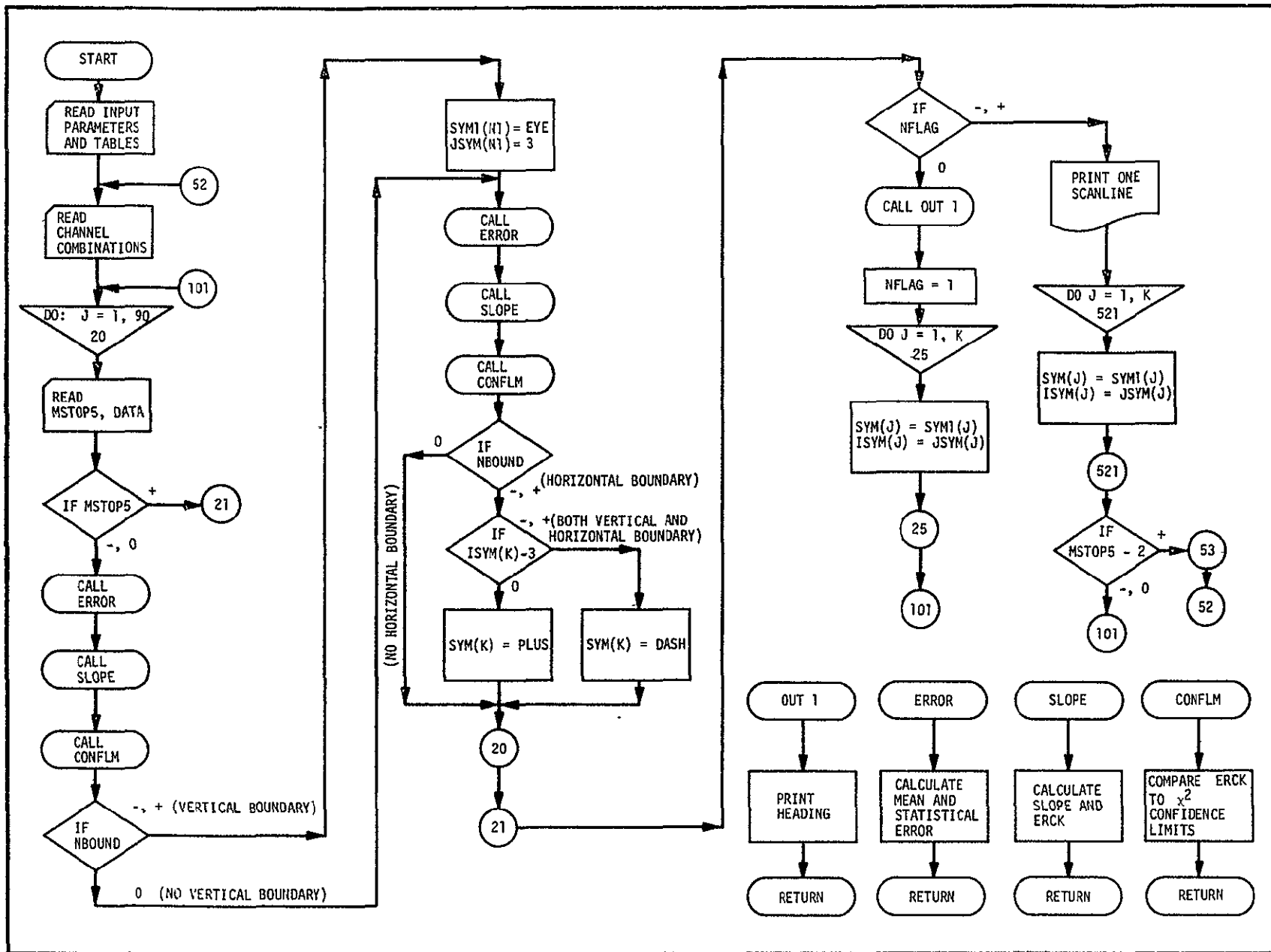


Figure 3-6. FLOWCHART OF INVENTORY BOUNDARY PROGRAM

```

1
  INTEGER U1
  INTEGER U2
  DIMENSION SYM[90], ISYM[90], SYM1[90], JSYM[90]
  DIMENSION CHIL1[175], CHIU1[175], CHIL2[175], CHIU2[175]
  DIMENSION CHAN[13], ICHAN[13], DATA[12], VBAR[12], VBAR1[12], VEACUM[12
1], XBAR[12,90], XBAR1[12,90], DELX[12,90], X[12], X1[12], XEACUM[12]
  DIMENSION SUM1[90], SUM2[90]
  DIMENSION NV[90]
  DIMENSION ALPHA1[14], ALPHA2[14]
  DIMENSION IDAT[12]
  NRD=5
  NWT=6
  READ (NRD,6000) DOT, DASH, EYE, PLUS, BLANK
C   SET MACH TO 44 FOR IBM 7044
C   SET MACH TO 32 FOR CDC 3200
  READ (NRD,51) L1, U1, L2, U2, IAVG, MACH
  READ (NRD,2003) XSTOP
  MSTOP1=XSTOP
  READ (NRD,201) [CHIL1[NU], NU=1, MSTOP1]
  READ (NRD,2003) XSTOP
  MSTOP2=XSTOP
  READ (NRD,201) [CHIU1[NU], NU=1, MSTOP2]
  READ (NRD,2003) XSTOP
  MSTOP3=XSTOP
  READ (NRD,201) [CHIL2[NU], NU=1, MSTOP3]
  READ (NRD,2003) XSTOP
  MSTOP4=XSTOP
  READ (NRD,201) [CHIU2[NU], NU=1, MSTOP4]
  READ (NRD,2003) SCALE
  READ (NRD,2003) CONF, CONF1
  ICONF=CONF
  ICONF1=CONF1
  WRITE (NWT,1001)
  READ (NRD,2004) [ALPHA1[I], I=1,14]
  READ (NRD,2004) [ALPHA2[I], I=1,14]
52. CONTINUE
  READ (NRD,2003) [CHAN[I], I=1,13]
  DO 60 I=1,13
  ICHAN[I]=CHAN[I]
60 CONTINUE
  NCHAN=CHAN[13]
  NFLAG=0
  NSTOP=0
  IPRINT=0
  IF (MACH=32) 62,61,62
61 NUNIT=54
  REWIND NUNIT
  GO TO 65

```

NOT REPRODUCIBLE

```

62 IF [MACH-44] 64,63,64
63 NUNIT=1
   REWIND NUNIT
   GO TO 65
64 IF [MACH-94] 67,66,67
66 NUNIT=9
   REWIND NUNIT
   GO TO 65
67 NUNIT=5
65 CONTINUE
   DO 6 J=1,90
   SUM1[J]=0.0
   SUM2[J]=0.0
   NV[J]=0
6 CONTINUE
101 CONTINUE
   DO 5000 J=1,90
   JSYM[J]=0
5000 SYM1[J]=DOT
   VSUM1=0.0
   VSUM2=0.0
   K=0
   N=0
   DO 20 J=1,90
   IF [MACH] 68,69,68
69 READ [NUNIT,1000] MSTOP5,[DATA[I],I=1,12]
   GO TO 70
C68 READ [NUNIT] MSTOP5,[DATA[I],I=1,12]
68 READ [NUNIT] MSTOP5,NDUMMY,NDUMMY,[IDAT[I],I=1,12]
   DO 71 I=1,12
71 DATA[I]=IDAT[I]
C DO 71 I=1,12
C71 DATA[I]=IDAT[I]
70 CONTINUE
   N=N+1
   NV[J]=NV[J]+1
   K=K+1
   N1=J-1
   DO 12 I=1,12
   DATA[I]=DATA[I]/SCALE
   IF [MSTOP5] 9,9,21
9 IF [NV[K]-1] 11,10,11
10 XBAR[I,K]=DATA[I]
   XBAR1[I,K]=DATA[I]
   DELX[I,K]=0.0
11 CONTINUE
12 CONTINUE
   CALL ERROR[VBAR,VBAR1,DATA,VEACUM,ICHAN,N]

```

```

13   IF [N-1] 14,14,13
      CONTINUE
      CALL SLOPE[VEACUM,ICHAN,N ,1,ERCK,VSUM1,VSUM2]
      IF [ERCK] 113,14,113
113  CONTINUE
      CALL CONFLM[CHIL1,CHIU1,CHIL2,CHIU2,MSTOP1,MSTOP2,MSTOP3,MSTOP4,N
1,IAVG,ERCK,NBOUND,ICONF]
114  IF [NBOUND] 376,14,376
376  SYM1[N1]=EYE
      JSYM[N1]=3
      N=0
      VSUM1=0.0
      VSUM2=0.0
14   CONTINUE
      DO 15 I=1,12
          X[I]=XBAR[I,K]
          X1[I]=XBAR1[I,K]
15   XEACUM[I]=DELX[I,K]
      CALL ERROR[X,X1,DATA,XEACUM,ICHAN,NV[K]]
      IF [NV[K]-1] 18,18,16
16   CONTINUE
      CALL SLOPE[XEACUM,ICHAN,NV[K],NV[K],ERCK,SUM1[K],SUM2[K]]
      IF [ERCK] 374,18,374
374  CONTINUE
      CALL CONFLM[CHIL1,CHIU1,CHIL2,CHIU2,MSTOP1,MSTOP2,MSTOP3,MSTOP4,
1NV[K],IAVG,ERCK,NBOUND,ICONF]
      NV1=NV[K]
375  IF[NBOUND] 377,18,377
377  IF [ISYM[K ]-3] 379,378,379
378  SYM [K ]=PLUS
      NV[K]=0
      GO TO 380
379  SYM [K ]=DASH
380  NV[K]=0
      SUM1[K]=0.0
      SUM2[K]=0.0
18   CONTINUE
      DO 17 I=1,12
          XBAR[I,K]=X[I]
          XBAR1[I,K]=X1[I]
          DELX[I,K]=XEACUM[I]
17   CONTINUE
20   CONTINUE
21   K=K-1
      IF [NFLAG] 31,30,31
30   CALL OUT1[ICHAN,ICONF,ICONF1,K,ALPHA1,ALPHA2,DASH,EYE,PLUS]
      K1=K
      NFLAG=1
      DO 25 J=1,K

```

```

SYM[J]=SYM1[J]
25 ISYM[J]=JSYM[J]
GO TO 101
41 CONTINUE
K=K1
IPRINT=IPRINT+1
IF [IPRINT-21] 500,501,502
00 WRITE [NWT,6001] IPRINT,[SYM[J],J=1,K]
GO TO 520
01 WRITE [NWT,6002] IPRINT,[SYM[J],J=1,K]
GO TO 520
02 IF [IPRINT-23] 503,504,505
03 WRITE [NWT,6003] IPRINT,[SYM[J],J=1,K]
GO TO 520
04 WRITE [NWT,6004] IPRINT,[SYM[J],J=1,K]
GO TO 520
05 IF [IPRINT-25] 506,507,508
06 WRITE [NWT,6005] IPRINT,[SYM[J],J=1,K]
GO TO 520

07 GO TO 500
08 IF [IPRINT-27] 509,510,511
09 WRITE [NWT,6006] IPRINT,[SYM[J],J=1,K]
GO TO 520
10 WRITE [NWT,6007] IPRINT,[SYM[J],J=1,K]
GO TO 520
11 IF [IPRINT-29] 512,513,514
12 WRITE [NWT,6008] IPRINT,[SYM[J],J=1,K]
GO TO 520
13 WRITE [NWT,6009] IPRINT,[SYM[J],J=1,K]
GO TO 520
14 GO TO 500
20 DO 521 J=1,K
SYM[J]=SYM1[J]
21 ISYM[J]=JSYM[J]
K1=K
IF [MSTOP5-2] 101,101,53
3 WRITE [NWT,1001]
GO TO 52
1 FORMAT[8I3]
01 FORMAT[13F6,0,2X]
000 FORMAT[11,8X,12F5,0]
001 FORMAT[1H1]
002 FORMAT[13F5,0]
004 FORMAT[13A6,A2]
5000 FORMAT[4[9X,A1],5X,A5]
5001 FORMAT[10X,I4,1X,90A1]
5002 FORMAT[9X,1HS,I4,1X,90A1]
5003 FORMAT[9X,1HC,I4,1X,90A1]
5004 FORMAT[9X,1HA,I4,1X,90A1]
6005 FORMAT[9X,1HN,I4,1X,90A1]

```

```

6006 FORMAT(9X,1HL,I4,1X,90A1)
6007 FORMAT(9X,1HI,I4,1X,90A1)
6008 FORMAT(9X,1HN,I4,1X,90A1)
6009 FORMAT(9X,1HE,I4,1X,90A1)
END

```

NOT REPRODUCIBLE

```

SUBROUTINE OUT1(ICHAN,ICONF,ICONF1,N,ALPHA1,ALPHA2,DASH,EYE,PLUS)
DIMENSION ITEM(90), IONE(90)
DIMENSION ICHAN(11), ICHAN1(12)
COMMON/DATA/WLNGTH(13)
DIMENSION WLNGTH(13)
DIMENSION ALPHA1(11), ALPHA2(11)
DATA [(WLNGTH(I),I=1,13)=.40,.44,.46,.48,.50,.52,.55,.58,.62,.66,.
1 72,.80,1.00]
DATA WLNGTH/.4,.44,.46,.48,.50,.52,.55,.58,.62,.66,.72,.8,1./
NWT=6
DO 9 I=1,12
9 ICHAN1[I]=0
I1=1
J1=ICHAN[I3]
DO 12 J=1,J1
DO 10 I=I1,12
I2=I
IF [ICHAN[I]-13] 11,10,11
10 CONTINUE
11 ICHAN1[J]=ICHAN[I2]
I1=I2+1
12 CONTINUE
WRITE (NWT,1001)
WRITE (NWT,1010)
WRITE (NWT,1007) (ALPHA1[I],I=1,14)
WRITE (NWT,1007) (ALPHA2[I],I=1,14)
WRITE (NWT,1010)
WRITE (NWT,1006)
DO 13 I=1,J1
M=ICHAN1[I]
13 WRITE (NWT,1008) M,WLNGTH[M],WLNGTH[M+1]
WRITE (NWT,1010)
WRITE (NWT,1005) ICONF1
WRITE (NWT,1010)
WRITE (NWT,1009) EYE,DASH,PLUS
WRITE (NWT,1010)
WRITE (NWT,1002)
WRITE (NWT,1010)
DO 20 I=1,N
ITEM[I]=I/10
IONE[I]=I-(I/10)*10
20 CONTINUE
WRITE (NWT,1003) (ITEM[I],I=10,N)
WRITE (NWT,1004) (IONE[I],I=1,N)
1001 FORMAT(1H0,28X,27HMAP OF INVENTORY BOUNDARIES/)

```



```

1002 FORMAT(36X,13HSAMPLE NUMBER/)
1003 FORMAT(24X,90I1)
1004 FORMAT(15X,90I1/)
1005 FORMAT(28X,I2,26H PERCENT CONFIDENCE LIMITS/)
1006 FORMAT(26X,32HCHANNEL WAVE LENGTH[MICRONS]/)
1007 FORMAT(14X13A6,A2/)
1008 FORMAT(28X,I2,12X,F5.2,3H - ,F5.2,/)
1009 FORMAT(14X,8HSYMBOLS=,3X,A1,20H - VERTICAL BOUNDARY,3X,A1,22H - HO
1RIZONTAL BOUNDARY/22X,A1,40H - BOTH VERTICAL AND HORIZONTAL BOUNDA
2RY/)
1010 FORMAT (1H0)
RETURN
END

```

1

```

SUBROUTINE ERROR(XMEAN,XMEAN1,XDATA,XEACUM,ICHAN,M)
DIMENSION XMEAN(12),XMEAN1(12),XEACUM(12),XDATA(12),ICHAN(1)
XM=M-1
DO 30 J=1,12
IF [ICHAN(J)-13] 20,30,30
10 IF [M-1] 21,21,22
21 XMEAN(J)=XDATA(J)
XMEAN1(J)=XMEAN(J)
XEACUM(J)=0.0
GO TO 30
22 CONTINUE
XMEAN(J)=[XM/[XM+1.0]]*XMEAN(J)+[1.0/[XM+1.0]]*XDATA(J)
XEACUM(J)=[(XM-1.0)/[XM+1.0]]*XEACUM(J)+[1.0/[XM+1.0]]*[XMEAN1(J)-
1XMEAN(J)]**2+[1.0/[XM*(XM+1.0)]]*[XDATA(J)-XMEAN(J)]**2
XMEAN1(J)=XMEAN(J)
30 CONTINUE
RETURN
END

```

```

SUBROUTINE SLOPE(EACUM,ICHAN,M,MDUM,ERCK,SUM1,SUM2)
DIMENSION EACUM(1) ,ICHAN(1)
CHAN13=ICHAN(13)
XM=M
HACUM1=0.0
DO 20 I=1,12
IF [ICHAN(I)-13] 10,20,10
10 HACUM1=HACUM1+EACUM(I)
20 CONTINUE
HACUM1=SQRT(HACUM1/CHAN13)
SUM1 =SUM1 + [XM*HACUM1]**2/[XM-1.0]
SUM2 =SUM2 + [XM*HACUM1]/SQRT[XM-1.0]
IF [SUM1] 30,40,30

```

```

30 IF [SUM2] 35,40,35
40 ERCK=0.0
   GO TO 45
35 CONTINUE
   A=SUM1 /SUM2
   ERCK=SQRT[XM]*HACUM1/A
45 CONTINUE
   RETURN
   END

```

```

1
SUBROUTINE CONFLM(CHIL1,CHIU1,CHIL2,CHIU2,MSTOP1,MSTOP2,MSTOP3,
1MSTOP4,M,IAVG,ERCK,NBOUND,ICONF)
DIMENSION CHIL1(1),CHIU1(1),CHIL2(1),CHIU2(1)
IAVG1=IAVG-1
NBOUND=0
IF [M-MSTOP3] 342,342,341
342 CHIU2=CHIL2[M]
   GO TO 343
341 CHIU2=CHIL2[MSTOP3]
343 IF [M-MSTOP4] 345,345,344
345 CHIU2=CHIU2[M]
   GO TO 346
344 CHIU2=CHIU2[MSTOP4]
346 CONTINUE
   IF [M-MSTOP2] 31,31,30
30 CHIU1=CHIU1[MSTOP2]
   GO TO 32
31 CHIU1=CHIU1[M]
32 IF [M-MSTOP1] 34,34,33
33 CHIU1=CHIL1[MSTOP1]
   GO TO 35
34 CHIU1=CHIL1[M]
35 IF [M-IAVG1] 20,37,37
37 CONTINUE
   IF [ICONF-1] 372,371,372
371 IF [ERCK-CHIU1] 376,376,36
36 IF [ERCK-CHIU2] 20,376,376
372 IF [ICONF-2] 376,373,376
373 IF [ERCK-CHIL1] 376,376,374
374 IF [ERCK-CHIL2] 20,376,376
376 NBOUND=1
20 CONTINUE
7000 FORMAT(60X,2F10.5)
RETURN
END

```

### 3.5 BOUNDARY ENHANCEMENT PROGRAM

This program is devised for determination of inventory boundaries through the enhancement of the difference in the multispectral data between homogeneous inventory areas. The mathematical formulation has been given in subsection 2.4.

This program consists of two links. Link 1 performs the moving or jumping averages of the input data. The output is in tape and may be input to Link 2. Link 2 performs the calculation of the finite difference of the averaged data and then calculates the absolute value or square of these differences. The outputs of Link 2 are (a) means and standard deviations for every channel of enhanced data and (b) a digital tape of the enhanced data. These means and standard deviations can be used for setting the class intervals for inputting to the Alphanumeric Plot Program to process the digital tape.

The input data to this program is on tape, while the control parameters for the program are inputted by NAMELIST statements which are documented in IBM FORTRAN IV manual, Form C28-6390-2.

The definitions of the input parameters to each LINK are as follows:

#### LINK0 INPUT PARAMETERS:

LINKNO - Specifies which LINKS to execute. LINKNO equal one LINK1 is executed and LINKNO equal two LINK2 is executed.

#### LINK1 INPUT PARAMETERS:

- NLOOP - Number of scan lines to be read in.
- NCT - Number of samples per scan line.
- NCHAN - Number of channels of data to be used.
- LTN - Logical tape number of input data tape.
- LTNI - Logical tape number of output data tape.
- NLOOP1 - Number of scan lines to sort, dependent on the number of scan lines read (NLOOP1 = NLOOP-NSKIPR).
- NSKIPR - Number of scan lines to skip, cannot be greater than the number averaged (NAVGR).
- NAVGC - Number of samples to average in a scan line.
- NSKIPC - Number of samples to skip in a scan line, cannot be greater than the number averaged (NAVGC).

- NAVGR - Number of scan lines to average.
- NFILE - Number of data files to process.
- NBEGIN - Scan line to start processing.

LINK2 INPUT PARAMETERS:

- NLOOP - Number of scan lines to be read in, must be greater than or equal to  $(2 \times \text{NDIFF} + 1)$ .
- NCT - Number of samples per scan line.
- NCHAN - Number of channels of data.
- LTN1 - Logical tape number of input data tape.
- LTN2 - Logical tape number of output data tape.
- NLOOP1 - Equals NLOOP minus one.
- NDIFF - Number of adjacent samples to skip in the cross differencing process.
- NFILE - Number of files of data to process.
- IABS - Calculates the sum of the absolute values of the differences about the adjacent data points. If IABS is not equal zero, it is calculated; if it equals zero, it is bypassed.
- ISQ - Calculates the sum of the squared values of the differences about the adjacent data points. If ISQ is not equal zero, it is calculated; if ISQ is equal zero, it is bypassed.
- ISUM - Position in the output array (W(I)) that the sum of the squared or absolute value of the differences from the channels is stored.
- NBEGIN - Scan line to start processing.

An example of the output is shown in Figure 3-7, which is followed by a complete program listing.

### 3.6 MEAN, CORRELATION, AND COVARIANCE PROGRAM

This program is devised for calculating the mean vector, correlation matrix, covariance matrix, and normalized covariance matrix of a given multi-spectral data sequence. The format of the input data is specified in the Tape Conversion Program. The mathematical expression for these quantities is given in subsection 2.6.

In addition to the printout, a punched card output for the mean vector and covariance matrix are available. These card outputs form part of the input to the Divergence Matrix Program.

INVENTORY BOUNDARY MAP BY BOUNDARY ENHANCEMENT

CRØPS C5-17,5-22,5-5,5-8, ALTITUDE 200C FT. DATE RECORDED 6/30/66

CHANNEL WAVE LENGTH  
13

SYMBOLS . = LESS THAN MEAN    . = MEAN-MEAN+1SD    . = MEAN+1SD-MEAN+2SD  
          - 2 = MEAN+2SD-MEAN+3SD    3 = GREATER THAN MEAN+3SD

00111  
00001111222233334444555566666777778888899999000001111222233334444555556  
24680246802468024680246802468024680246802468024680246802468024680246802468024680

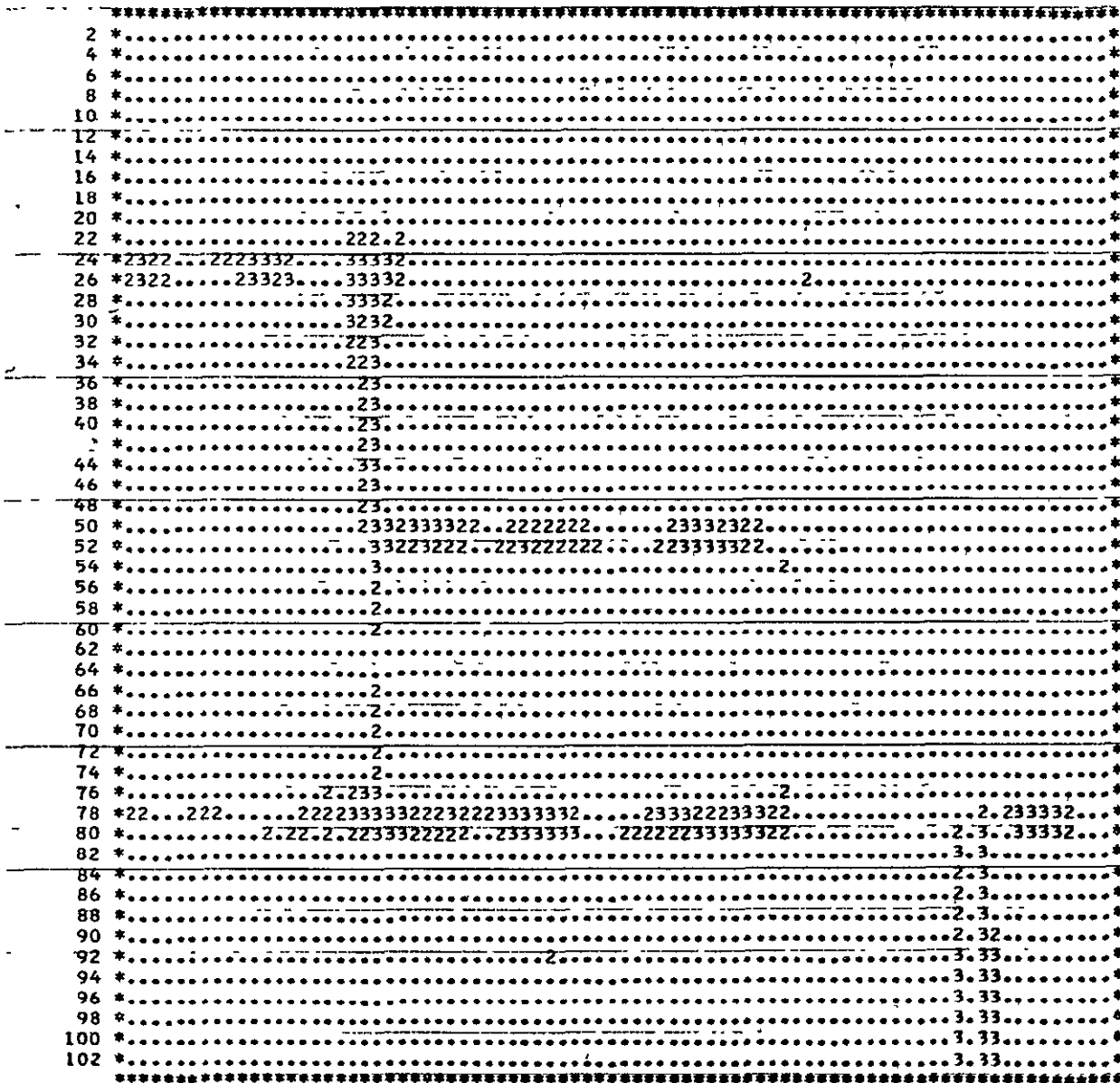


Figure 3-7. INVENTORY BOUNDARY MAP BY BOUNDARY ENHANCEMENT

```

C      BOUNDARY ENCHANCEMENT      PROGRAM
      DIMENSION LINKNO[6]
      NAMELIST/NAMDAT/LINKNO
      READ[5,NAMDAT]
      WRITE[6,NAMDAT]
      IF[LINKNO[1],EQ,0] GO TO 1
      CALL LINK1
1     CONTINUE
      IF[LINKNO[2],EQ,0] GO TO 2
      CALL LINK2
2     CONTINUE
      STOP
      END
SORIGIN      ALPHA,REW
$IBFTC TWO   NODECK
      SUBROUTINE LINK1
C      MOVING OR JUMPING AVERAGE PROGRAM
      DIMENSION DUMMY[13]
      DIMENSION DATA[6,200,12],X[200,12]
      NAMELIST/SIZE/NLOOP,NCT,NCHAN,LTN,LTN1,LTN2,NLOOP1,NSKIPR,NAVGC,
1     1NSKIPC,NAVGR,NFILE,NBEGIN
C     NSKIPR MUST BE LESS THAN OR EQUAL TO NAVGR
C     NSKIPC MUST BE LESS THAN OR EQUAL TO NAVGC
      READ[5,SIZE]
      WRITE[6,SIZE]
      DO 101 IAB=1,NFILE
      IZERO=0
      IONE=1
      ITWO=2
      ITHREE=3
      KS=0
      XNAVGC=NAVGC
      XNAVGR=NAVGR
100  CONTINUE
      LL=1
      KK=NAVGC
      DO 10 I=NBEGIN,NLOOP
      KS=KS+1
      DO 11 J=1,NCT
      RFAD[LTN] ICHEK,IDUM,[DATA[I,J,L],L=1,NCHAN]
C     WRITE [6,1003] ICHEK,KS, J ,[DATA[I,J,L],L=1,NCHAN]
      IF[ICHEK-3] 11,7,11
      7  IF[J,NE,NCT] GO TO 13
      11 CONTINUE
      10 CONTINUE
      DO 12 I=1,NCT
      DO 12 J=1,NCHAN
      X[I,J]=0.0
      12 CONTINUE
      NCT1=NCT-NAVGC
      DO 1 I=1,NCT1

```

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```

      DO 3 J=1,NAVGR
      DO 3 K=LL,KK
      DO 4 M=1,NCHAN
      X[I,M]=X[I,M]+DATA[J,K,M]
4     CONTINUE
3     CONTINUE
      DO 2 M=1,NCHAN
      X[I,M]=X[I,M]/(XNAVGC*XNAVGR)
2     CONTINUE
      WRITE(LTN1) IZERO,(X[I,M],M=1,NCHAN)
C     WRITE(6,1004) IZERO,(X[I,M],M=1,NCHAN)
      LL=LL+NSKIPC
      KK=LL+NAVGC-1
1     CONTINUE
      IF(ICHEK-3) 9,8,9
9     WRITE(LTN1) IONE,(DUMMY[I],I=1,NCHAN)
      IF(NSKIPR,EQ,NLOOP) GO TO 100
      NBEGIN=NLOOP+1
      DO 5 I=1,NLOOP1
      DO 6 J=1,NCT
      DO 6 L=1,NCHAN
      LZ=I+NSKIPR
      DATA[I,J,L]=DATA[LZ,J,L]
6     CONTINUE
5     CONTINUE
      GO TO 100
13    WRITE (6,1002) KS
8     WRITE(LTN1) ITWO,(DUMMY[I],I=1,NCHAN)
101   CONTINUE
      WRITE(LTN1) ITHREE,(DUMMY[I],I=1,NCHAN)
      END FILE LTN1
      REWIND LTN1
1000  FORMAT(I1,8X,12F6,3)
1001  FORMAT(I1,8X,12F6,3)
1002  FORMAT(1X,11HEND FILE IN,I5,9HSCAN LINE)
1003  FORMAT(1X,3I5,12F6,3)
1004  FORMAT(1X,I3,12F6,3)
      RETURN
      END
$ORIGIN ALPHA,REW
$IBFTC THREE NODECK
SUBROUTINE LINK2
C     CROSS DIFERENCE PROGRAM
      DIMENSION DUMMY(13)
      DIMENSION DATA(6,200,12),W(15),W1(15)
      DIMENSION XBAR(15),XMSBAR(15),SIG(15),RMS(15),SIGSQ(15)
      NAMLIST/SIZE/NLOOP,NCT,NCHAN,LTN1,LTN2,NLOOP1,NDIFF,NFILE,
1     IABS,ISQ,ISUM,NBEGIN
      READ(5,SIZE)
      WRITE (6,SIZE)
      NCHAN1=NCHAN+1
      DO 102 IAB=1,NFILE
      IZERO=0
      IONE=1
      ITWO=2

```

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```

      ITHREE=3
      MS=0
      KS=0
      DO 18 I=1,NCHAN1
      SIG[I]=0.0
      XBAR[I]=0.0
      XMSBAR[I]=0.0
      RMS[I]=0.0
      SIGSQ[I]=0.0
18  CONTINUE
100 IF[KS,GT,0] NBEGIN=NLOOP
      DO 1 I=NBEGIN,NLOOP
      KS=KS+1
      DO 2 J=1,NCT
      READ[LTN1] ICHEK,[DATA[I,J,L],L=1,NCHAN]
C  WRITE [6,1003] ICHEK,KS, J ,[DATA[I,J,L],L=1,NCHAN]
      IF[ICHEK-3] 2,4,2
4  IF[J,NE,NCT] GO TO 7
2  CONTINUE
1  CONTINUE
      NCT1=NCT-NDIFF-1
      NDIFF1=NDIFF+1
      NLOOP2=NLOOP-NDIFF
      DO 10 I=NDIFF1,NLOOP2
      DO 11 J=NDIFF1,NCT1
      SM=MS
      MS=MS+1
      W[ISUM]=0.0
      DO 12 K=1,NCHAN
      IZ=I-NDIFF
      JZ=I+NDIFF
      KZ=J+NDIFF
      LZ=J-NDIFF
C  ABSOLUTE VALUE OF CROSS DIFFERENCES
      IF[IABS] 9,8,9
9  CONTINUE
      AVSUM=ABS[DATA[I,J,K]-DATA[IZ,J,K]]+ABS[DATA[I,J,K]-DATA[I,KZ,K]]+
      1ABS[DATA[I,J,K]-DATA[JZ,J,K]]+ABS[DATA[I,J,K]-DATA[I,LZ,K]]
      W[K]=AVSUM
8  CONTINUE
C  SQUARED VALUE OF CROSS DIFFERENCES
      IF[ISQ] 14,13,14
14 CONTINUE
      AVSUM1=[DATA[I,J,K]-DATA[IZ,J,K]]**2+[DATA[I,J,K]-DATA[I,KZ,K]]**2
      1+[DATA[I,J,K]-DATA[JZ,J,K]]**2+[DATA[I,J,K]-DATA[I,LZ,K]]**2
      W[K]=AVSUM1
13 CONTINUE
      W[ISUM]=W[ISUM]+W[K]
12 CONTINUE
      DO 15 L=1,NCHAN1
      XMSBAR[L]=[SM/[SM+1.0]]*XMSBAR[L]+[1.0/[SM+1.0]]*W[L]**2
      XBAR[L]=[SM/[SM+1.0]]*XBAR[L]+[1.0/[SM+1.0]]*W[L]
15 CONTINUE
      WRITE[LTN2] IZERO,[W[K],K=1,NCHAN1]
C  WRITE [6,1001] IZERO,[W[K],K=1,NCHAN]

```



```

C      WRITE (6,1001)  IZERO, (W1[K],K=1,NCHAN)
11     CONTINUE
      IF (ICHEK=3)  10,3,10
10     WRITE (LTN2)  IONE, (DUMMY[K],K=1,NCHAN)
      DO 5 I=1,NLOOP1
      DO 6 J=1,NCT
      DO 6 L=1,NCHAN
      DATA (I,J,L)=DATA (I+1,J,L)
6      CONTINUE
5      CONTINUE
      GO TO 100
7      WRITE (6,1002)  KS
3      WRITE (LTN2)  ITWO, (DUMMY[I],I=1,NCHAN)
101    CONTINUE
      DO 16 I=1,NCHAN1
      SIG(I)=XMSBAR(I)-XBAR(I)**2
      SIGSQ(I)=SQRT(SIG(I))
      RMS(I)=SQRT(XMSBAR(I))
16     CONTINUE
      WRITE (6,1004)
      DO 17 L=1,NCHAN1
      WRITE (6,1005)  L,XBAR(L),XMSBAR(L),SIG(L),SIGSQ(L)
17     CONTINUE
102    CONTINUE
      WRITE (LTN2)  ITHREE, (DUMMY[I],I=1,NCHAN)
      END FILE LTN2
      REWIND LTN2
1000  FORMAT (I1,8X,12F6,3)
1001  FORMAT (I1,8X,12F6,3)
1002  FORMAT (1X,11HEND FILE IN,15,9HSCAN LINE)
1003  FORMAT (1X,3I5,12F6,3)
1004  FORMAT (10X,2HCH,5X,4HMEAN,6X,11HMENN-SQUARE,6X,8HVARIANCE,6X,
17HSTD-DEV)
1005  FORMAT (10X,I3,F10,7,5X,F10,7,3X,F10,7,3X,F10,7,3X,F10,7)
      RETURN
      END

```

```

$DATA
$NAMDAT
LINKNO=0,2,4*0
$END
$SIZE
NLOOP=3
NCT=164
NCHAN=12
LTN1=9
LTN2=11
NLOOP1=2
NDIFF=1
NFILE=1
NBEGIN=1
IABS=0
ISQ=1
ISUM=13
$END
$SIZE

```

```
NLOOP=5  
NCT=168  
NCHAN=12  
LTN=9  
LTN1=10  
LTN2=11  
NLOOP1=4  
NSKIPR=1  
NAVGC=5  
NSKIPC=1  
NBGNC=1  
MENDC=5  
NAVGR=5  
NBFGIN=1  
NFILE=1  
$END
```

```
-  
-
```

The input card setup is shown in Figure 3-8.

DEFINITIONS OF INPUT PARAMETERS:

CARD 1

- NSCAN - The number of scan lines in a field
- NCHAN - Total number of channels in a field.
- NCOMP - Number of channel cross products calculated to generate the Covariance Matrix.
- NTOTAL - Total number of samples in a scan line.
- NFIELD - Number of fields to process in a data set.
- ISCAN - The number of scan lines to skip before starting calculations in a field.
- NFDL1 - Number of times to process the data set (N X NFIELD)

CARD 2

- An 80 Holerith card used for field identification.

CARD 3

- NBEGIN - Sample number to start with in a specific scan line for a certain field.
- NEND - Sample number to stop on in a specific scan line for a certain field.

CARD 4

- An 80 Holerith card used for field identification.

A listing of the output from this program is given in Figure 3-9. A flowchart of this program is given in Figure 3-10.

The program listing is given below.

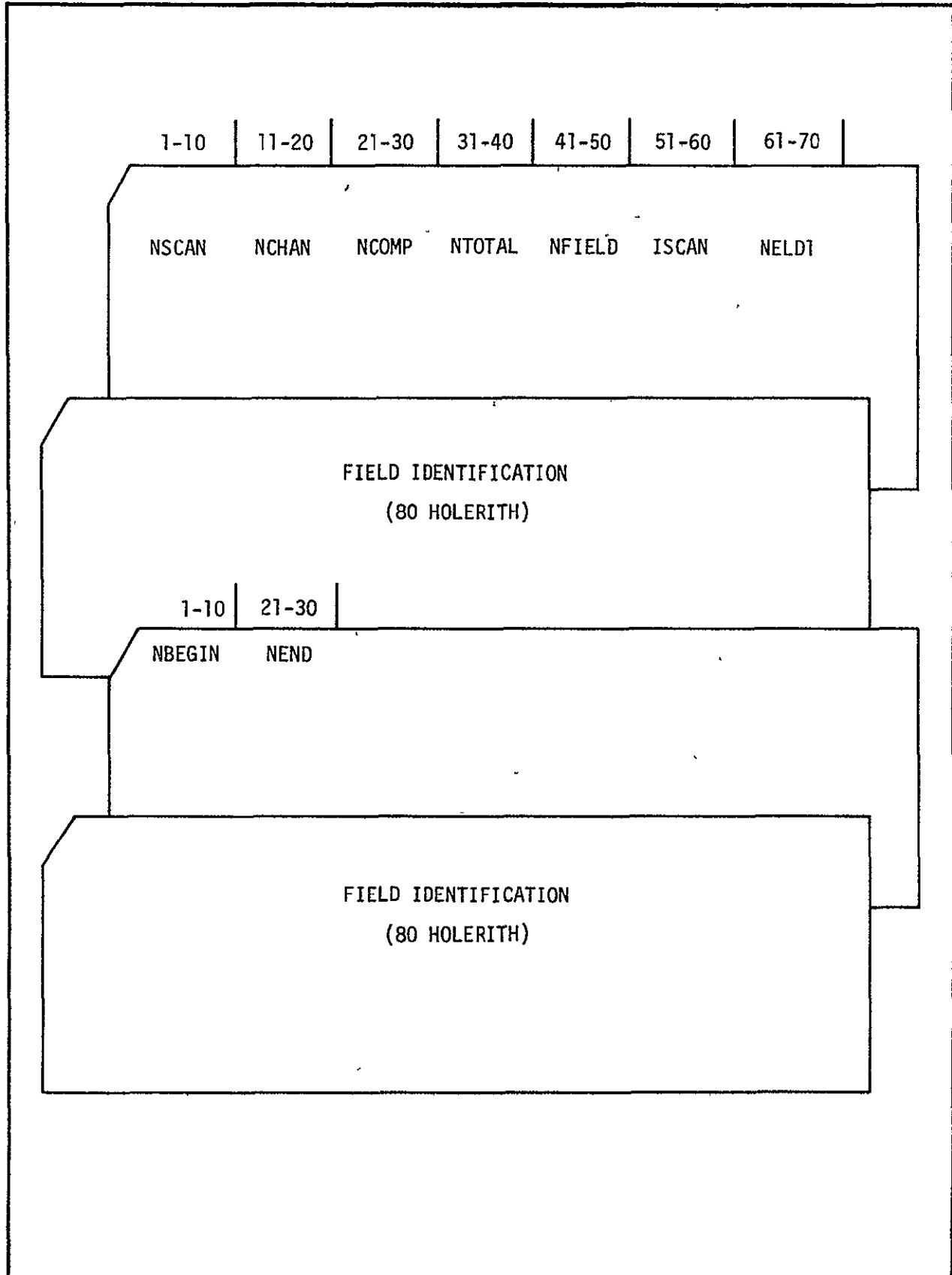


Figure 3-8. INPUT CARD DECK

SCAN	C(5-17) LINE	SECTION START	A STZP
1		1	56
2		1	56
3		1	54
4		1	54
5		1	54
6		1	54
7		1	54
8		1	54
9		1	54
10		1	54
11		1	54
12		1	54
13		1	54
14		1	54
15		1	52
16		1	58
17		1	56
18		1	56
19		1	54
20		1	54
21		1	54
22		1	54
23		1	52
24		1	52
25		1	52
26		1	52
27		1	52

Figure 3-9. OUTPUTS OF THE PROGRAM

C(5-17) SFCT17N 4 0

MEAN VECTOR

CH	*	1	2	3	4	5	6	7	8	9	10	11	12
1	*	1.13450	1.64770	1.14216	1.02106	1.06431	1.04311	0.80106	1.01016	0.46364	0.63174	0.93581	0.72408

CORRELATION MATRIX

CH	*	1	2	3	4	5	6	7	8	9	10	11	12
1	*	1.29448	1.87150	1.29875	1.16064	1.20975	1.18529	0.91027	1.14810	0.52692	0.71737	1.06134	0.82111
2	*	1.87150	2.72780	1.88613	1.68587	1.75709	1.72116	1.32215	1.66716	0.76575	1.04181	1.54035	1.19234
3	*	1.29875	1.88613	1.31314	1.16975	1.21775	1.19354	0.91642	1.15721	0.53188	0.72268	1.06552	0.82490
4	*	1.16064	1.68587	1.16979	1.04972	1.08874	1.06632	0.81949	1.03485	0.47623	0.64609	0.95135	0.73677
5	*	1.20975	1.75709	1.21775	1.08374	1.14085	1.11169	0.85564	1.07968	0.49579	0.67382	0.99366	0.75941
6	*	1.18529	1.72116	1.19354	1.06632	1.11169	1.09531	0.83699	1.05501	0.48402	0.65967	0.97782	0.75613
7	*	0.91027	1.32215	0.91642	0.81949	0.85564	0.83689	0.64716	0.81229	0.37289	0.50695	0.74945	0.58046
8	*	1.14810	1.66716	1.15721	1.03485	1.07968	1.05501	0.81229	1.03081	0.47294	0.63976	0.93955	0.72739
9	*	0.52692	0.76575	0.53188	0.47623	0.49579	0.48402	0.37289	0.47294	0.22164	0.29306	0.42837	0.33228
10	*	0.71737	1.04181	0.72268	0.64609	0.67382	0.65967	0.50695	0.63976	0.29306	0.40282	0.59004	0.45651
11	*	1.06134	1.54035	1.06552	0.95135	0.99366	0.97782	0.74945	0.93955	0.42837	0.59004	0.89433	0.68781
12	*	0.82111	1.19234	0.82490	0.73677	0.76941	0.75613	0.58046	0.72739	0.33228	0.45651	0.68781	0.53618

COVARIANCE MATRIX

CH	*	1	2	3	4	5	6	7	8	9	10	11	12
1	*	0.00739	0.00219	0.00297	0.00225	0.00229	0.00188	0.00147	0.00207	0.00092	0.00066	-0.00034	-0.00036
2	*	0.00219	0.01290	0.00420	0.00348	0.00343	0.00243	0.00224	0.00271	0.00180	0.00090	-0.00158	-0.00073
3	*	0.00297	0.00420	0.00861	0.00358	0.00213	0.00214	0.00149	0.00344	0.00233	0.00113	-0.00332	-0.00212
4	*	0.00225	0.00348	0.00358	0.00716	0.00201	0.00125	0.00156	0.00341	0.00282	0.00105	-0.00416	-0.00256
5	*	0.00229	0.00343	0.00213	0.00201	0.00809	0.00149	0.00306	0.00455	0.00233	0.00145	-0.00233	-0.00124
6	*	0.00188	0.00243	0.00214	0.00125	0.00149	0.00723	0.00130	0.00129	0.00039	0.00070	0.00167	0.00083
7	*	0.00147	0.00224	0.00148	0.00156	0.00306	0.00130	0.00546	0.00309	0.00149	0.00089	-0.00018	0.00042
8	*	0.00207	0.00271	0.00344	0.00341	0.00455	0.00129	0.00309	0.01038	0.00459	0.00160	-0.00577	-0.00405
9	*	0.00092	0.00180	0.00233	0.00282	0.00233	0.00039	0.00149	0.00459	0.00668	0.00015	-0.00551	-0.00343
10	*	0.00066	0.00090	0.00113	0.00105	0.00145	0.00070	0.00089	0.00160	0.00015	0.00373	-0.00115	-0.00092
11	*	-0.00034	-0.00159	-0.00332	-0.00416	-0.00233	0.00167	-0.00018	-0.00577	-0.00551	-0.00115	0.01859	0.01020
12	*	-0.00036	-0.00073	-0.00212	-0.00256	-0.00124	0.00083	0.00042	-0.00405	-0.00343	-0.00092	0.01020	0.01188

NORMALIZED COVARIANCE MATRIX

CH	*	1	2	3	4	5	6	7	8	9	10	11	12
1	*	1.00000	0.22442	0.37232	0.30954	0.29612	0.25743	0.23174	0.23612	0.13042	0.12555	-0.02887	-0.03883
2	*	0.22442	1.00000	0.39844	0.36209	0.33532	0.25137	0.26733	0.23444	0.19443	0.12931	-0.10191	-0.05864
3	*	0.37232	0.39844	1.00000	0.45614	0.25549	0.27056	0.21556	0.36411	0.30744	0.19968	-0.26247	-0.20957
4	*	0.30954	0.36209	0.45614	1.00000	0.26425	0.17308	0.24927	0.39575	0.40798	0.20245	-0.36068	-0.27787
5	*	0.29612	0.33532	0.25548	0.26425	1.00000	0.19454	0.46018	0.49623	0.31687	0.26472	-0.19027	-0.12606
6	*	0.25743	0.25137	0.27056	0.17308	0.19454	1.00000	0.20639	0.14922	0.05594	0.13470	0.14408	0.08981
7	*	0.23174	0.26733	0.21556	0.24927	0.46018	0.20639	1.00000	0.41050	0.24678	0.19758	-0.01837	0.05237
8	*	0.23612	0.23444	0.36411	0.39575	0.49623	0.14922	0.41050	1.00000	0.55093	0.25650	-0.41557	-0.36464
9	*	0.13042	0.19443	0.30744	0.40798	0.31687	0.05594	0.24678	0.55093	1.00000	0.03099	-0.49461	-0.38526
10	*	0.12555	0.12931	0.19968	0.20245	0.26472	0.13470	0.19758	0.25650	0.03099	1.00000	-0.13767	-0.13817
11	*	-0.02887	-0.10191	-0.26247	-0.36068	-0.19027	0.14408	-0.01837	-0.41557	-0.49461	-0.13767	1.00000	0.68642
12	*	-0.03883	-0.05864	-0.20957	-0.27787	-0.12606	0.08981	0.05237	-0.36464	-0.38526	-0.13817	0.68642	1.00000

Figure 3-9: OUTPUTS OF THE PROGRAM (Concluded)

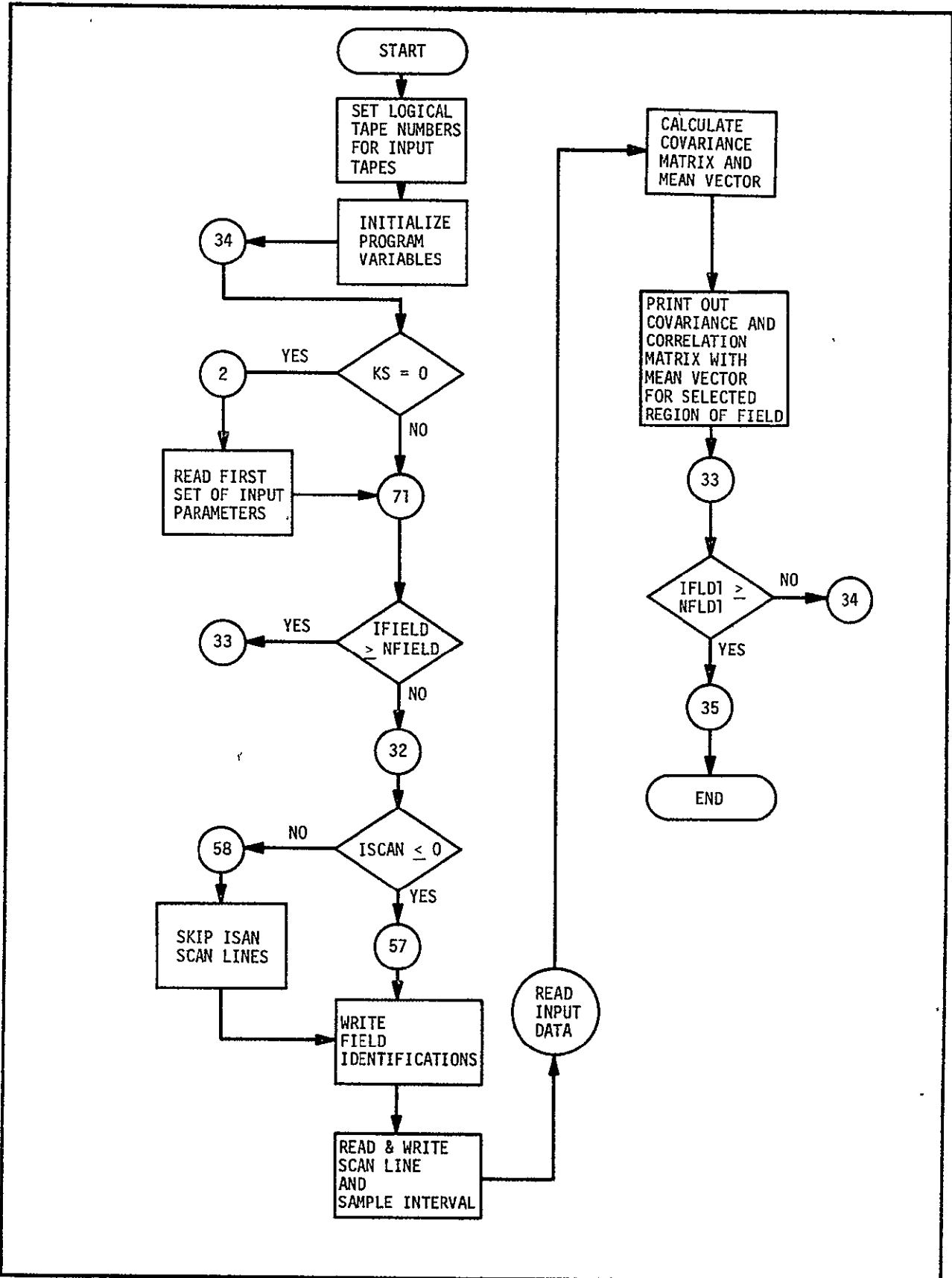


Figure 3-10. CORRELATION AND COVARIANCE MATRIX PROGRAM

```
C CORRELATION AND COVARIANCE MATRIX PROGRAM
  DIMENSION XXXXX(12,12)
  DIMENSION XMEAN(12),DATA(12),CORR(12,12)
  DIMENSION ACORR(12,12),ACOV(12,12),XRAR(12)
C LTN LOGICAL TAPE NUMBER OF DATA TAPE
  LTN=9
C LTN5 LOGICAL NUMBER OF INPUT PARAMETERS
  LTN5=5
C LTN6 LOGICAL NUMBER OF OUTPUT
  LTN6=6
C LTN7 LOGICAL NUMBER OF PUNCH OUTPUT
  LTN7=7
C INPUT PARAMETERS INITIALIZED
  KS=0
  SCALE=100.0
  IONE=1
  IFLDI=1
34  IFIELD=1
  IF (KS) 71,2,71
  2  CONTINUE
  READ (LTN5,100) NSCAN,NCHAN,NCOMP,NTOTAL,NFIELD,ISCAN,NFLDI
71  CONTINUE
  IF(IFIELD-NFIELD)32,32,33
32  CONTINUE
  MS=0
C OPTION TO SKIP SCAN LINES
  IF(ISCAN) 57,57,58
58  CONTINUE
  DO 55 I=1,ISCAN
  DO 55 J=1,NTOTAL
  READ (LTN) IDUM
55  CONTINUE
57  CONTINUE
  ISKIP=ISCAN+1
  WRITE (LTN6,110)
  WRITE (LTN6,105)
  READ (LTN5,106)
  WRITE (LTN6,106)
  WRITE (LTN6,105)
  WRITE (LTN6,105)
  WRITE (LTN6,103)
  DO 50 IAP=ISKIP,NSCAN
  DO 1 J=1,12
  XMEAN(J)=0.0
  DO 1 I=1,12
  CORR(J,I)=0.0
1  CONTINUE
  READ (LTN5,100) NBEGIN,NEND
  WRITE (LTN6,104) IAB,NBEGIN,NEND
  WRITE (LTN6,105)
  NSAMP=NEND-IBEGIN+1
  SAMP=ISAMP
  NSTART=NBEGIN-1
  IF(NSTART) 62,61,62
```

NOT REPRODUCIBLE



```

62  CØNTINUE
    DØ 10 II=1,NSTART
10  READ (LTN)      IDUM
61  CØNTINUE
C   INPUT DAT READ FRØM LTN
    DØ 20 I=NBEGIN,NEND
    READ (LTN)      ICHEK, IDUM, (DATA(J), J=1, NCHAN)
    DØ 26 L=1, NCØMP
    DØ 21 J=1, NCHAN
    CØRR(L, J)=CØRR(L, J)+DATA(L)*DATA(J)
21  CØNTINUE
26  CØNTINUE
C   MEAN VECTØR CALCULATED
    DØ 20 K=1, NCHAN
    XMEAN(K)=XMEAN(K)+DATA(K)
20  CØNTINUE
    NTERM=NEND+1
    DØ 25 I=NTERM, NTØTAL
25  READ (LTN)      ICHEK
    SM=MS
    MS=MS+1
    DØ 22 J=1, NCHAN
    XMEAN(J)=XMEAN(J)/(SAMP)
22  CØNTINUE
C   CØRRELATION AND CØVARIANCE MATRIX CALCULATED
    DØ 23 J=1, NCØMP
    DØ 23 I=1, NCHAN
    CØRR(J, I)=CØRR(J, I)/(SAMP)
23  CØNTINUE
    DØ 51 J=1, NCØMP
    XBAR(J) =(SM/(SM+1.0))*XBAR(J) +(1.0/(SM+1.0))*XMEAN(J)
    DØ 51 I=1, NCHAN
    ACØRR(J, I)=(SM/(SM+1.0))*ACØRR(J, I)+(1.0/(SM+1.0))*CØRR(J, I)
51  CØNTINUE
50  CØNTINUE
    WRITE (LTN6,110)
    WRITE (LTN6,105)
    READ (LTN5,106)
    WRITE (LTN6,106)
    WRITE (LTN6,105)
    WRITE (LTN6,107)
    WRITE (LTN6,105)
    WRITE (LTN6,112) (K,K=1,NCHAN)
    WRITE (LTN6,102) IØNE, (XBAR(J), J=1, NCHAN)
    WRITE (LTN7,113)      (XBAR(J), J=1, NCHAN)
    WRITE (LTN6,105)
    WRITE (LTN6,108)
    WRITE (LTN6,105)
    WRITE (LTN6,112) (K,K=1,NCHAN)
    DØ 53 J=1, NCØMP
    WRITE (LTN6,102) J, (ACØRR(J, I), I=1, NCHAN)
53  CØNTINUE
    DØ 54 J=1, NCØMP
    DØ 54 I=1, NCHAN
    ACØVR(J, I)=ACØRR(J, I)-(XBAR(J)*XBAR(I))

```

NOT REPRODUCIBLE

```

54  CONTINUE
    WRITE (LTN6,105)
    WRITE (LTN6,109)
    WRITE (LTN6,105)
    WRITE (LTN6,112) (K,K=1,NCHAN)
    DO 56 J=1,NCOMP
    WRITE (LTN6,102) J,(ACQVR(J,I),I=1,NCHAN)
    DO 2004 L=1,12
    XXXXX(J,L)=ACQVR(J,L)*SCALE
2004 CONTINUE
    WRITE (LTN7,113) (XXXXX(J,I),I=1,NCHAN)
56  CONTINUE
    DO 60 J=1,NCOMP
    DO 60 I=1,NCHAN
    ABSCPV=ABS(ACQVR(J,J)*ACQVR(I,I))
    ACQRR(J,I)=ACQVR(J,I)/SQRT(ABSCPV)
60  CONTINUE
    WRITE (LTN6,105)
    WRITE (LTN6,111)
    WRITE (LTN6,105)
    WRITE (LTN6,112) (K,K=1,NCHAN)
    DO 59 J=1,NCOMP
    WRITE (LTN6,102) J,(ACQRR(J,I),I=1,NCHAN)
59  CONTINUE
    IFLD1=IFLD1+1
    IFIELD=IFIELD+1
    IF(ICHEK-2) 24,2,2
24  WRITE(LTN6,115)
    GO TO 35
100  FORMAT(7I10)
101  FORMAT(11,8X,12F6.3)
102  FORMAT(2X,14,4X,1H*,12F10.5)
103  FORMAT(20X,11HSCAN LINE,10X,5HSTART,10X,4HSTOP)
104  FORMAT(20X,15,14X,15,10X,15)
105  FORMAT(1F )
106  FORMAT(1X,80H
1
107  FORMAT(30X,14HMEAN VECTOR)
108  FORMAT(30X,20HCORRELATION MATRIX)
109  FORMAT(30X,20HCOVARIANCE MATRIX)
110  FORMAT(1F1)
111  FORMAT(20X,32HNORMALIZED COVARIANCE MATRIX)
112  FORMAT(4X,2HCH,4X,1H*,12(15,5X))
113  FORMAT(1X,12F6.3)
114  FORMAT(1X,12F6.4)
115  FORMAT(1X,40HNØ END OF FIELD DESIGNATION ON THIS TAPE)
33  CONTINUE
    KS=KS+1
    WRITE (LTN6,100) KS
    REWIND LTN
    IF(IFLD1-NFLD1) 34,34,35
35  CONTINUE
    STOP
    END

```

### 3.7 PIECEWISE CORRELATION AND COVARIANCE PROGRAM

This program is devised for calculating the piecewise mean, root-mean-square, and cross-correlation of a specified channel with respect to the rest of the channels in the multi-channel data set. The program also calculates the piecewise covariance, the second derivative of the piecewise correlation. The associated statistical errors of the above correlation or covariance are also calculated.

#### DEFINITION OF INPUT PARAMETERS:

##### CARD 1

PIECE - Option for piecewise printout  $\neq 0$  for printout.  
LTERM - TERMINATES JOB  
     $\neq 0$  for next case  
    = 0 to terminate  
NTOTAL - Total NR. of samples in scan line.  
NARRNG - Rearrange input data for correlations.  
     $\neq 0$

##### CARD 2

NBEGIN - 1<sup>st</sup> data point to use in each scan line.  
NEND - Last data point to use in each scan line.  
ICHAN - Reference channel for correlations.  
NSAMP - No. of samples/piece, for piecewise calculations cannot be greater than (NEND-NBEGIN).  
NORM -  $\neq 0$  for normalization.  
JFIELD - No. of fields to process.

The input deck setup is shown in Figure 3-11.

The flowchart of the program is shown in Figure 3-12 which is followed by a listing of the program.

### 3.8 PROBABILITY HISTROGRAM PROGRAM

This program is devised for calculating the univariate (first order) probability density functions of the multispectral data set within a specified inventory area. The program can handle up to 12 channels of data simultaneously.

3-46

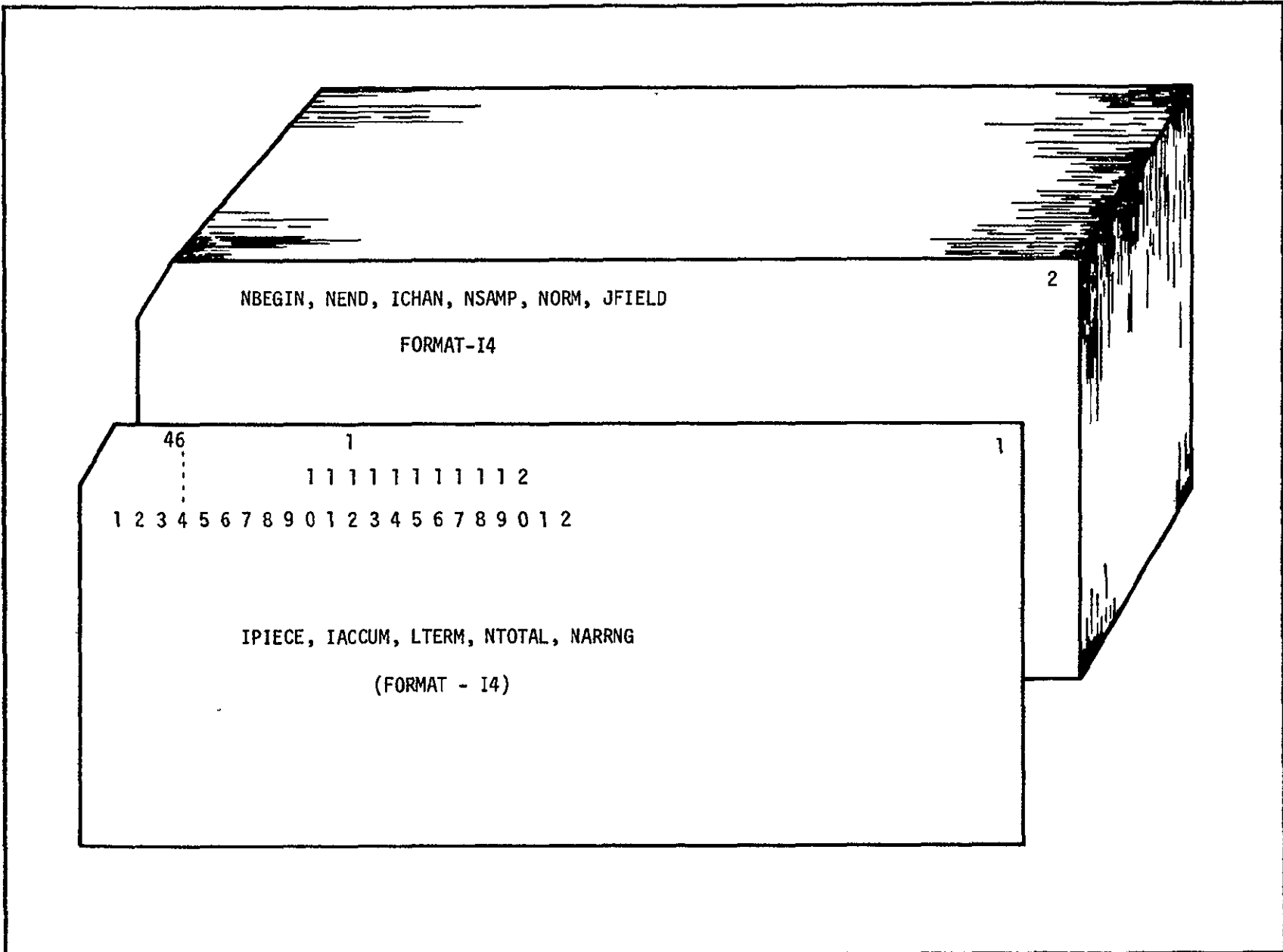


Figure 3-11. INPUT DECK SETUP

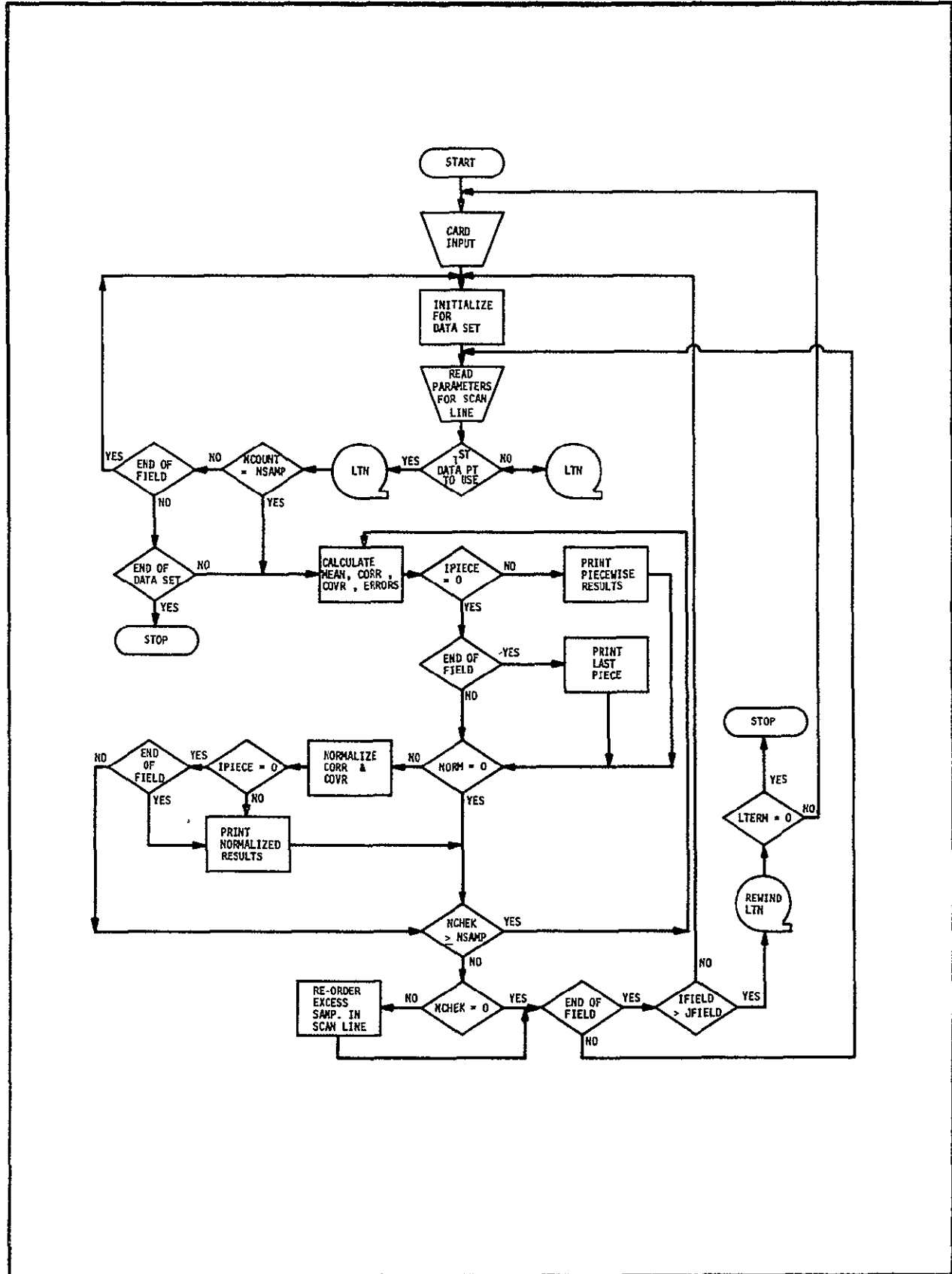


Figure 3-12. FLOWCHART FOR CORRELATION AND COVARIANCE PROGRAM

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```

C*****
C CORRELATION AND COVARIANCE PROGRAM W/ERRORS
C*****
  DIMENSION XMEAN(12),COVR(12),ACOVR(12),BCOVR(12),ECOVR(12),
  IFCOVR(12),FRROR(12)
  DIMENSION FCORR(12)
  DIMENSION ARMS1(13)
  DIMENSION DATA(150,12),TEMP(150,12),CORR(12),DAT(150,12)
  DIMENSION ACORR(12),ECORR(12),DUM(12)
  DIMENSION DATS(150,12),ERROR(12),IDAT(12)
  DIMENSION ARMS(13),BRMS(13),BCORR(12),CCORR(13)
  EQUIVALENCE (TEMP,DAT)
  LTN=54
  LTN1=61
  LTN2=60
2000 CONTINUE
  READ (LTN2,100) IPIECE,IACCUM,LTERM,NTOTAL,NARRNG
  ICHEK=0
  IFIELD=0
  JFIELD=1
  ICHEK=0
200 CONTINUE
  IFIELD=IFIELD+1
  C PUNCH 116, IFIELD
  C
  C JFIELD IS NR. OF CROPS + 1
  C TO TERMINATE JOB.
  C
  IF(IFIELD=JFIELD) 201,201,113
201 CONTINUE
  ICHEK1=0
  DO 302 I=1,12
  ACOVR(I)=0.0
  ECOVR(I)=0.0
  BCORR(I)=0.0
  BCOVR(I)=0.0
  FCORR(I)=0.0
  FCOVR(I)=0.0
  ACORR(I)=0.0
  ECORR(I)=0.0
302 CONTINUE
  MSS=0
  MS=0
  NCOUNT=0
  WRITE (LTN1,108)
2 CONTINUE
  C
  C READ PARAMETERS FOR EACH SCAN LINE
  C
  READ (LTN2,100) NBEGIN,NEND,ICHAN,NSAMP,NORM,JFIELD
  NTERM=NEND+1
  NEND=NEND-NBEGIN+1
  MSS=MSS+1
  SAMP=NSAMP
  JEND=NBEGIN-1
  IF (JEND) 501,501,500
500 CONTINUE

```

```

DO 10 II=1,JEND
10 READ(LTN,100) IDUM
501 CONTINUE
DO 20 I=1,NEND
READ(LTN,101) ICHEK,(DAT(I,J),J=1,12)
20 CONTINUE
DO 23 I=NTERM,NTOTAL
23 READ(LTN,101) ICHEK
PRINT 100,ICHEK
IF(NARRNG) 50,35,50
50 CONTINUE
KM=MSS/2
XM=MSS/2
BM=KM
XM=XM-BM
KM=2.0*XM
IF(KM-1)35,32,32
32 JJ=NEND
KKK=1
DO 33 II=1,NEND
DO 28 J=1,12
DATS(KKK,J)=DAT(JJ,J)
28 CONTINUE
KKK=KKK+1
JJ=JJ-1
33 CONTINUE
DO 305 I=1,NEND
DO 305 J=1,12
DAT(I,J)=DATS(I,J)
305 CONTINUE
35 CONTINUE
DO 36 II=1,NEND
NCOUNT=NCOUNT+1
DO 37 J=1,12
DATA(NCOUNT,J)=DAT(II,J)
37 CONTINUE
36 CONTINUE
KK=1
DO 25 I=1,NCOUNT
LL=I+1
DO 24 J=1,12
TEMP(KK,J)=DATA(I,J)-DATA(LL,J)
24 CONTINUE
KK=KK+1
25 CONTINUE
IF(NCOUNT=NSAMP) 2002,2003,2003
2002 CONTINUE
PRINT 100,ICHEK
IF(ICHEK=2) 2004,200,200
2004 CONTINUE
IF(NCOUNT=NSAMP) 2,2003,2003
2003 CONTINUE
MCOUNT=0
ICOUNT=0
26 CONTINUE
MS=MS+1
DO 1 J=1,12

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      COVR(J)=0.0
      ARMS1(J)=0.0
      XMEAN(J)=0.0
      ARMS(J)=0.0
      CORR(J)=0.0
      ERROR(J)=0.0
      FRROR(J)=0.0
1 CONTINUE
      DO 403 J=1,NSAMP
      MCOUNT=MCOUNT+1
      DO 403 I=1,12
403 XMEAN(I)=XMEAN(I)+DATA(MCOUNT,I)/SAMP
      CONTINUE
      DO 30 KK=1,NSAMP
      ICOUNT=ICOUNT+1
      DO 29 J=1,12
      COVR(J)=COVR(J)+(DATA(ICOUNT,ICHAN)-XMEAN(ICHAN))
1 *(DATA(ICOUNT,J)-XMEAN(J))
      CORR(J)=CORR(J)+TEMP(ICOUNT,ICHAN)*TEMP(ICOUNT,J)
      ARMS(J)=ARMS(J)+TEMP(ICOUNT,J)*TEMP(ICOUNT,J)
      ARMS1(J)=ARMS1(J)+DATA(ICOUNT,J)*DATA(ICOUNT,J)
29 CONTINUE
30 CONTINUE
      SM=MS-1
      DO 207 J=1,12
      COVR(J)=COVR(J)/SAMP
      ARMS1(J)=SQRT ((ARMS1(J)/SAMP)-XMEAN(J)**2)
      ARMS(J)=SQRT (ARMS(J)/SAMP)
      CORR(J)=CORR(J)/SAMP
      ACORR(J)=(SM/(SM+1.0))*ACORR(J)+(1.0/(SM+1.0))*CORR(J)
      ACOVR(J)=(SM/(SM+1.0))*ACOVR(J)+(1.0/(SM+1.0))*COVR(J)
      ECORR(J)=(SM/(SM+1.0))*ECORR(J)+(1.0/(SM+1.0))*(CORR(J)**2)
      ECOVR(J)=(SM/(SM+1.0))*ECOVR(J)+(1.0/(SM+1.0))*COVR(J)**2
      IF(ECORR(J)-ACORR(J)**2) 207,207,206
206 ERROR(J)=SQRT ((1./SM)*(ECORR(J)-ACORR(J)**2))
207 CONTINUE
      IF(ECOVR(J)-ACOVR(J)**2) 204,204,205
205 FRROR(J)=SQRT ((1.0/SM)*(ECOVR(J)-ACOVR(J)**2))
204 CONTINUE
      IF(PIECE) 3001,3000,3001
3000 IF(ICHEK-2) 3003,3002,3003
3002 CONTINUE
3001 CONTINUE
C
C      PIECEWISE PRINTOUT
C
      WRITE(LTN1,105)
      WRITE(LTN1,106) MS,( CORR(J),J=1,12)
      WRITE(LTN1,600) MS,( COVR(J),J=1,12)
      WRITE(LTN1,110) MS,( ACORR(J),J=1,12)
      WRITE(LTN1,603) MS,( ACOVR(J),J=1,12)
      WRITE(LTN1,112) MS,( ERROR(J),J=1,12)
      WRITE(LTN1,602) MS,( FRROR(J),J=1,12)
C      PUNCH 115, MS,( CORR(J),J=1,12)
C      PUNCH 115, MS,( COVR(J),J=1,12)
      WRITE(LTN1,109)
3003 CONTINUE

```



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      IF(NORM) 321,320,321
321  CONTINUE
C
C          CALCULATE NORMALIZED CORRELATIONS, COVARIANCE
C
      DO 323 J=1,12
      CORR(J)=CORR(J)/(ARMS(J)*ARMS(ICHINA))
      COVR(J)= COVR(J)/(ARMS1(J)*ARMS1(ICHINA))
      BCORR(J)=(SM/(SM+1.0))*BCORR(J)+(1.0/(SM+1.0))*CORR(J)
      BCOVR(J)=(SM/(SM+1.0))*BCOVR(J)+(1.0/(SM+1.0))*COVR(J)
      FCORR(J)=(SM/(SM+1.0))*FCORR(J)+(1.0/(SM+1.0))*(CORR(J)**2)
      FCOVR(J)=(SM/(SM+1.0))*FCOVR(J)+(1.0/(SM+1.0))*COVR(J)**2
      IF(FCORR(J)-BCORR(J)**2)318,319,319
319  ERROR(J)=SQRT ((1./SM)*(FCORR(J)-BCORR(J)**2))
      GO TO 322
      318 ERROR(J)=0.0
322  IF(FCOVR(J)-BCOVR(J)**2)317,316,316
316  FRROR(J)=SQRT ((1.0/SM)*(FCOVR(J)-BCOVR(J)**2))
      GO TO 323
      317 FRROR(J)=0.0
323  CONTINUE
      IF(PIECE) 3004,3005,3004
3005 IF(ICHEK-2) 320,3004,320
3004 CONTINUE
      WRITE(LTN1,325)
325  FORMAT(35X,47H***** NORMALIZED CORRELATIONS *****
      WRITE(LTN1,105)
      WRITE(LTN1,114)MS,(ARMS(J),J=1,12)
      WRITE(LTN1,106)MS,(CORR(J),J=1,12)
      WRITE(LTN1,600)MS,(COVR(J),J=1,12)
      WRITE(LTN1,110)MS,(BCORR(J),J=1,12)
      WRITE(LTN1,601)MS,(BCOVR(J),J=1,12)
      WRITE(LTN1,112)MS,(ERROR(J),J=1,12)
      WRITE(LTN1,602)MS,(FRROR(J),J=1,12)
      WRITE(LTN1,605)MS,(XMEAN(J),J=1,12)
      WRITE(LTN1,604)MS,(ARMS1(J),J=1,12)
C      PUNCH 115, MS,(CORR(J),J=1,12)
C      PUNCH 115, MS,(COVR(J),J=1,12)
      WRITE(LTN1,109)
320  CONTINUE
      NCHEK=NCOUNT-ICOUNT
C
C          CHECK FOR SAMPLES LEFT IN SCAN LINE TO SORT AND GROUP
C          WITH BEGINNING OF NEXT SCAN.
C          NCHEK = 0 - NO SAMPLES LEFT ON PRESENT SCAN LINE
C
      IF(NCHEK=NSAMP)44,26,26
44  NCOUNT=0
      IF(NCHEK)45,98,45
45  CONTINUE
      NSTOP=ICOUNT+NCHEK
      DO 40 II=ICOUNT,NSTOP
      NCOUNT=NCOUNT+1
      DO 41 J=1,12
      DATA(NCOUNT,J)=DATA(II,J)
41  CONTINUE
40  CONTINUE

```

```
98 IF(ICHEK-2) 2,200,200
100 FORMAT(6I4)
101 FORMAT(I1,6X,12F6.3)
105 FORMAT (1X//7X,4HCH 1,5X,4HCH 2,5X,4HCH 3,5X,4HCH 4,5X,4HCH
15X,4HCH 6,5X,4HCH 7,5X,4HCH 8,5X,4HCH 9,5X,4HCH10,5X,4HCH11,
24HCH12/)
106 FORMAT(1X,I3,12F9.6,8H PC CORR/)
110 FORMAT(1X,I3,12F9.6,8H AC CORR/)
112 FORMAT(1X,I3,12F9.6,8H ER CORR/)
114 FORMAT(1X,I3,12F9.6,8H RMS COR/)
115 FORMAT(I3,2X,12F6.4)
116 FORMAT(20X,14H***** FIELD I3,8H *****)
108 FORMAT(1H1//)
109 FORMAT(1X/)
600 FORMAT(1X,I3,12F9.6,8H PC COVR/)
601 FORMAT(1X,I3,12F9.6,8H AC COVR/)
602 FORMAT(1X,I3,12F9.6,8H ER COVR/)
603 FORMAT(1X,I3,12F9.6,8H AC COVR/)
604 FORMAT(1X,I3,12F9.6,8H PC STD /)
605 FORMAT(1X,I3,12F9.6,8H PC MEAN/)
113 REWIND LTN
IF(LTERM) 2000,2001,2000
2001 CONTINUE
STOP
END
```

The main outputs are univariate probability histograms for every channel. In addition, a normal distribution curve is superimposed on the histograms. The normal curve has the mean equal to the most probable value of the calculated probability density function and the same standard deviation as the calculated one.

It is optional to read a header identification record at the beginning of each data (IHEAD  $\neq$  0) or to input some header identification via NAMELIST variable IDENT (IHEAD = 0). The one selected can be printed out as a title heading for each data set for the plotted probability density functions and for the printed mean and variance. Bit manipulation on a single variable on the read in header identification may also be done (IFLD  $\neq$  0).

The program uses as input a tape reformatted by the tape conversion program or a standard FORTRAN and/or Binary tape. The program's input control parameters are inputted by NAMELIST and the calling routines are NAMFIL and NAMDAT.

DEFINITION OF INPUT PARAMETER:

NAMFIL

- NFILE1 - Total number of data sets (files) to be processed cannot exceed four.

NAMDAT

- NBEAMS - Total number of channels of data to be processed (cannot exceed 12)
- NWHICH - Specify the numerical value of the files on tape to be processed (not to exceed 4). Does not apply to tapes reformatted by the tape conversion program.
- TIMSAM - Specifies the time displacement between samples in the same channel.
- LTN - Logical tape number of the input tape.
- NBLK - Total number of variables for each channel in a data record. For a tape reformatted by the Tape Conversion Program, it specifies the number of samples in a scan line.
- NBEGIN - The sample number of the data value in a scan line to start with that will be used in probability density calculation.
- NSTOP - The sample number of the data value in a scan line to stop with that will be used in probability density calculation.

- NTOTAL - The total number of intervals in the range of the values to be considered in the probability density function.
- TINCRE - The increment of data value range considered in the probability density calculation.
- ISKIP - Number of data records to skip at the start of each data set.
- NSCANS - Total number of scan lines in a data set.
- LTABLE - Minimum value of the data range to be considered in the probability calculation.
- IBCD - Option to read header identification record at start of each data set in either Binary (IBCD = 0) or Alpha-Numerically (IBCD  $\neq$  0).
- IFLD - Option to do bit manipulation on a variable in the header identification record. IFLD  $\neq$  0 bit manipulation executed.
- NA - Starting bit position in NBLK where bits will be transferred in direction left to right.
- NAB - Number of bit to be transferred.
- NB - Starting bit position in RCDID(ISVB) where bit will be transferred in direction left to right.
- ISVB - Array position in RCDID from which bit will be transferred to NBLK.
- IDWORD - Number of header identification words to be read in.
- IMODE - Mode that system REDTPC is to be read in. REDTPC is documented in 7094 Computer Manual of Marshall Space Flight Center.
- IHEAD - Option to read header identification record. IHEAD  $\neq$  0 header record read. IHEAD = 0 identification put on with IDENT NAMELIST variable.
- IRDTPC - Option to either read input tape under system REDTPC (IRDTPC  $\neq$  0) or under format of output from tape conversion program (IRDTPC = 0).
- IDENT - Labeling used in place of header identification record.

Figure 3-13 shows the flowchart of the computer program, which is followed by a complete listing of the program. Some plot outputs are shown in Figures 4-31 through 4-40. The symbol A's designate the actual calculated probability curves, while the symbol B's designated an expected normal distribution curve with its mean equal to the most probable value of the actual curve and with the same standard derivation as the actual curve. Figure 3-14 is a printout result of the program.

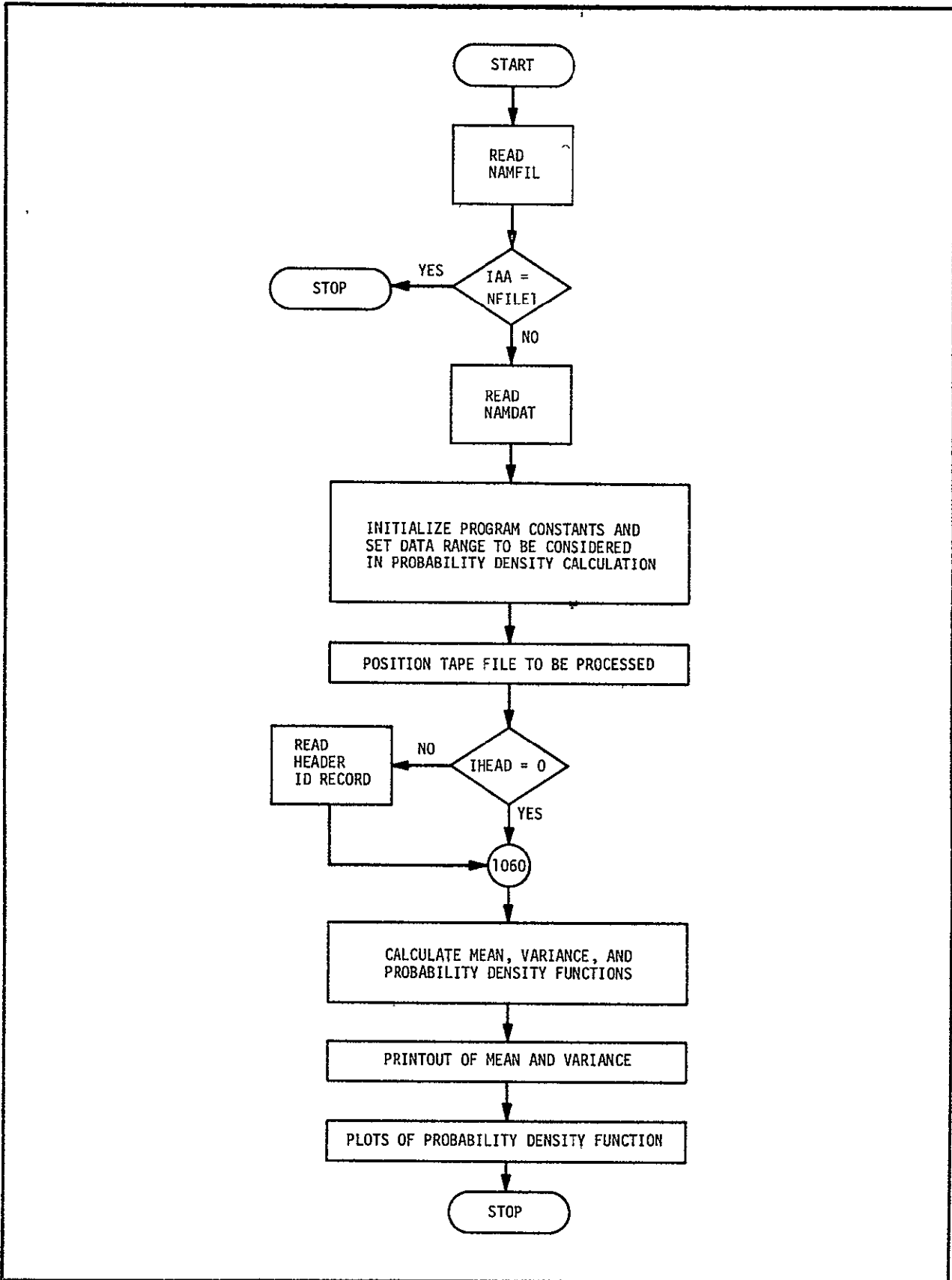


Figure 3-13. FLOWCHART OF MULTI-CHANNEL PROBABILITY DENSITY PROGRAM

EARTH - EFN SOURCE STATEMENT - IFN(S) -

```

C      MULTI-CHANNEL      PROBABILITY      DENSITY      PROGRAM
      DIMENSION NBEGIN(27),NSTOP(27)
      DIMENSION SAMP(12)
      DIMENSION BTABLE(12),GTABLE(12)
      DIMENSION AMAX(12),P(201)
      DIMENSION PCDDID(15),DATA(5000),DAT(5000),TABLE(201),PLAM(201,12)
      DIMENSION AVGCL(12),AAVGCL(12),RMS(12),ARMS(12),SIG(12),ASIG(12)
      DIMENSION XARRAY(12),XLAM(12),NWHICH(5),IDENT(5)
1007  FORMAT(12A6)
      EQUIVALENCE (PCDDID(13),NCOUNT)
      CALL CAMRAV(9)
      NAMELIST /NAMDAT/ NBEAMS,NWHICH,TIMSAM,LTN,NPLK,NBEGIN,
INSTOP,NTOTAL,TINCRE,ISKIP,NSCANS,LTABLE,IBCC,
ZIFLD,NA,NAB,NB,ISUB,IDWORD,IMODE,IHEAD,IRDTPC,IDENT
      READ (5,1007) (XARRAY(I),I = 1,12)
      READ(5,1007) (XLAM(I),I = 1,12)
      NAMELIST /NAMFIL/ NFILE1
      READ(5,NAMFIL)
      DØ 798 IAA=1,NFILE1
C      INPUT NAMELIST DATA
      READ (5,NAMDAT)
      WRITL (6,NAMDAT)
C      INITIALIZE CONSTANTS
      TIME = 0.0
      NCT=NBLK
1004  FORMAT(1H 14F8.4)
      DELT = TIMSAM
      DØ 3 I=1,NTOTAL
      P(I) = 0.0
      TABLE(I) = 0.0
3      CONTINUE
      DØ 106 I = 1,NBEAMS
      GTABLE(I) = 0.0
      BTABLE(I) = 0.0
      SIG(I) = 0.0
      AMAX(I) = 0.0
      AAVGCL(I) = 0.0
      ARMS(I) = 0.0
106  CONTINUE
      DØ 71 II = 1,12
      DØ 71 I = 1,201
      71 PLAM(I,II) = 0.0
C SET DATA RANGE TO BE CONSIDERED IN PROBABILITY DENSITY
      TABLE(1)=LTABLE
      DØ 1011 I = 2,NTOTAL
      TABLE(I) = TABLE (I-1)+TINCRE
1011 CONTINUE
C POSITION TAPE FILES AND NUMBER OF FILES
      IF(IRDTPC.EQ.0) GO TØ 11
      REWIND LTN
      IAB = NWHICH(IAA)-1
      IF (IAB) 11,11,12

```

NOT REPRODUCIBLE

12 CONTINUE  
DØ 10 IAC=1,IAB  
CALL SKFBIN(9,1,RD)

NOT REPRODUCIBLE

EARTH - EFN SOURCE STATEMENT - IFN(S) -

10 CONTINUE  
11 CONTINUE

C READ HEADER IDENTIFICATION RECORD

IF(IHEAD.EQ.0) GØ TØ 1060  
IF(IBCD.EQ.0) GØ TØ 1013  
READ (LTN,1051) (RCDID(I),I=1,IDWØRD)  
1051 FØRMAT(15A6)  
RCDID(ISUB)=0.0  
RCDID(ISUB)=NBLK  
NCT=NBLK  
GØ TØ 1014

1013 CONTINUE  
READ (LTN) (RCDID(I),I=1,IDWØRD)  
IF(IFLD.EQ.0) GØ TØ 1014  
NCT=0  
CALL FLD(NCT,NA,NAB,NB,RCDID(ISUB))

1014 CONTINUE  
NCØUNT = NCT  
NBLK = NCT  
WRITE (6,1000) (RCDID(I),I = 1,15)

1000 FØRMAT(1X,12A6,16,5X,2F8.4)  
1060 CONTINUE  
IF(IHEAD.NE.0) GØ TØ 1070  
WRITE(6,1071)  
WRITE(6,1051) (IDENT(I),I=1,IDWØRD)  
WRITE(6,1071)

1071 FØRMAT(1HØ)  
DØ 1072 I=1,IDWØPD  
RCDID(I)=IDENT(I)

1072 CONTINUE

1070 CONTINUE  
WRITE(6,24)  
24 FØRMAT(17X,3HCH1,6X,3HCH2,6X,3HCH3,6X,3HCH4,6X,3HCH5,6X,  
13HCH6,6X,3HCH7,6X,3HCH8,6X,3HCH9,6X,4HCH10,5X,4HCH11,5X,4HCH12)  
NCØUNT=NCT  
NUP = JCØUNT\*NBEAMS  
MS = 0

C OPTION TØ SKIP SCAN LINES

NRIN=ISKIP+1  
IF(ISKIP.EQ.0) GØ TØ 1032  
DØ 1031 J=1,ISKIP  
CALL SKRBIN(9,1,RD)

1031 CONTINUE

1032 CONTINUE  
DØ 1 IAD=NRIN,NSCANS  
NWDS=(NSTØP(IAD)+1-NBEGIN(IAD))\*(NBEAMS+1)  
DØ 104 I = 1,NBEAMS

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      AVGCL(I) = 0.0
      RMS(I) = 0.0
      SAMP(I)=0.0
104  CONTINUE
      MS = MS+1
      IA = 1
      IF(IRDTPC.NE.0) GO TO 1061
      DO 60 J=1,NUP,NBEAMS
      JZ=J+NBEAMS-1

          EARTH      - EFM      SOURCE STATEMENT - IFN(S) -

      READ (LTN) ICHEK,(DAT(L),L=J,JZ)
160  CONTINUE
      GO TO 1062
1061 CONTINUE
      CALL REDTPC(LTN,IMODE,IERR,NW,NUP,DAT)
      GO TO (50,51,50,50,51),IERR
      51 GO TO 999
      50 CONTINUE
1062 CONTINUE
      NSTART=NBEGIN(IA)
      NTERM=NSTOP(IA)
      DO 80 ICC=NSTART,NTERM
      NFRM=ICC*NBEAMS-NBEAMS+1
      NTOT=NFRM+NBEAMS-1
      J = 0
      DO 81 I = NFRM,NTOT
      J = J+1
      IF(DAT(I).LT.TABLE(1)) GO TO 70
      IF(DAT(I).GT.TABLE(NTOTAL)) GO TO 70
      AVGCL(J)=AVGCL(J)+DAT(I)
      RMS(J) = RMS(J)+DAT(I)**2
70  IF(DAT(I).LT.TABLE(1)) SAMP(J)=SAMP(J)+1.0
      IF(DAT(I).GT.TABLE(NTOTAL)) SAMP(J)=SAMP(J)+1.0
81  CONTINUE
      DATA(IA)=TIME
      TIME=TIME+DELT
      DO 83 I = NFRM,NTOT
      IA = IA+1
      DATA(IA)=DAT(I)
83  CONTINUE
      IA = IA+1
      IF(IA.GE.NWDS) GO TO 100
80  CONTINUE
100  CONTINUE
      SAMPN0=NSTOP(IA)-NBEGIN(IA)+1
      SM = MS
      DO 101 I = 1,NBEAMS
      RMS(I)=RMS(I)/(SAMPN0-SAMP(I))
      AVGCL(I)=AVGCL(I)/(SAMPN0-SAMP(I))
      ARMS(I) = (((SM-1.)/SM)*ARMS(I) +RMS(I)/SM)
      AAVGCL(I) = (((SM-1.)/SM)*AAVGCL(I)+AVGCL(I)/SM)
      SIG(I)=SQRT(RMS(I)-AVGCL(I)**2)
      RMS(I)=SQRT(RMS(I))

```



```

101 CONTINUE
    WRITE (6,9000) ( AVGCL(I) ,I=1,NBEAMS)
    WRITE (6,9001) ( RMS(I) ,I=1,NBEAMS)
    WRITE (6,9002) ( SIG(I) ,I=1,NBEAMS)
9000 F0RMAT(1X,8HPC MEAN,1X,12F9.4)
9001 F0RMAT(1X,8HPC RMS ,1X,12F9.4)
9002 F0RMAT(1X,8HPC SD ,1X,12F9.4)
    D0 94 I = 1,NBEAMS
    SIG(I)=SQRT(ARMS(I)-AAVGCL(I)**2)
    RMS(I)=SQRT(ARMS(I))
74 CONTINUE
    WRITE (6,9003) ( AAVGCL(I),I=1,NBEAMS)
    WRITE (6,9004) ( RMS(I) ,I=1,NBEAMS)

```

EARTH - EFN SOURCE STATEMENT - IFN(S) -

```

    WRITE (6,9005) ( SIG(I) ,I=1,NBEAMS)
9003 F0RMAT(1X,8HAC MEAN,1X,12F9.4)
9004 F0RMAT(1X,8HAC RMS,1X,12F9.4)
9005 F0RMAT(1X,8HAC SD ,1X,12F9.4)
    II = 0
    NXYZ=NST0P(IAD)-NBEGIN(IAD)+1
    D0 32 I=1,NXYZ
    II = II+1
    D0 32 III = 1,NBEAMS
    L = 1
    II = II+1
33 CONTINUE
    IF(DATA(II).LT.TABLE(1)) G0 T0 30
    IF(DATA(II).GT.TABLE(NT0TAL)) G0 T0 30
    IF(DATA(II).GT.TABLE(L)) G0 T0 34
    G0 T0 30
34 IF(DATA(II).LT.TABLE(L+1)) G0 T0 31
    G0 T0 30
31 PLAM(L,III) = PLAM(L,III)+1.0
    G0 T0 32
30 CONTINUE
    IF(DATA(II).LT.TABLE(1)) BTABLE(III) = BTABLE(III)+1.
    IF(DATA(II).GT.TABLE(NT0TAL)) GTABLE(III)=GTABLE(III)+1.
    IF(DATA(II).LT.TABLE(1)) G0 T0 32
    IF(DATA(II).GT.TABLE(NT0TAL)) G0 T0 32
    L=L+1
    IF(L.LT.NT0TAL) G0 T0 33
    G0 T0 31
32 CONTINUE
1002 F0RMAT(1H 13F9.4)
1003 F0RMAT(1H 12F9.4)
1 CONTINUE
999 CONTINUE
    D0 90 I=1,NBEAMS
    D0 90 J = 1,NT0TAL
    IF(PLAM(J,I).GT.AMAX(I)) G0 T0 92
    G0 T0 90
92 AMAX(I) = PLAM(J,I)

```

```
90 CONTINUE
  WRITE(6,9006)
9006 FORMAT(35X,37HNUMBER OF VALUES LESS THAN TABLE)
  WRITE (6,1003) (BTABLE(I),I = 1,NBEAMS)
  WRITE(6,9007)
9007 FORMAT(35X,40HNUMBER OF VALUES GREATER THAN TABLE)
  WRITE (6,1003) (GTABLE(I),I = 1,NBEAMS)
  WRITE(6,9008)
9008 FORMAT(35X,31HMAXIMUM VALUE OF EACH TABLE)
  WRITE (6,1003) (AMAX(I),I = 1,NBEAMS)
  NP = ITZTAL
  DO 93 I = 1,NBEAMS
  DO 95 J = 1,NTOTAL
    BASE=(TABLE(J)-AAVGCL(I))**2/(2.*SIG(I)**2)
    IF(BASE.GE.89.) GO TO 73
    P(J) = AMAX(I)/EXP(BASE)
  GO TO 72
73 P(J)=0.0
```

EARTH - EFN SOURCE STATEMENT - IFN(S) -

```
72 CONTINUE
95 CONTINUE
  CALL QUIK3V(-1,IHA,XARRAY,XLAM , -NP, TABLE, PLAM(1,I))
  CALL QUIK3V ( 0,IHB,XARRAY,XLAM , -NP, TABLE, P)
  CALL PRINTV(90,RCDDI,212,1010)
93 CONTINUE
998 CONTINUE
  CALL CLEAN
  STOP
  END
```

NOT REPRODUCIBLE



PC	RMS	1.2632	1.7097	1.1411	1.0234	0.9281	0.7962	0.6413	0.8451	0.4002	0.4758	0.5936	0.4250
PC	SD	0.0767	0.0684	0.0427	0.0392	0.0362	0.0374	0.0260	0.0467	0.0372	0.0380	0.0495	0.0385
AC	MEAN	1.2683	1.7112	1.1411	1.0240	0.9460	0.8317	0.6223	0.8517	0.4080	0.4737	0.6011	0.4419
AC	RMS	1.2708	1.7122	1.1422	1.0246	0.9468	0.8326	0.6228	0.8531	0.4094	0.4751	0.6030	0.4440
AC	SD	0.0785	0.0580	0.0492	0.0361	0.0389	0.0381	0.0257	0.0487	0.0340	0.0354	0.0488	0.0433
PC	MEAN	1.2923	1.7073	1.1605	1.0188	0.9653	0.8386	0.6382	0.8481	0.4304	0.4635	0.6040	0.4619
PC	RMS	1.2952	1.7084	1.1617	1.0194	0.9661	0.8392	0.6388	0.8491	0.4320	0.4643	0.6060	0.4646
PC	SD	0.0867	0.0632	0.0524	0.0340	0.0397	0.0310	0.0270	0.0398	0.0366	0.0271	0.0499	0.0492
AC	MEAN	1.2723	1.7105	1.1444	1.0231	0.9492	0.8329	0.6249	0.8511	0.4117	0.4720	0.6016	0.4452
AC	RMS	1.2749	1.7116	1.1455	1.0238	0.9500	0.8337	0.6255	0.8524	0.4133	0.4733	0.6035	0.4475
AC	SD	0.0804	0.0589	0.0502	0.0358	0.0397	0.0371	0.0266	0.0474	0.0355	0.0344	0.0490	0.0450
PC	MEAN	1.2664	1.7038	1.1331	1.0018	0.9424	0.8237	0.6362	0.8404	0.4151	0.4634	0.5772	0.4202
PC	RMS	1.2687	1.7045	1.1336	1.0026	0.9431	0.8240	0.6366	0.8414	0.4163	0.4643	0.5791	0.4218
PC	SD	0.0773	0.0496	0.0325	0.0402	0.0363	0.0235	0.0236	0.0404	0.0316	0.0288	0.0472	0.0370
AC	MEAN	1.2715	1.7096	1.1428	1.0201	0.9482	0.8315	0.6265	0.8496	0.4122	0.4708	0.5981	0.4417
AC	RMS	1.2740	1.7105	1.1438	1.0208	0.9490	0.8323	0.6271	0.8509	0.4137	0.4720	0.6001	0.4439
AC	SD	0.0800	0.0577	0.0483	0.0372	0.0393	0.0356	0.0265	0.0466	0.0350	0.0338	0.0495	0.0448
PC	MEAN	1.2503	1.6955	1.1446	1.0269	0.9336	0.8437	0.6367	0.8362	0.4121	0.4583	0.6105	0.4400
PC	RMS	1.2524	1.6967	1.1454	1.0277	0.9344	0.8446	0.6371	0.8374	0.4140	0.4591	0.6131	0.4422
PC	SD	0.0725	0.0636	0.0431	0.0381	0.0390	0.0386	0.0206	0.0449	0.0398	0.0269	0.0565	0.0439
AC	MEAN	1.2688	1.7078	1.1430	1.0210	0.9464	0.8331	0.6278	0.8479	0.4122	0.4692	0.5996	0.4414
AC	RMS	1.2713	1.7088	1.1440	1.0216	0.9472	0.8339	0.6284	0.8492	0.4137	0.4704	0.6018	0.4437
AC	SD	0.0794	0.0587	0.0477	0.0374	0.0396	0.0362	0.0260	0.0466	0.0356	0.0333	0.0506	0.0447
PC	MEAN	1.2542	1.7058	1.1229	1.0190	0.9480	0.8424	0.6271	0.8513	0.4219	0.4684	0.5907	0.4499
PC	RMS	1.2573	1.7073	1.1246	1.0197	0.9482	0.8427	0.6277	0.8520	0.4230	0.4697	0.5920	0.4527
PC	SD	0.0876	0.0707	0.0606	0.0386	0.0216	0.0220	0.0255	0.0363	0.0307	0.0357	0.0391	0.0505
AC	MEAN	1.2672	1.7076	1.1408	1.0207	0.9466	0.8341	0.6277	0.8483	0.4133	0.4691	0.5986	0.4424
AC	RMS	1.2698	1.7086	1.1418	1.0214	0.9473	0.8348	0.6283	0.8495	0.4148	0.4703	0.6007	0.4447
AC	SD	0.0805	0.0601	0.0497	0.0375	0.0380	0.0351	0.0260	0.0456	0.0352	0.0336	0.0495	0.0454
NUMBER OF VALUES LESS THAN TABLE													
0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
NUMBER OF VALUES GREATER THAN TABLE													
0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
MAXIMUM VALUE OF EACH TABLE													
21.0000	29.0000	30.0000	35.0000	41.0000	48.0000	59.0000	41.0000	53.0000	55.0000	34.0000	32.0000		

3-62

Figure 3-14. PRINT-OUT OF THE PROBABILITY PROGRAM (Concluded)

### 3.9 DIVERGENCE MATRIX PROGRAM

This program is devised for calculating the "divergence" measure which is a similarity criterion between two homogeneous populations whose probability density functions are normally distributed. The mathematical formulation of this divergence criterion is given in subsection 2.6. The program is coded such that up to 12 homogeneous populations can be compared simultaneously. The main input parameters are mean vectors, covariance matrices, and selected channels for all populations. The main output is a square matrix of divergence between all combinations of the given populations. The divergence matrix consists of two terms, which are called Trace 1 and Trace 2 matrix representing the first and second terms of the right hand side of equation (2-11) in Section II.

Four subroutines are used in this program: Matrix Multiplication (MMPY), Matrix Subtraction (MSUB), Matrix Addition (MADD), and Matrix Inversion (MINV).

#### DEFINITION OF INPUT PARAMETERS:

##### CARD 1 (7I10) Format

- NSCLE1 - Scale factor for Mean Vectors.
- NSCLE2 - Scale factor for Covariance Matrices.
- NCYCLE - Number of times to cycle through the program comparing the matrices.
- KKK - Maximum row size of Covariance Matrix to be read.
- III - Maximum column size of Covariance Matrix to be read.
- NLOOP - Number of times to cycle through the matrices for different row and column configurations.
- NMEANS - Number of Mean vectors or Covariance Matrices to be used in the calculation.

##### CARD 2 (3I10) Format

- NLOW - Lower range of field identification to be read.
- NUP - Upper range of field identification to be read.
- NPRINT - Option to print out intermediate calculation of cross products of comparisons of two populations.

##### CARD 3 (20A4) Format

- Z(L) - Array in which field identifications are stored.

CARD 4 (12I5) Format

- ICH(L) - Specifies which columns of Covariance Matrices to use in calculations. ICH(L) = 0 column not used.

CARD 5 (12I5) Format

- NSC(I) - Specifies which rows of Covariance Matrices to use in calculations. NSC(I) = 0 row not used.

CARD 6 (5I10) Format

- NSCTS - Specifies number of rows actually used in Divergence calculation from NSC(I) selection.
- ICHAN - Specifies number of columns actually used in Divergence calculation from ICH(L) selection.
- ICHAN1 - Used to specify that the mean is a 1 X NCHAN vector. Nominal value is one.
- NCHAN - Maximum row size of covariance Matrix to be read.
- NSCANS - Maximum column size of Covariance Matrix to be read.

CARD 7 (12F6.0) Format

- YBAR(KK,I) - Array that Mean vectors for each population is stored. KK specifies population and I the dimension of the vector.

CARD 8 (12F6.0) Format

- X(KK,J,I) - Array that Covariance Vectors for each population is stored. KK specifies population, I the row dimension, and J the column dimension.

Figure 3-15 shows a flowchart of the divergence matrix program, which is followed by a complete listing of the program. Some sample outputs are shown in Tables 4-1 through 4-5.

**3.10 SI-TABLE PROGRAM**

This program is devised for calculating the so-called  $S_i$ -value which represents a measure of similarity between two inventory areas which, in turn, are characterized by the mean vectors and the standard deviations. Let the mean vectors for  $i^{\text{th}}$  and  $j^{\text{th}}$  inventory areas be denoted by  $M_i(k)$  and  $M_j(k)$ , and the standard deviations be  $\sigma_i(k)$  and  $\sigma_j(k)$ , where  $k$  stands for the channel number, ( $k=1,2,\dots,K$ ). The  $S_i$ -value between  $i^{\text{th}}$  and  $j^{\text{th}}$  inventory areas can be expressed as

;

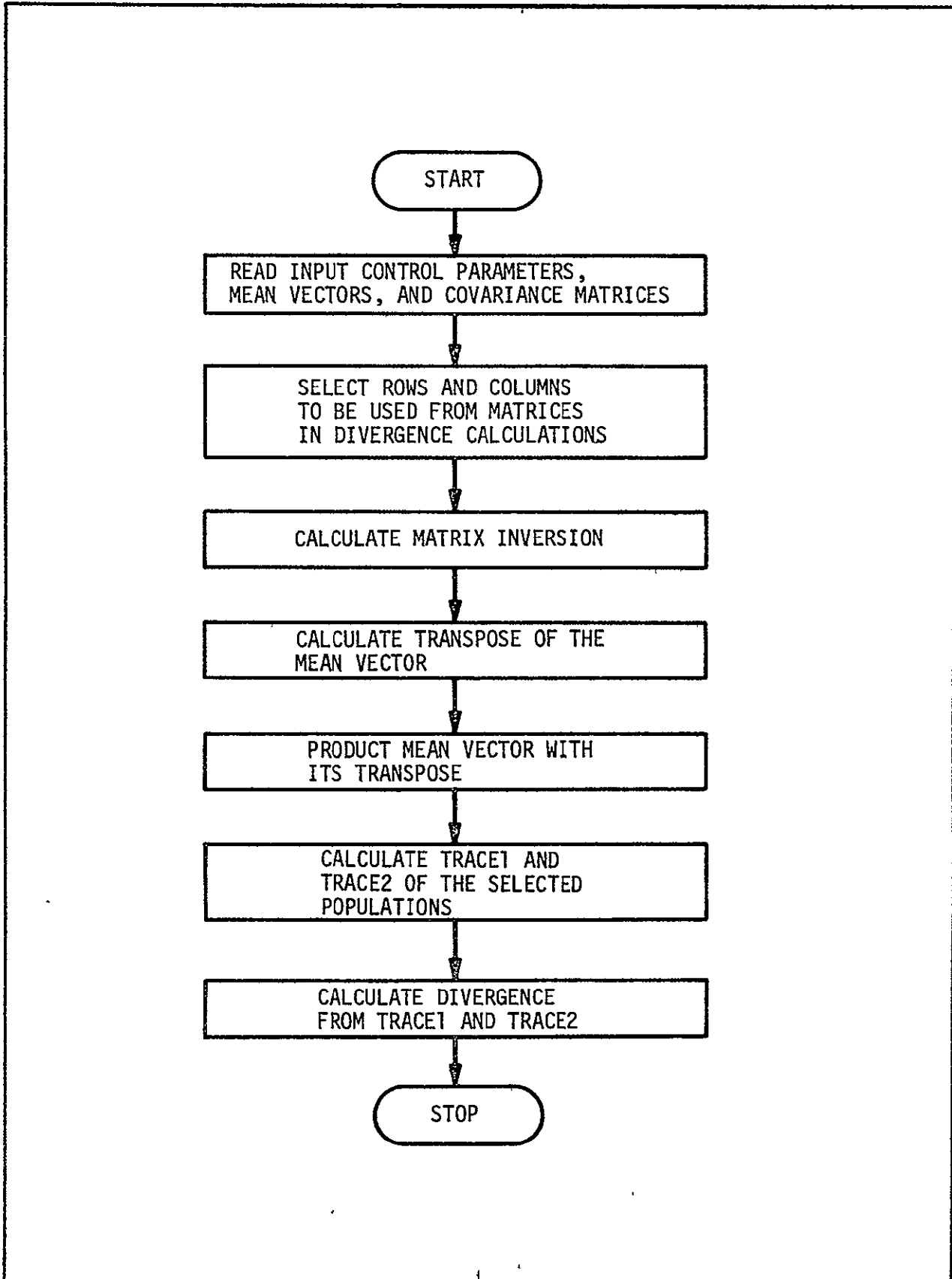


Figure 3-15. FLOWCHART OF DIVERGENCE MATRIX PROGRAM

```

C   PROGRAM TO CALCULATE DIVERGENCE OF TWO MATRICES
      DIMENSION Z(240)
      DIMENSION ZBAR(12,12)
      DIMENSION X1(12,12)
      DIMENSION DIV(12,12)
      DIMENSION V(12,12),V1(12,12),VT(12,12),VT1(12,12)
      DIMENSION VPROD(12,12),VXPROD(12,12),VDIFF(12,12),VTDIFF(12,12),
AVSUM(12,12),VTSUM(12,12)
      DIMENSION XBAR(12,12),XTBAR(12,12),XPROD(12,12)
      DIMENSION X(12,12,12),ICH(12),NSC(12)
      DIMENSION YBAR(12,12)
      DIMENSION TRACE(12,12),TRACE1(12,12)
1000 FORMAT(7I10)
1001 FORMAT(1X,12F6.0)
1002 FJRMAT(1H0)
1003 FORMAT(80H
1
1004 FORMAT(1X,5HDETV=F13.8,6HDETV1=F13.8,6HTRACE=F10.3,7HTRACE1=F10.3)
1005 FORMAT(2X,14,4X,1H*,12F10.3)
1006 FORMAT(1X,80H*****Q
1*****Q)
1007 FORMAT(4X,2HCH,4X,1H*,12(I5,5X))
1008 FORMAT(12I5)
1009 FORMAT(30X,4HDIV=F10.3)
1010 FORMAT(1H1)
1011 FORMAT(2X,14,4X,1H*,12F10.5)
1012 FORMAT(30X,20HCOVARIANCE MATRIX)
1013 FORMAT(30X,14HMEAN VECTOR)
1014 FORMAT(30X,29HINVERSE COVARIANCE MATRIX)
1015 FORMAT(30X,39H(V1(J,I)-V2(J,I)) (INV2(J,I)-INV1(J,I)))
1016 FORMAT(10X,79H(INV1(J,I)-INV2(J,I)) (XBAR1(J,I)-XBAR2(J,I)) (TRANS
1POSE(XBAR1(J,I)-XBAR2(J,I)))
1017 FORMAT(30X,8HFIELD ,I5)
1018 FORMAT(30X,34HPRODUCT OF MATRIX WITH INVERSE)
1019 FORMAT(30X,20HDIVERGENCE MATRIX)
1020 FORMAT(30X,16HTRACE1 MATRIX)
1021 FORMAT(30X,16HTRACE2 MATRIX)
1022 FORMAT(30X,36HCHANNELS USED IN THIS CALCULATION)
1023 FORMAT(20A4)
1024 FJRMAT(1X,5HFIELD,4X,1H*,12(I5,5X))
1025 FORMAT(10X,5HFIELD,14,4X,8HCOMPARED,4X,5HFIELD,I4)
      IOVE=1
      READ 1000,NSCLE1,NSCLE2,NCYCLE,KKK,III,NLOOP,NMEANS
      NCOVR=NMEANS
      SCALE1=NSCLE1
      SCALE2=NSCLE2
      DO 251 IFF=I,NLOOP
      READ 1000,NLOW,NUP,NPRINT
      PRINT 1010
      PRINT 1006
      NBEGIN=NLOW
      VSTOP=NUP
      DO 205 JJ=1,NMEANS
      IF( IFF-1) 2012,2013,2012

```



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```

2013 READ 1023,(Z(L),L=NBEGIN,NSTOP)
2012 PRINT 1023,(Z(L),L=NBEGIN,NSTOP)
      NBEGIN=NBEGIN+NUP
      NSTOP=NUP+NBEGIN-1
205  CONTINUE
      PRINT 1006
      DO 206 J=1,KKK
      DO 206 I=1,III
      DIV(J,I)=0.0
      TRACE(J,I)=0.0
      TRACE1(J,I)=0.0
      ZBAR(J,I)=0.0
      V(J,I)=0.0
206  CONTINUE
      READ 1008,(ICH(I),I=1,KKK)
      READ 1008,(NSC(I),I=1,III)
      READ 1000,NSCTS,ICHAN,ICHAN1,NFILE,NCHAN,NSCANS,NSCALE
      SCALE=NSCALE
      MS=1
      DO 200 IAB=1,NCYCLE
      IF(MS-1) 203,202,203
202  CONTINUE
      IF(IFF-1) 203,2003,203
2003 CONTINUE
      DO 21 KK=1,NCOVR
      PRINT 1010
      PRINT 1002
      READ 1003
      PRINT 1003
      PRINT 1002
      PRINT 1013
      PRINT 1002
      READ 1001,(YBAR(KK,I),I=1,NCHAN)
      DO 201 I=1,NCHAN
      YBAR(KK,I)=YBAR(KK,I)/SCALE1
201  CONTINUE
      PRINT 1007,(K,K=1,NCHAN)
      PRINT 1005,(KK,(YBAR(KK,I),I=1,NCHAN))
      PRINT 1002
      PRINT 1012
      PRINT 1002
      PRINT 1007,(K,K=1,NCHAN)
      DO 21 J=1,NSCANS
      READ 1001,(X(KK,J,I),I=1,NCHAN)
      DO 5 I=1,NCHAN
      X(KK,J,I)=X(KK,J,I)/SCALE
5  CONTINUE
      PRINT 1011,TJ,(X(KK,J,I),I=1,NCHAN))
21  CONTINUE
203  CONTINUE
      DO 402 KK=1,NMEANS
      M=0
      DO 40 I=1,NCHAN
      IF(ICH(I)) 42,40,42
42  M=M+1

```

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```

      ZBAR(KK,M)=YBAR(KK,I)
40  CONTINUE
402 CONTINUE
      M=0
      DO 22 J=1,NCHAN
      IF(ICH(J)) 24,22,24
24  M=M+1
      N=0
      DO 23 I=1,NSCANS
      IF(NSC(I)) 25,23,25
25  N=N+1
      VT(M)=X(MS,I;J)
23  CONTINUE
22  CONTINUE
C    MATRIX      INVERSION      AND      CHECK
      CALL MINV(V,VT,DET,ICHAN)
      DET1=DET
      CALL MMPY(ICHAN,NSCTS,ICHAN,V,VT,X1)
      IF(NPRINT) 2007,2006,2007
2007 CONTINUE
      IF(MS-1) 2004,2005,2004
2005 CONTINUE
      PRINT 1010
      PRINT 1002
      PRINT 1002
      PRINT 1002
      PRINT 1002
      PRINT 1006
      PRINT 1002
      PRINT 1022
      PRINT 1002
      PRINT 1008,(ICH(I),I=1,NCHAN)
      PRINT 1002
      PRINT 1006
2004 CONTINUE
      PRINT 1010
      PRINT 1002
      PRINT 1006
      PRINT 1017,IAB
      PRINT 1002
      PRINT 1006
      PRINT 1002
      PRINT 1013
      PRINT 1002
      PRINT 1007,(K,K=1,ICHAN)
      PRINT 1005,(IDNE,(ZBAR(IAB,I),I=1,ICHAN))
      PRINT 1002
      PRINT 1012
      PRINT 1002
      PRINT 1007,(K,K=1,ICHAN)
      DO 501 J=1,NSCTS
      PRINT 1005,(J,(V(J,I),I=1,ICHAN))
501 CONTINUE
      PRINT 1002
      PRINT 1014

```

```

        PRINT 1002
        PRINT 1007,(K,K=1,ICHAN)
        DO 502 J=1,NSCTS
        PRINT 1005,(J,(VT(J,I),I=1,ICHAN))
502  CONTINUE
        PRINT 1002
        PRINT 1018
        DO 503 J=1,NSCTS
        PRINT 1005,(J,(X1(J,I),I=1,ICHAN))
503  CONTINUE
2006 CONTINUE
        NS=MS+1
        DO 20 IAA=NS,NFILE
        DO 10 J=1,NSCTS
        DO 10 I=1,ICHAN
        XBAR(J,I)=0.0
        V1(J,I)=0.0
        VT1(J,I)=0.0
        VPROD(J,I)=0.0
        VXPROD(J,I)=0.0
        VDIFF(J,I)=0.0
        VTDIFF(J,I)=0.0
        VSUM(J,I)=0.0
        VTSUM(J,I)=0.0
        XTBAR(J,I)=0.0
        XPROD(J,I)=0.0
10   CONTINUE
        M=0
        DO 30 J=1,NCHAN
        IF(ICH(J)) 31,30,31
31   M=M+1
        V=0
        DO 33 I=1,NSCANS
        IF(NSC(I)) 32,33,32
32   N=N+1
        VI(N,M)=X(IAA,I,J)
33   CONTINUE
30   CONTINUE
C     MATRIX      INVERSION      AND      CHECK
        CALL MINV(V1,VT1,DET,ICHAN)
        DET2=DET
        CALL MPPY(ICHAN,NSCTS,ICHAN,V1,VT1,X1)
        IF(NPRINT) 2009,2008,2009
2009 CONTINUE
        PRINT 1010
        PRINT 1002
        PRINT 1006
        PRINT 1002
        PRINT 1017,IAA
        PRINT 1002
        PRINT 1006
        PRINT 1002
        PRINT 1013
        PRINT 1007,(K,K=1,ICHAN)
        PRINT 1005,(IONE,(ZBAR(IAA,I),I=1,ICHAN))

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```

        PRINT 1002
        PRINT 1012
        PRINT 1002
        PRINT 1007,(K,K=1,ICHAN)
        DO 504 J=1,NSCTS
        PRINT 1005,(J,(V1(J,I),I=1,ICHAN))
504  CONTINUE
        PRINT 1002
        PRINT 1014
        PRINT 1002
        PRINT 1007,(K,K=1,ICHAN)
        DO 505 J=1,NSCTS
        PRINT 1005,(J,(VT1(J,I),I=1,ICHAN))
505  CONTINUE
        PRINT 1002
        PRINT 1018
        PRINT 1002
        PRINT 1007,(K,K=1,ICHAN)
        DO 506 J=1,NSCTS
        PRINT 1005,(J,(X1(J,I),I=1,ICHAN))
506  CONTINUE
2008 CONTINUE
        DO 3 J=1,ICHAN1
        DO 3 I=1,ICHAN
        XBAR(J,I)=ZBAR(IAB,I)-ZBAR(IAA,I)
3    CONTINUE
        DO 8 J=1,ICHAN1
        DO 8 I=1,ICHAN
        XTBAR(I,J)=XBAR(J,I)
8    CONTINUE
        CALL MMPY(ICHAN,ICHAN1,ICHAN,XTBAR,XBAR,XPROD)
        CALL MSUB(ICHAN,NSCTS,V,V1,VDIFF)
        CALL MSUB(ICHAN,NSCTS,VT,VT1,VTDIFF)
        CALL MADD(ICHAN,NSCTS,VT,VT1,VTSUM)
        CALL MMPY(ICHAN,NSCTS,ICHAN,VDIFF,VTDIFF,VPROD)
        CALL MMPY(ICHAN,NSCTS,ICHAN,VTSUM,XPROD,VXPROD)
        IF (NPRINT) 2014,2015,2014
2014 CONTINUE
        PRINT 1002
        PRINT 1015
        PRINT 1002
        PRINT 1002
        PRINT 1025,IAB,IAA
        PRINT 1002
        PRINT 1007,(K,K=1,ICHAN)
        DO 507 J=1,NSCTS
        PRINT 1005,(J,(VPROD(J,I),I=1,ICHAN))
507  CONTINUE
        PRINT 1002
        PRINT 1016
        PRINT 1002
        PRINT 1002
        PRINT 1025,IAB,IAA
        PRINT 1002
        PRINT 1007,(K,K=1,ICHAN)

```

```

DO 508 J=1,NSCTS
PRINT 1005,(J,(VXPROD(J,I),I=1,ICHAN))
508 CONTINUE
2015 CONTINUE
KK=0
JJ=0
DO 4 J=1,NSCTS
KK=KK+1
JJ=JJ+1
TRACE(IAB,IAA)=TRACE(IAB,IAA)+VPROD(KK,JJ)
TRACE1(IAB,IAA)=TRACE1(IAB,IAA)+VXPROD(KK,JJ)
4 CONTINUE
DIV(IAB,IAA)=(TRACE(IAB,IAA)+TRACE1(IAB,IAA))/2.0
C PRINT 1009,DIV(IAB,IAA)
C PRINT 1004,DET1,DET2,TRACE(IAB,IAA),TRACE1(IAB,IAA)
20 CONTINUE
MS=MS+1
200 CONTINUE
PRINT 1010
PRINT 1002
PRINT 1002
NBEGIN=NLOW
NSTOP=NUP
DO 2010 JJ=I,NMEANS
PRINT 1023,(Z(L),L=NBEGIN,NSTOP)
NBEGIN=NBEGIN+NUP
NSTOP=NUP+NBEGIN-1
2010 CONTINUE
PRINT 1002
PRINT 1002
PRINT 1022
PRINT 1002
PRINT 1008,(ICH(I),I=1,NCHAN)
PRINT 1002
PRINT 1019
PRINT 1002
PRINT 1002
PRINT 1006
PRINT 1002
PRINT 1024,(K,K=1,NCOVR)
DO 2000 IAB=1,NCOVR
PRINT 1005,(IAB,(DIV(IAB,IAA),IAA=1,NCOVR))
2000 CONTINUE
PRINT 1002
PRINT 1006
PRINT 1002
PRINT 1002
PRINT 1002
PRINT 1010
PRINT 1002
PRINT 1020
PRINT 1002
PRINT 1002
PRINT 1002
PRINT 1006
PRINT 1024,(K,K=1,NCOVR)

```

HUNTSVILLE

```

DO 2001 IAB=1, NCOVR
PRINT 1005, (IAB, (TRACE (IAB, IAA), IAA=1, NCOVR))
2001 CONTINUE
PRINT 1002
PRINT 1006
PRINT 1002
PRINT 1021
PRINT 1002
PRINT 1002
PRINT 1006
PRINT 1002
PRINT 1024, (K, K=1, NCOVR)
DO 2002 IAB=1, NCOVR
PRINT 1005, (IAB, (TRACE1 (IAB, IAA), IAA=1, NCOVR))
2002 CONTINUE
PRINT 1002
PRINT 1006
251 CONTINUE
STOP
END

```

## \$IBFTC TWO

```

SUBROUTINE MMPY(J, K, L, P, Q, R)
DIMENSION P(12, 12), Q(12, 12), R(12, 12)
DO 100 JJ=1, J
DO 100 LL=1, L
100 R(JJ, LL)=0.0
DO 200 LL=1, L
DO 200 JJ=1, J
DO 200 KK=1, K
R(JJ, LL)=R(JJ, LL)+P(JJ, KK)*Q(KK, LL)
200 CONTINUE
RETURN
END

```

## \$IBFTC THREE

```

SUBROUTINE MADD(M, N, A, B, C)
DIMENSION A(12, 12), B(12, 12), C(12, 12)
DO 2 I=1, M
DO 2 J=1, N
C(I, J)=A(I, J)+B(I, J)
2 CONTINUE
RETURN
END

```

## \$IBFTC FOUR

```

SUBROUTINE MSUB (M, N, A, B, C)
DIMENSION A(12, 12), B(12, 12), C(12, 12)
DO 2 I=1, M
DO 2 J=1, N
C(I, J)=A(I, J)-B(I, J)
2 CONTINUE
RETURN
END

```

```

$IBFTC FIVE
SUBROUTINE MINV(A,AI,DET,M)
DIMENSION A(12,12),AI(12,12),IORD(12)
N=M
DO 100 I=1,N
DO 100 J=I,N
100 AI(I,J)=A(I,J)
DO 51 I=1,N
51 IORD(I)=I
DET=1.
DO 1 K=1,N
KPI=K+1
TEST=ABS(AI(K,K))
IND=K
IF(K-N)21,22,21
21 DO 23 L=KPI,N
TEST1=ABS(AI(L,K))
IF(TEST-TEST1)24,23,23
24 TEST=TEST1
IND=L
23 CONTINUE
IF(IND-K)25,22,25
25 DO 26 J=1,N
TESTI=AI(IND,J)
AI(IND,J)=AI(K,J)
26 AI(K,J)=TESTI
DET=-DET
LL=IORD(K)
IORD(K)=IORD(IND)
IORD(IND)=LL
22 CONTINUE
IF(AI(K,K))31,32,31
31 AI(K,K)=1./AI(K,K)
DO 2 J=1,N
IF(J-K)3,2,3
3 QUOT=AI(K,J)*AI(K,K)
AI(K,J)=QUOT
IF(QUOT)42,2,42
42 DO 4 I=1,N
IF(I-K)5,4,5
5 TEST=AI(I,J)-AI(I,K)*QUOT
IF(ABS(TEST)-ABS(AI(I,J))*1.0E-5)70,71,71
70 AI(I,J)=0.
GO TO 4
71 AI(I,J)=TEST
4 CONTINUE
2 CONTINUE
DO 11 I=I,N
IF(I-K)12,11,12
12 AI(I,K)=-AI(I,K)*AI(K,K)
11 CONTINUE
DET=DET/AI(K,K)
1 CONTINUE
55 DO 52 I=1,N
IND=IORD(I)

```

```
IF(IND-1)53,52,53
53 LL=IORD(I)
   IORD(I)=IORD(IND)
   IORD(IND)=LL
   DO 54 K=1,N
   TEST=AI(K,IND)
   AI(K,IND)=AI(K,I)
54 AI(K,I)=TEST
   GO TO 55
52 CONTINUE
33 RETURN
32 DET=0.
   RETURN
   END
```



$$\psi_{ij} = \frac{|M_i(k) - M_j(k)|}{\sqrt{\Delta^2 |M_i(k) - M_j(k)|}}$$

or

$$\psi_{ij} = \frac{\left\{ \sum_{k=1}^{\bar{K}} [M_i(k) - M_j(k)]^2 \right\}^{1/2}}{2 \left\{ \sum_{k=1}^{\bar{K}} [M_i(k) - M_j(k)]^2 [\sigma_i^2(k) + \sigma_j^2(k)] \right\}^{1/2}}$$

The program is coded such that up to 12 inventory areas can be compared simultaneously, i.e.,  $\chi_{i,j}$  ( $i, j = 1, 2, \dots, 12$ )

DEFINITION OF INPUT PARAMETERS:

CARD 1

- NCHAN = Total number of channels.
- NTAU = Number of channels used.
- ICHAN = Reference channel used in correlations.
- ICHEK = 1 for absolute value calculations of input.
- ITERM = 1 for each additional case or data set combination.

CARD 2

- ICROP1 = Identification of data set 1.
- JIDEN = Output identification of ICROP1.
- ICROP2 = Identification of data set 2.
- KIDEN = Output identification of ICROP2.

CARD 3

- CRN1(I) = Means for data set 1.
- CRN2(I) = Standard deviation for data set 1.
- WHT1(I) = Means for data set 2.
- WHT2(I) = Standard deviation for data set 2.

The input card setup is shown in Figure 3-16. A listing of the program is given below.

3-76

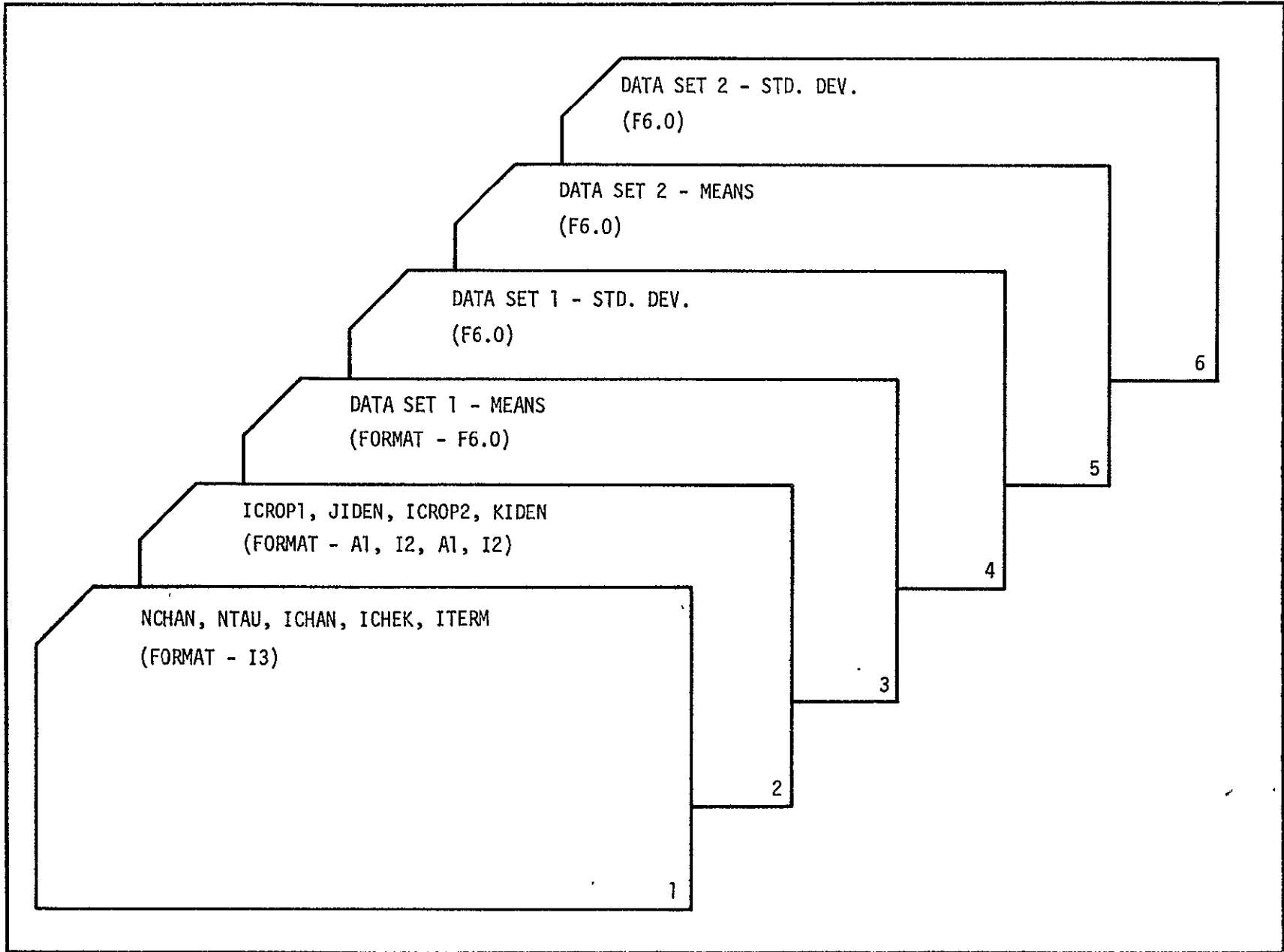


Figure 3-16. INPUT CARD SETUP

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```

C *****
C CALCULATION OF SI VALUES FOR SELECTION OF OPTIMUM
C COLOR SPACE PLOTS.
C *****
  DIMENSION CRN1[3,12],CRN2[3,12],WHT1[3,12],WHT2[3,12],
  1 DGV[25],XNUM[25],RATIO[25],RZERO[25]
  1 CONTINUE
  READ 80, NCHAN,NTAU,ICHAN,ICHEK,ITERM
  ITAU=NTAU
  XTAU=NTAU
  READ 64, ICROP1,JIDEN,ICROP2,KIDEN

C
C NCHAN=NR. OF CHANNEL COMBINATIONS
C NTAU=TOTAL NR. OF CHANNELS
C ICHAN=REF. CHANNEL USED FOR CORRELATIONS
C
  READ 50, [CRN1[1,J],J=1,NTAU]
  READ 50, [CRN2[1,J],J=1,NTAU]
  READ 50, [WHT1[1,J],J=1,NTAU]
  READ 50, [WHT2[1,J],J=1,NTAU]
C *****
  PRINT 62
  PRINT 65
  PRINT 89, ICROP1,JIDEN
  PRINT 95
  PRINT 88, [J,J=1,NTAU]
  PRINT 98
  PRINT 96, [CRN1[1,J],J=1,NTAU]
  PRINT 97, [CRN2[1,J],J=1,NTAU]
  PRINT 61
  PRINT 89, ICROP2,KIDEN
  PRINT 95
  PRINT 88, [J,J=1,NTAU]
  PRINT 98
  PRINT 96, [WHT1[1,J],J=1,NTAU]
  PRINT 97, [WHT2[1,J],J=1,NTAU]
  IF [ICHEK]16,19,16
  16 DO 15 J=1,NTAU
  CRN1[1,J]=ABSF[CRN1[1,J]]
  CRN2[1,J]=ABSF[CRN2[1,J]]
  WHT1[1,J]=ABSF[WHT1[1,J]]
  WHT2[1,J]=ABSF[WHT2[1,J]]
  15 CONTINUE

C
C CALC. SI FOR EACH CHANNEL COMB.
C
  19 CONTINUE
  NSTOP=NTAU
  K=0
  NSTART=0
  NBEGIN=0
  ICOUNT=0.
  PRINT 62
  PRINT 67
  PRINT 90, ICROP1,JIDEN,ICROP2,KIDEN
  
```

NOT REPRODUCIBLE

```
60 FORMAT(3X,2HCH/)
61 FORMAT(1X//)
62 FORMAT(1H1//)
64 FORMAT(A1,I2,A1,2I2)
67 FORMAT(53X,8HSI TABLE/)
69 FORMAT(9X,1H*,12F8.4/9X,1H*)
70 FORMAT(1X,119H*****
1*****
1*/9X,1H*,98X,12H* *)
71 FORMAT (18X,1H*,12F8.3 /18X,1H*)
80 FORMAT(6I3)
82 FORMAT(1X,I4,4X,1H*,12F8.3,
1 2X,1H*,F8.3,2X,1H*/
2 9X,1H*,98X,12H* *)
83 FORMAT(53X,7HCHANNEL/
1 9X,1H*,98X,12H* *)
84 FORMAT(3X,2HCH,4X,1H*,12([5,3X],2X,1H*,11H MEAN */
1 9X,1H*,98X,12H* *)
85 FORMAT(51X,11HINPUT DATA//)
88 FORMAT(9X,1H*,12([5,3X])/ 9X,1H*)
89 FORMAT(7X,3HC5-,I2,8X,7HSECTION,5X,A1,10X,15HREF CHANNEL 6//)
90 FORMAT(1X,4HDERIVATIVE CORRELATIONS -UN-NORMALIZED - C5-,I2,
12X,4HSEC A1,1X,3HC5-,I2,2X,4HSEC A1,4X,9H30 SAM/PC//)
91 FORMAT(1X,119H*****
1*****
2*)
92 FORMAT(1X///10X,13HTRACE MEAN = F8.4//)
93 FORMAT(10X,13HMATRIX MEAN =F8.4)
94 FORMAT(2X,12F8.3)
95 FORMAT(53X,7HCHANNEL/9X,1H*)
96 FORMAT(1X,8HAC MEAN ,1H*,12F8.4/9X,1H*)
97 FORMAT(1X,8HSTD DEV ,1H*,12F8.4/9X,1H*)
98 FORMAT(1X,108H*****
1*****/9X,1H*)
100 CONTINUE
C *****
IF[ITERM-1]200,1,1
200 CONTINUE
END
```

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```

PRINT 83
PRINT 84, [J,J=1,12]
PRINT 70
XSUM=0.0
YSUM=0.0
DO 40 I1=1,NTAU
K=K+1
SUM=0.0
DO 38 J=1,NTAU
XNUM[J] = [WHT1[1,K]-CRN1[1,K]]**2+[WHT1[1,J]-CRN1[1,J]]**2
DGV[J] =4.0*[[[WHT1[1,K]-CRN1[1,K]]**2 * [WHT2[1,K]**2+CRN2[1,K]
1**2] +[[[WHT1[1,J]-CRN1[1,J]]**2 * [WHT2[1,J]**2+CRN2[1,J]**2]]]]]
RATIO[J]= [2.0*XNUM[J]]/SQRT[DGV[J]]
IF[RATIO[J]-100.0]30,35,35
35 RATIO[J]=0.0
TTAU=TTAU-1.0
SUM=SUM+RATIO[J]
YSUM=YSUM+RATIO[J]
GO TO 38
30 SUM=SUM+RATIO[J]
YSUM=YSUM+RATIO[J]
ICOUNT=ICOUNT+1
38 CONTINUE
AVG=SUM/TTAU
NBEGIN=NSTART+1
XBEGIN=NBEGIN
RZERO[NSTART]=0.0
IF[K-1]39,36,39
36 CONTINUE
PRINT 82, K, [RATIO[J],J=1,NTAU],AVG
NSTART=NSTART+1
XSUM=XSUM+RATIO[1]
GO TO 40
39 CONTINUE
PRINT 82, K, [RZERO[J],J=1,NSTART],[RATIO[J],J=NBEGIN,NTAU],AVG
NSTART=NSTART+1
XBEGIN=NBEGIN
NSTOP=NSTOP-1
N=N+12
IF[RATIO[NBEGIN]-100.0]32,33,33
33 RATIO[NBEGIN]=0.0
XTAU=XTAU-1.0
XSUM=XSUM+RATIO[NBEGIN]
GO TO 40
32 XSUM=XSUM+RATIO[NBEGIN]
40 CONTINUE
PRINT 91
YTOT=ICOUNT
XSUM=XSUM/XTAU
XTAU=NTAU
TTAU=NTAU
YSUM=YSUM/YTOT
PRINT 92, XSUM
PRINT 93, YSUM
50 FORMAT[12F6.0]

```

## Section IV

# APPLICATIONS TO MULTISPECTRAL REMOTE SENSING DATA OF AGRICULTURAL FIELDS

### 4.1 INTRODUCTION

In order to test and demonstrate the capability of the algorithms and associated computer programs developed, which have been described in the last two sections, we have employed these computer programs to process and analyze a set of multispectral data records which were made available to us by Dr. R. R. Legault of the University of Michigan. In this section, we shall present the results of the analysis of those actual data.

### 4.2 MULTISPECTRAL DATA DESCRIPTION

The data to be presented were obtained by the University of Michigan Multispectral Scanner (ref. 11). This particular set of data was obtained over an agricultural area near Lafayette, Indiana, from a flight altitude of 2000 feet at 2:00 p.m., June 30, 1966. In particular, we are dealing with only a small portion of the area designated as field C5-17, C5-22, C5-5, and C5-8, respectively, as shown in Figure 4-1. C5 represents the square area about 1 mile square with 5 marked in the figure. The number following the dash represents a more specific location of each field.

The electromechanical scanner onboard this aircraft used a rotating mirror to scan the ground normal to the flight path. Successive scan lines were separated along the flight path by approximately 6 feet due to the motion of the aircraft. All observations were stored on analog tape. Subsequent analog to digital conversion used a sampling time interval that corresponded to a ground separation of 6 feet along the scan line. The digital data points thus represent the radiation intensity that were received from square resolution elements of 6 feet by 6 feet area.

Spectroscopic observations of each resolution element were conducted by passing the radiation from the rotating mirror through a prism. This prism spectrograph was designed to measure the reflectance between 0.4 and 1.0  $\mu$ . The radiation from the ground refers to reflected sunlight. The spectral range was split into 12 different channels which are listed in Table 4-1.

Table 4-1. SPECTRAL BANDS OF MICHIGAN MULTISPECTRAL SCANNER

CHANNEL NO.	SPECTRAL BANDWIDTH (microns)	CHARACTERISTIC COLOR
1	0.40 - 0.44	Violet
2	0.44 - 0.46	Blue
3	0.46 - 0.48	
4	0.48 - 0.50	Blue-Green
5	0.50 - 0.52	
6	0.52 - 0.55	Green
7	0.55 - 0.58	
8	0.58 - 0.62	Yellow
9	0.62 - 0.66	Red
10	0.66 - 0.72	Red
11	0.72 - 0.80	} Reflective near infrared
12	0.80 - 1.00	



Twelve digital time series of the spectral reflectance from the agricultural target were obtained. The channel number,  $\lambda$ , of these time series is directly related to the optical wavelength. The sample number along these time series denotes the position of a resolution element along a scan line. Sample and scan line numbers thus provide a two-dimensional, Cartesian coordinate for the agricultural target.

The data received from each of the four agricultural fields cover only an area of 162 by 1000 feet, i.e. 27 scan lines and 167 samples per scan line. Since we want to test our algorithms for inventory boundary detection and other comparison studies, we have deliberately patched these four fields together as shown in Figure 4-2.

#### 4.3 RAW DATA PLOTS

To have a quick and overall view of the magnitude distribution of the data record, a plotting program was used to plot the raw digital data record in analog form one scan line per agricultural field for selected channels, as shown in Figures 4-3 through 4-8. From these plots, one observes that sections of distinctly different reflectances exist for each agricultural field. These differences are particularly obvious in channels 1, 2, 11, and 12. Although only one scan line per field has been shown, it is representative for each field. This observation tends to imply that each field may consist of three different targets or inventory areas.

It was also found that some resolution elements have negative value (about -1) for all 12 channels, which was obviously caused by human error in data handling prior to our data analysis. Since these negative reflectance cannot be true, we have replaced them when they occur by the mean reflectance of the adjacent resolution elements.

#### 4.4 GREY-LEVEL PLOTS

Figures 4-9 through 4-12 show grey-level plots for the constructed agricultural field for channel 1, 2, 11, and 12, respectively. The grey level plots resemble very crude photographs of the target. In these plots 11 levels of grey as indicated by numerical numbers are used. The original data have



been averaged over 4 resolution elements (i.e., a area of 12 feet by 12 feet) first so that the number of scan lines is reduced to 52 and the number of samples per scan is reduced to 83. Human inspection of the plots revealed several areas with difference reflectances. Identifiable boundaries between these areas are indicated by solid lines. Many of these lines coincide with the constructed boundaries that separate the four agricultural fields. This agreement gives a good confidence in the qualitative human judgement for selection of inventory boundaries. It should be noted that the identifiable boundaries for different channels are not exactly the same, as would be expected. Superposition of the inventory boundaries from all the channels is shown in Figure 4-13. The figure indicates that no boundary exists between two middle portions of C5-17 and C5-22, even though they belong to different fields. Some of the inventory boundaries are not so definite from the grey-level plots and they are so designated in the figure by hashed lines. Those boundaries in Figure 4-13 will be regarded as the expected inventory boundaries and will be used for comparison with automatic computer results to be presented in the next two subsections.

#### 4.5 BOUNDARY ENHANCEMENT

Subsection 2.4 discussed the underlying principle for the enhancement of inventory boundaries. To illustrate the principle more vividly, the hypothetical illustrations in Figure 2-10 are now replaced by actual data. Figure 4-14 shows the original raw data for channel 11, of each Scan 13 from the 4 fields. It can be seen that fairly large and frequent fluctuations exist in the samples from each scan line. Figure 4-15 shows the corresponding smoothed data by applying the 2-dimensional moving average over the given raw data. For the results shown, a moving average over 25 resolution elements in the form of 5 x 5 array was used. The curve in Figure 4-15 are not only smoother than the corresponding curves in Figure 4-14, but also reveal more clearly trends of slow variation existing in each scan line. Figure 4-16 shows the resulting enhanced data from the smoothed data using all 12 channels. The peaks in this Figure indicate the location of inventory boundaries in each scan. The larger the peak value, the greater difference exists between any two adjacent inventory areas.

The computer program, which is developed according to the above algorithm has been applied to the multispectral data of the constructed agricultural field containing C5-17, C5-22, C5-5, and C5-8. The computer outputs are shown in Figures 4-17 through 4-21. Figures 4-17 through 4-19 employ the second type of boundary enhancement, while Figures 4-20 and 4-21 employ the first type of boundary enhancement. In Figure 4-17 a 4-level plot is used which prints a dot (.) if the enhanced data lies below the mean plus one  $\sigma$ -value, prints 1 if it lies between the mean plus one  $\sigma$ -value and the mean plus 2  $\sigma$ -value, and similar definitions for prints 2 and 3. It can be seen that too many boundaries appear in this plot. Figure 4-18 shows a new plot without all those symbol 1's. One can now see very distinct inventory boundaries which correspond very well to those inventory boundaries determined by the human photo-interpretation (Figure 4-13). Figure 4-19 employs only 4 channels instead of all 12 available channels. Close resemblance of this plot to that in Figure 4-18 would imply that these 4 channels may be sufficient to represent all 12 channels. Figures 4-20 and 4-21 are counterparts of Figures 4-18 and 4-19. Very close resemblance between these two sets of plots further indicates that the two types of boundary enhancements, i.e., either taking the absolute value or taking the square of the difference between the 2-dimensional moving averaged data are about the same. For economy of computation time, the second type of boundary enhancement seems to be better. In order to see the effect of the 2-dimensional moving averaging on the enhancement of boundary, we have employed another moving average for 9 resolution elements in the form of a 3 x 3 array. The resulting inventory boundary map is shown in Figure 4-22. Comparing this with Figure 4-18 one can see that the major boundaries are almost the same in the two figures, and that Figure 4-22 shows more isolated boundary spots than Figure 4-18. This implies that using the 5 x 5 array of resolution elements for moving average yields better and more clear-cut boundaries than using the 3 x 3 array. This clearly indicates the importance of the 2-dimensional moving average on the performance of boundary enhancement.

#### 4.6 INVENTORY BOUNDARY DETECTION BY STATISTICAL VARIANCE TECHNIQUE

Figures 4-23 and 4-24 show the inventory boundary map obtained by the statistical variance technique using channel 1 and channel 11, respectively, with 99 percent of confidence limit. The symbol V represents the locations of inventory boundaries as detected in the scanwise direction. The symbol H

represents the location of inventory boundaries as detected normal to the scan line. Finally, the symbol X represents the location of inventory boundaries as detected in both directions. Comparing Figure 4-23 with Figure 4-9 (grey-level plot), and Figure 4-24 with Figure 4-11, one can see that the inventory boundaries determined automatically by the statistical variance method compare reasonably well to those selected by the human photo-interpretation.

Figure 4-25 shows the inventory boundary map using channels 1 and 11 together. Comparing this figure with Figures 4-23 and 4-24, one can see that the new inventory boundaries fall roughly in between those indicated by using the individual channels. Two more maps of inventory boundaries using 4 channels (1, 2, 11, and 12) and 12 channels, respectively, are shown in Figures 4-26 and 4-27. Figures 4-25 and 4-26 are quite similar to each other. The only major differences between Figures 4-26 and 4-27 appear in field C5-8. Finally, comparing Figure 4-27 with Figure 4-13, it is seen that good agreement in inventory boundaries are observed for C5-17, C5-22, and C5-5; and that the vertical boundaries in C5-8 are completely different in these two figures. This poor performance detection in C5-8 might be due to the existence of a vertical boundary in C5-8 locating very close to the left end of the field, where the scanwise inventory boundary detection is initiated. It is recalled that at least 4 samples need to be used for the initial estimate of the statistical variations (see subsection 2.5) prior to testing for boundaries. This requirement makes it very difficult to detect the left vertical boundary in C5-8 and further cause misdetection later. In this respect, the boundary enhancement method (Figure 4-22) is more powerful than the statistical variation method for detecting inventory boundaries.

#### 4.7 STATISTICAL FEATURES OF INVENTORY AREAS

Once the inventory boundaries within a given target area (or image) are determined as presented in subsections 4.5 and 4.6, the statistical features of each individual inventory area, which are the areas bounded by the inventory boundaries, may be calculated. For convenience of discussions, we shall designate various inventory areas as indicated in Figure 4-13.

Figure 4-28 is a computer printout of the mean vector, correlation matrix, covariance matrix, and normalized covariance matrix of the inventory

area C5-17 Section A, The magnitude of the covariance matrix is about two orders of magnitude less than that of the correlation matrix. This implies that the standard deviation for each channel is about one-tenth of the corresponding mean value. The fact that roughly the average value of the element of the normalized covariance matrix is about 0.50 implies that the 12 channels of the data record are statistically correlated within each inventory area.

Figure 4-29 shows the mean vectors of reflectance for 6 inventory areas in fields C5-17 and C5-22, while Figure 4-30 shows the mean vectors of reflectance for 6 other inventory areas in fields C5-5 and C5-8. It is noted that the mean vectors of C5-17, Section B, and C5-22, Section B, are much closer to each other as compared with other mean vectors. This agrees with the computer results that no inventory boundary is found between these two inventory areas.

We shall next examine the univariate probability density functions of the multispectral agricultural data. It is recalled that among the 12 available channels of data for the four agricultural fields under consideration, we have found that only channels 1, 2, 11, and 12 are almost sufficient for determining inventory boundaries. Thus, the discussion shall be restricted to the univariate probability densities of only these four channels. Figures 4-31 through 4-34 show the univariate probability histograms for field C5-22 for channels 1, 2, 11, and 12, respectively. The curves marked by symbol A are obtained from actual data, while the curves marked by symbol B are gaussianly distributed curves with the same standard deviation and peak value as the actual data. The figures clearly indicate that the reflectance over field C5-22 is definitely not gaussianly distributed, and that the actual distribution are multiple-mode. For channel 1 we can see two distinctly large peaks. For channel 2, there are three main peaks. Figures 4-33 and 4-34 show that the distribution is skew to the low reflectance value. In order to provide one more check to see whether the inventory areas we have established are really composed of statistically homogeneous samples, we have also plotted the probability histograms for C5-22, Section A, B, and C with channel 1 and 11 (Figures 4-35 through 4-40). These figures clearly indicate that the univariate probability histograms are practically Gaussian for all the three inventory areas under consideration. In other words, field C5-22 is composed of three different homogeneous areas, each of which may be approximated by a different gaussian distribution.

Therefore, the division of the field C5-22 into three inventory areas as shown in Figure 4-13 is reasonable.

#### 4.8 DIVERGENCE MATRIX AMONG INVENTORY AREAS

To calculate the divergence matrix among various inventory areas (or populations) and thus to compare the statistical dissimilarity (or separability) among them, we need to input the mean vectors and covariance matrices of all inventory areas into the divergence matrix program. Tables 4-2 and 4-3 show two such inputs for C5-17, Sections A and B. Table 4-4 shows the divergence matrix for the 12 inventory areas as indicated in field designations. (Note that the larger the value of divergence between two inventory areas, the less similar they are.) We have observed in an earlier part of the Section that C5-17, Section A is more similar to C5-22 Section B than any others. The table gives a divergence of 3.303 between these two inventory areas, which happens to be the smallest element of the divergence matrix. Tables 4-5 and 4-6 show two contributing parts, called trace 1 and trace 2 matrices, to the divergence matrix; they represent the first and second term (without the factor 1/2) of the right-hand side of equation (2-11). If covariance matrices of all inventory areas are identical, then trace 1 matrices will vanish. On the other hand, if the mean vectors of all inventory areas are the same, then trace 2 matrix will vanish. Comparing Tables 4-5 and 4-6 indicate that the elements of trace 1 matrix are much larger than those of trace 2 matrix. This would imply that the dissimilarity among those 12 inventory areas is mainly due to their difference in mean vectors rather than their covariance matrices.

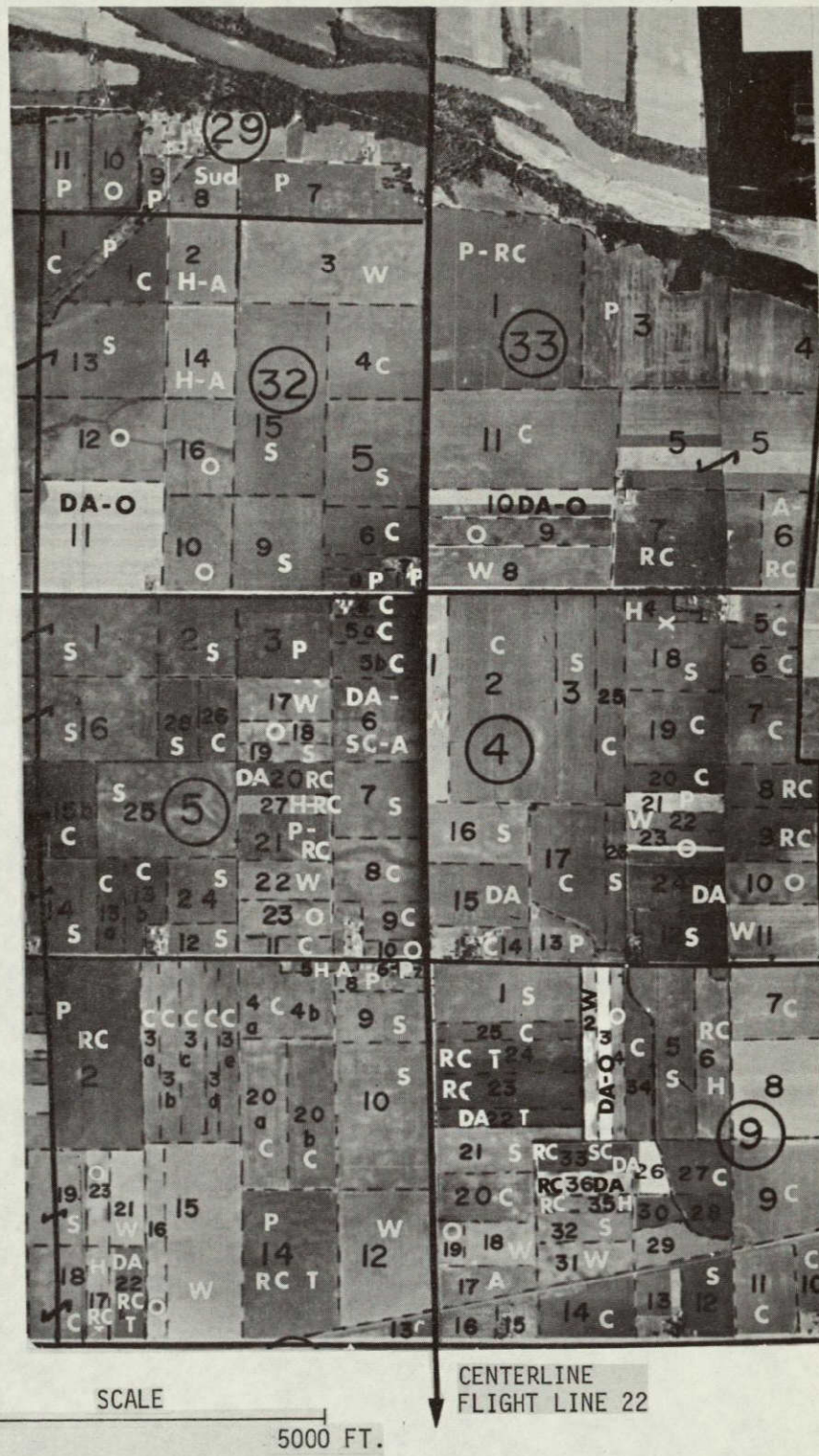


Figure 4-1. AERIAL PHOTOGRAPH OF THE AGRICULTURE FIELD

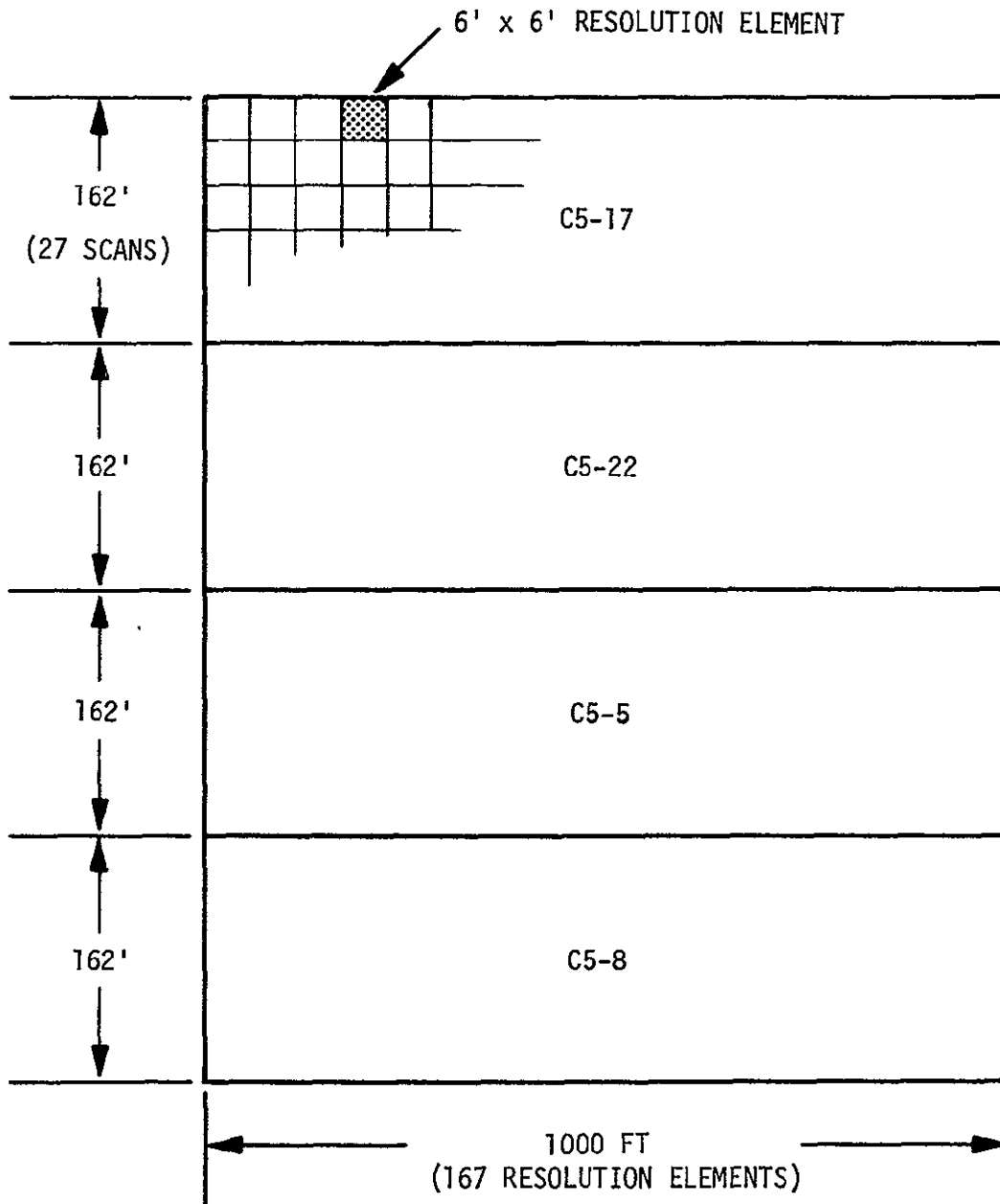


Figure 4-2. A CONSTRUCTED MAP OF FOUR AGRICULTURAL FIELDS

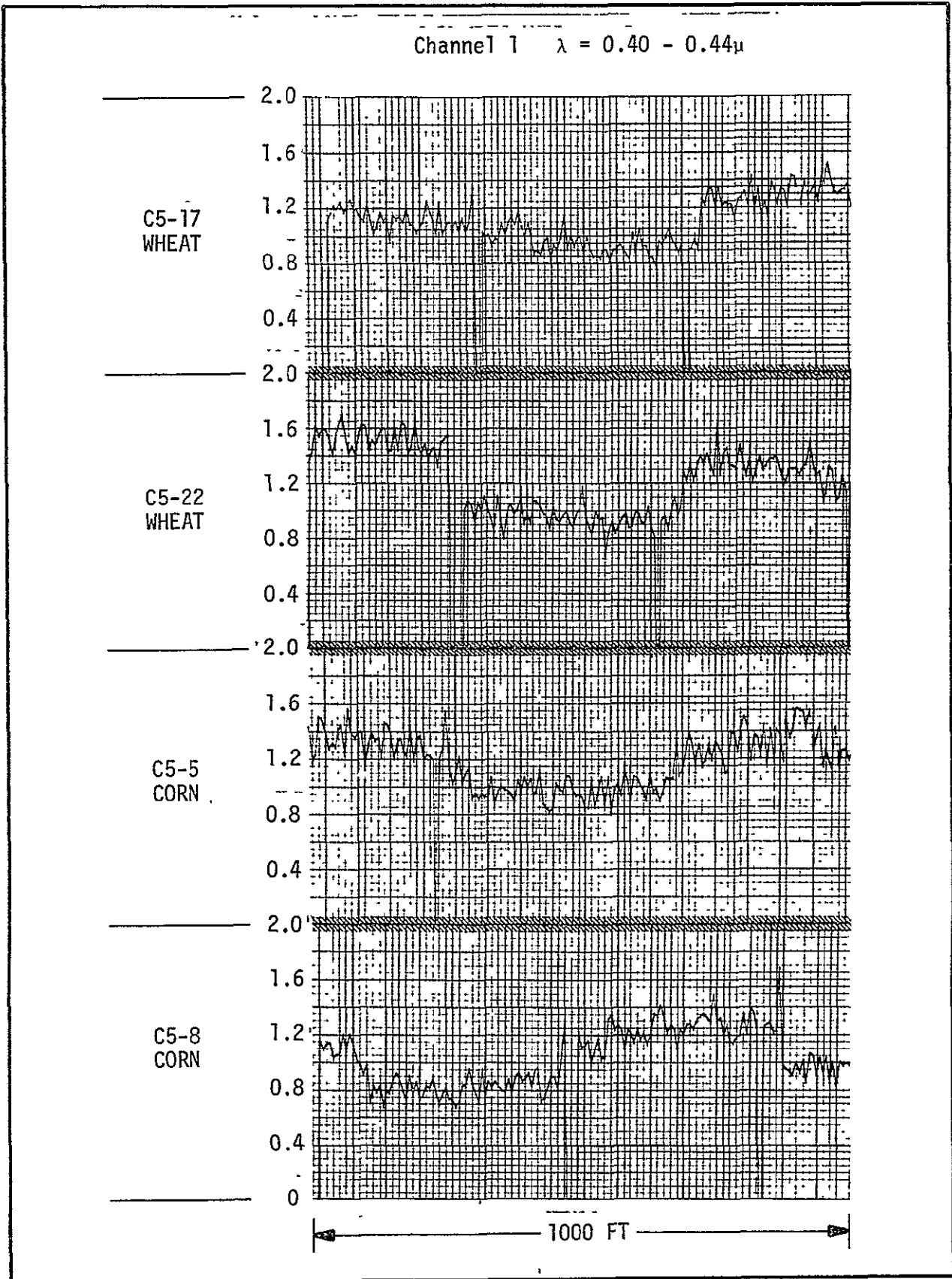


Figure 4-3. RAW DATA PLOT OF CHANNEL 1 FOR ONE SCAN LINE PER FIELD



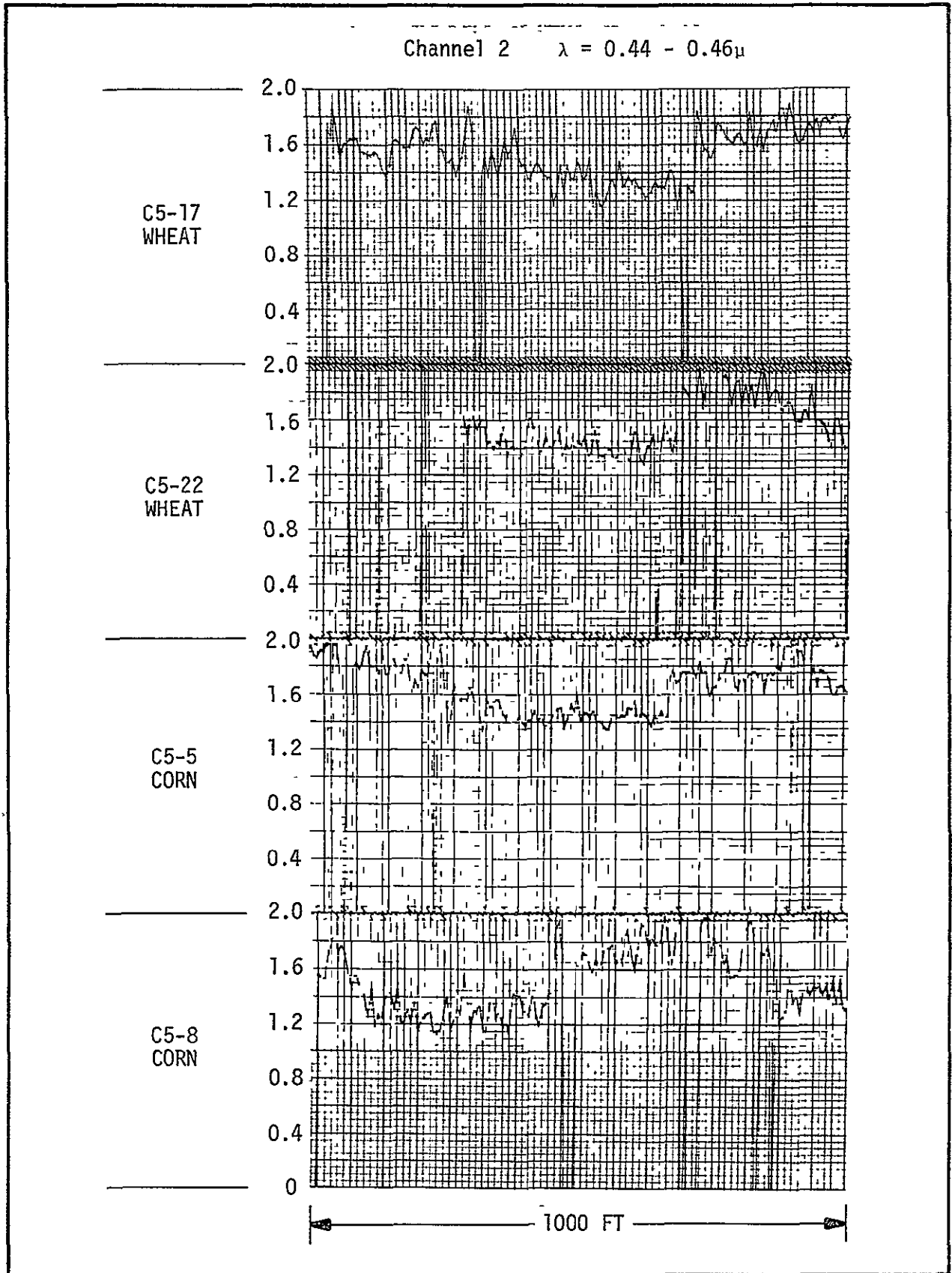


Figure 4-4. RAW DATA PLOT OF CHANNEL 2 FOR ONE SCAN LINE PER FIELD

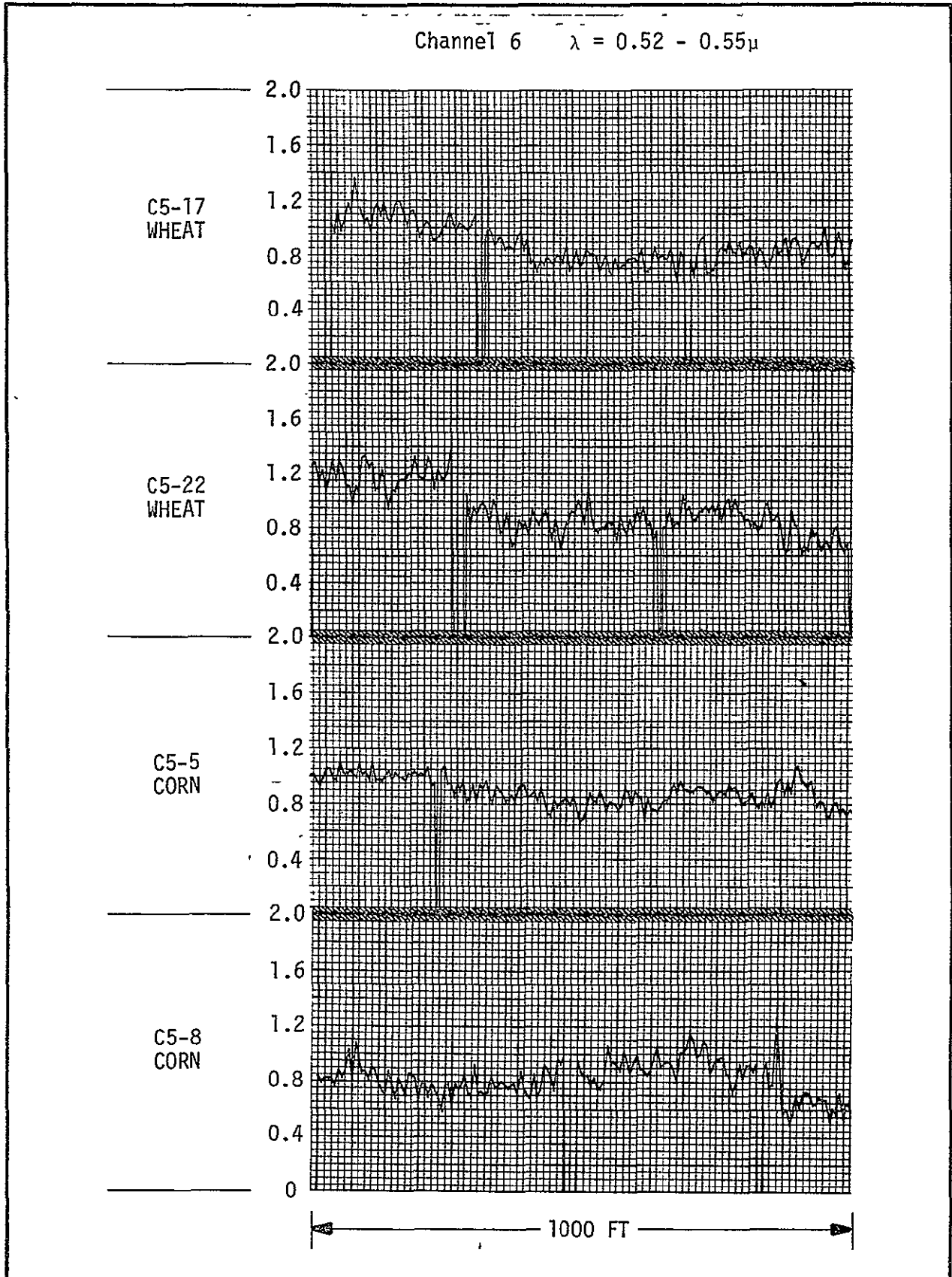


Figure 4-5. RAW DATA PLOT OF CHANNEL 6 FOR ONE SCAN LINE PER FIELD

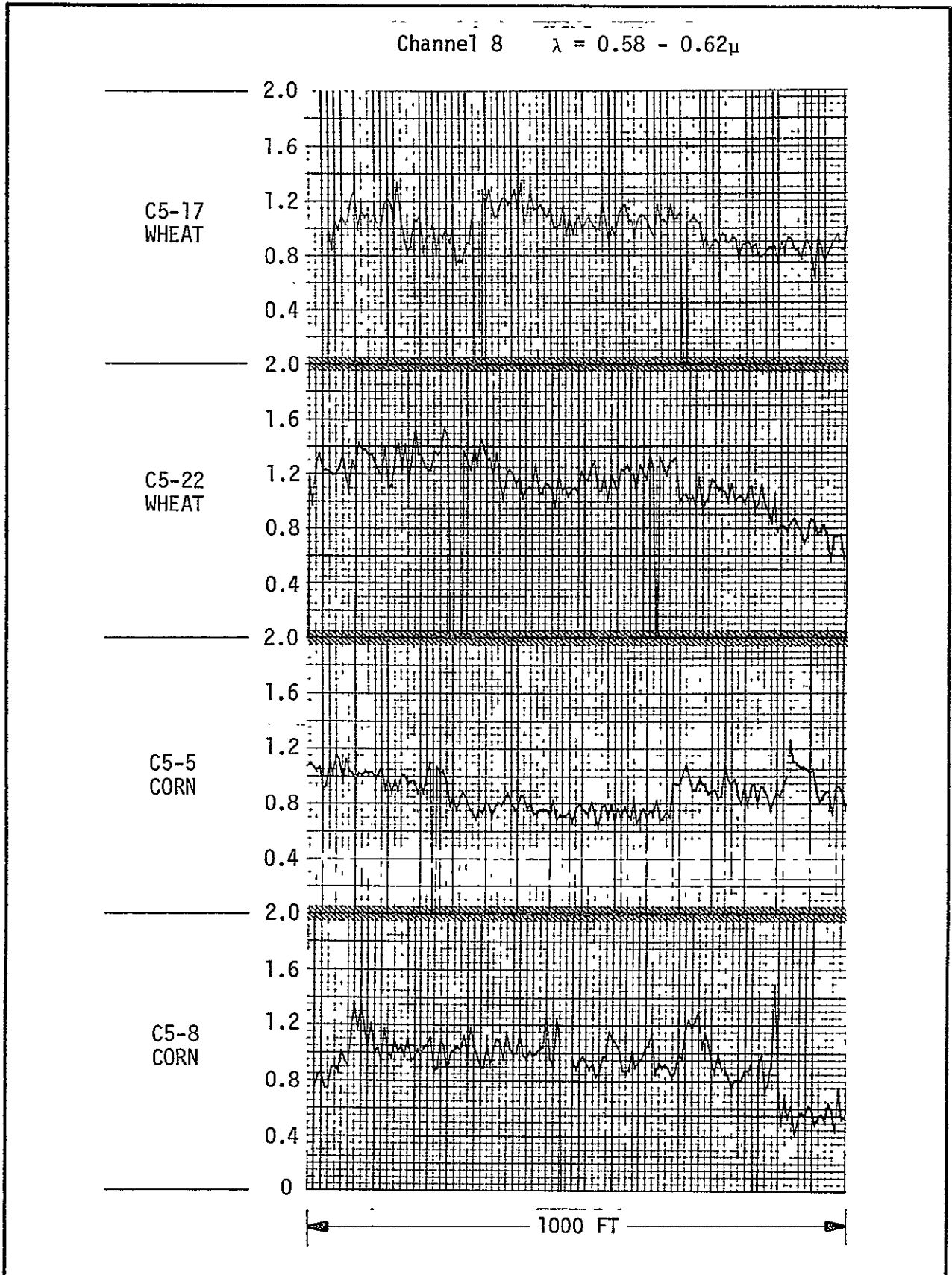


Figure 4-6. RAW DATA PLOT OF CHANNEL 8 FOR ONE SCAN LINE PER FIELD

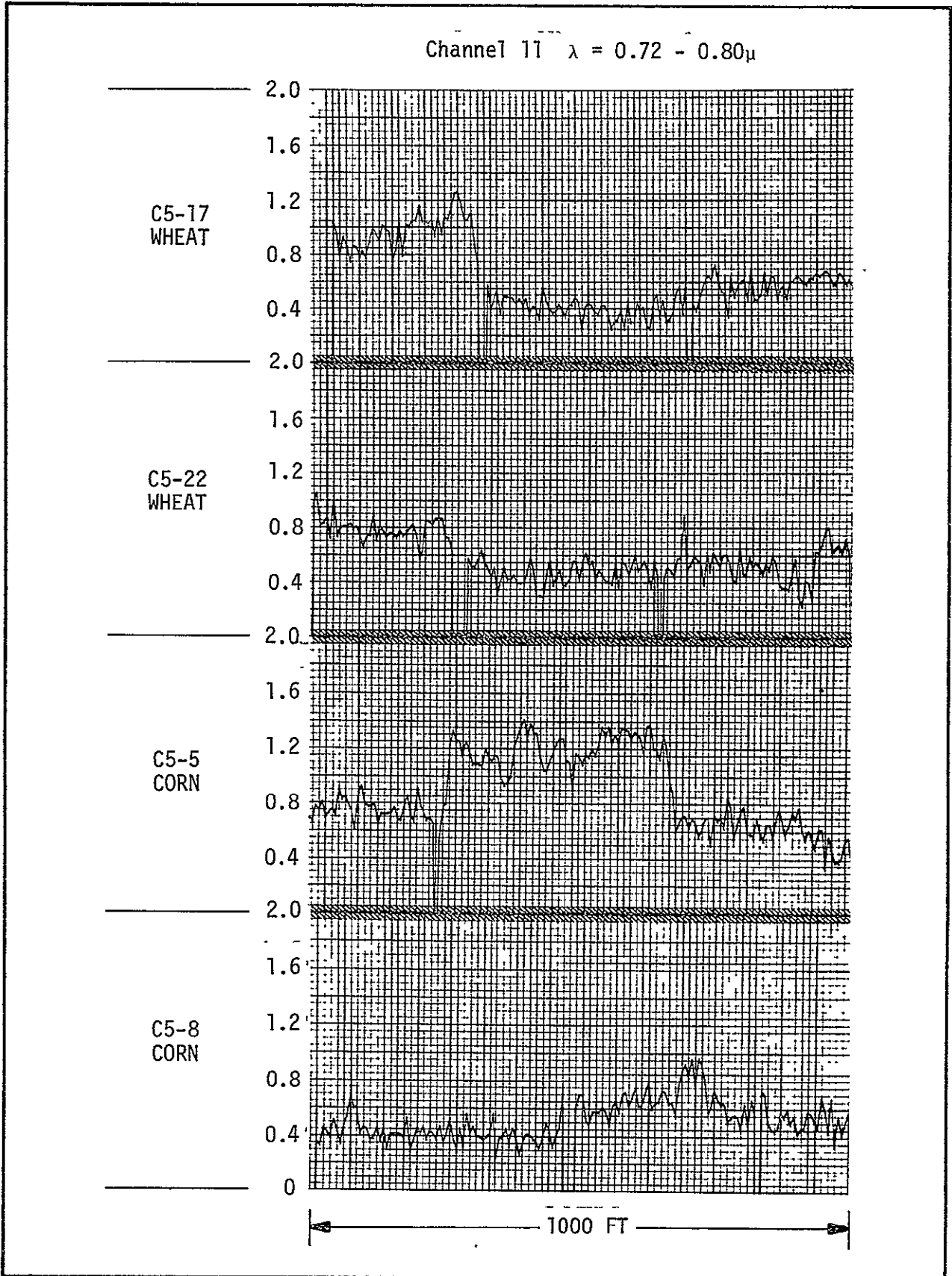


Figure 4-7. RAW DATA PLOT OF CHANNEL 11 FOR ONE SCAN LINE PER FIELD

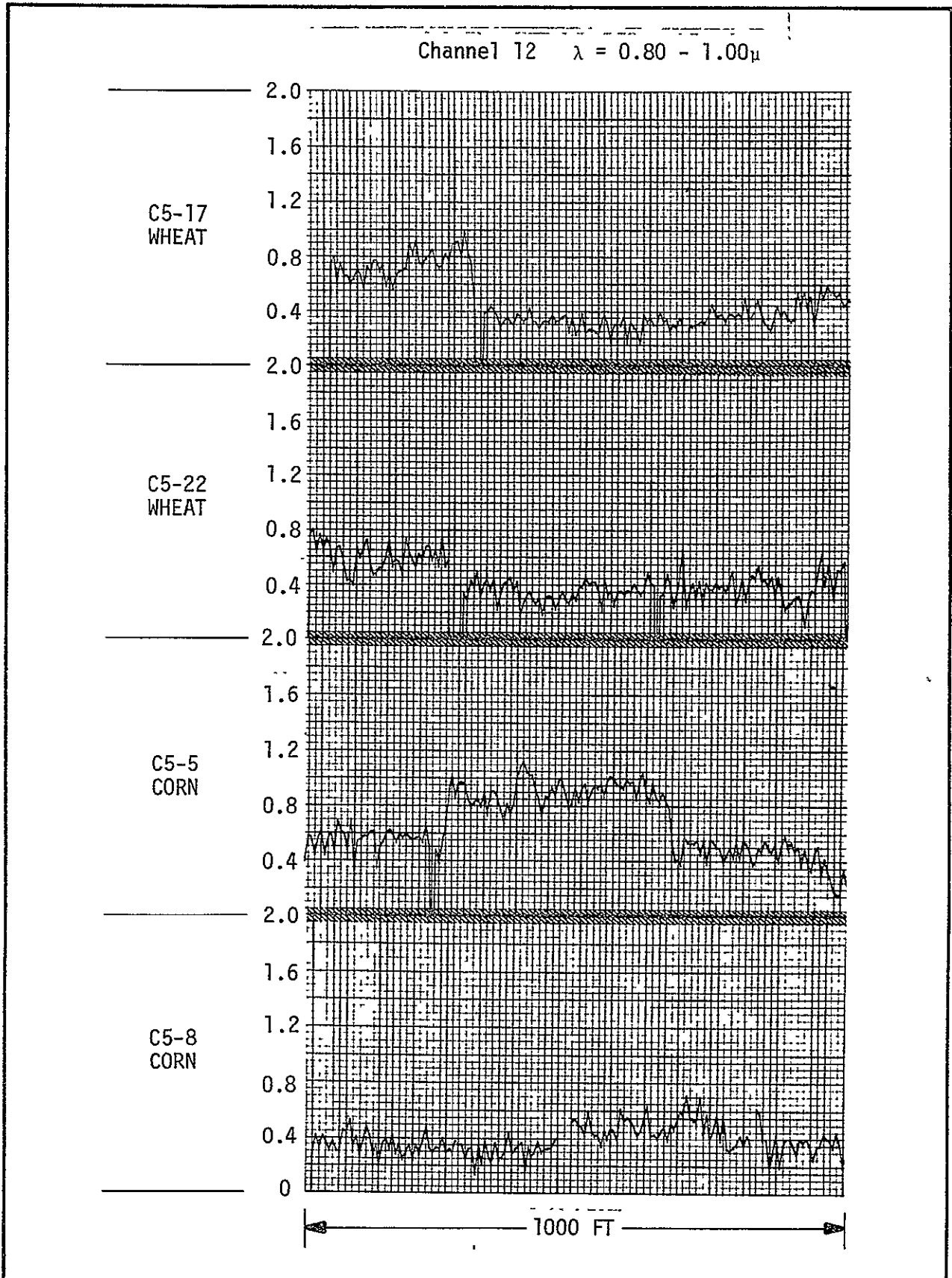


Figure 4-8. RAW DATA PLOT OF CHANNEL 12 FOR ONE SCAN LINE PER FIELD





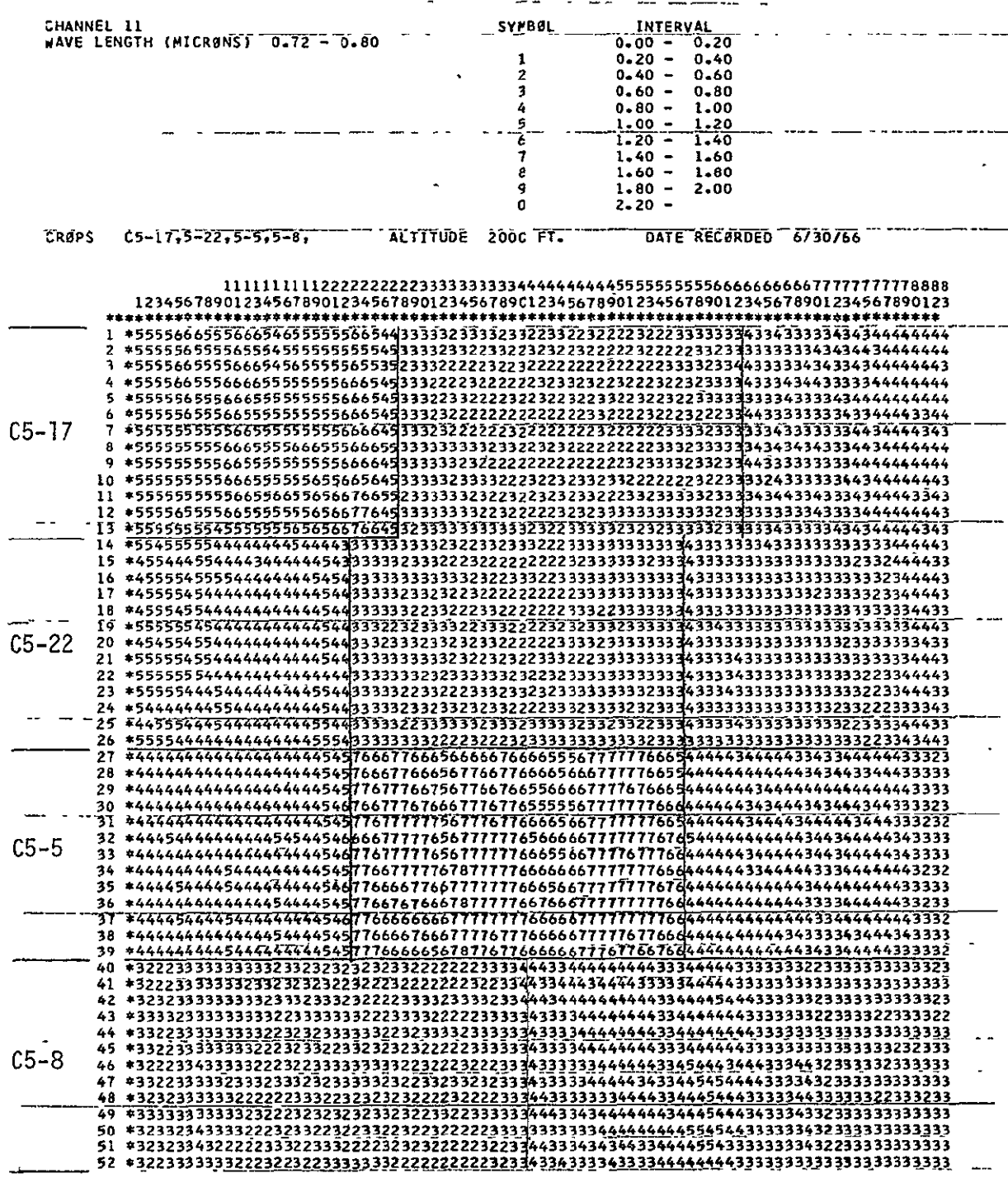


Figure 4-11. GREY-LEVEL PLOT (Channel 11)





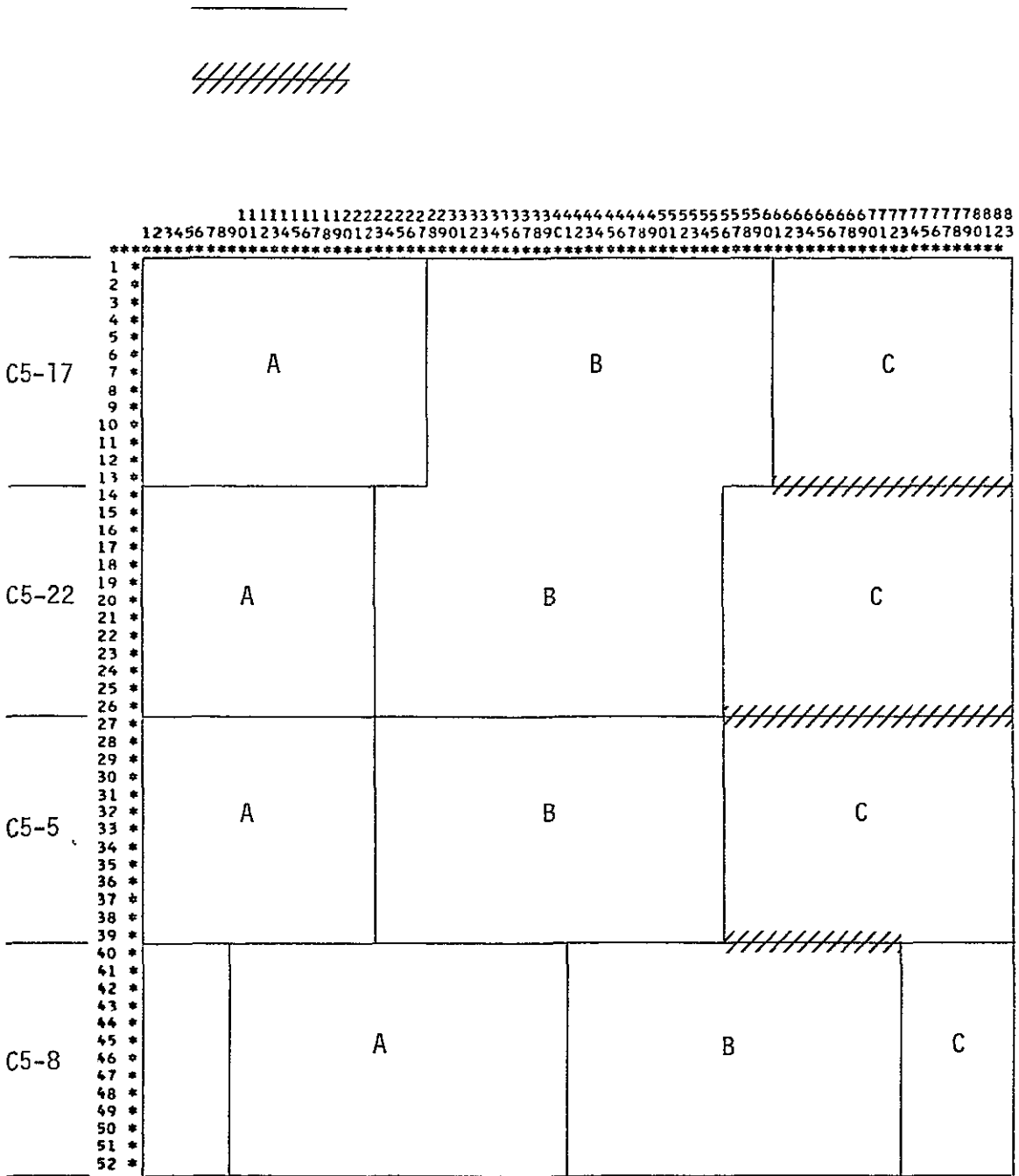


Figure 4-13. INVENTORY BOUNDARIES OBSERVED FROM GREY-LEVEL PLOTS

4-22

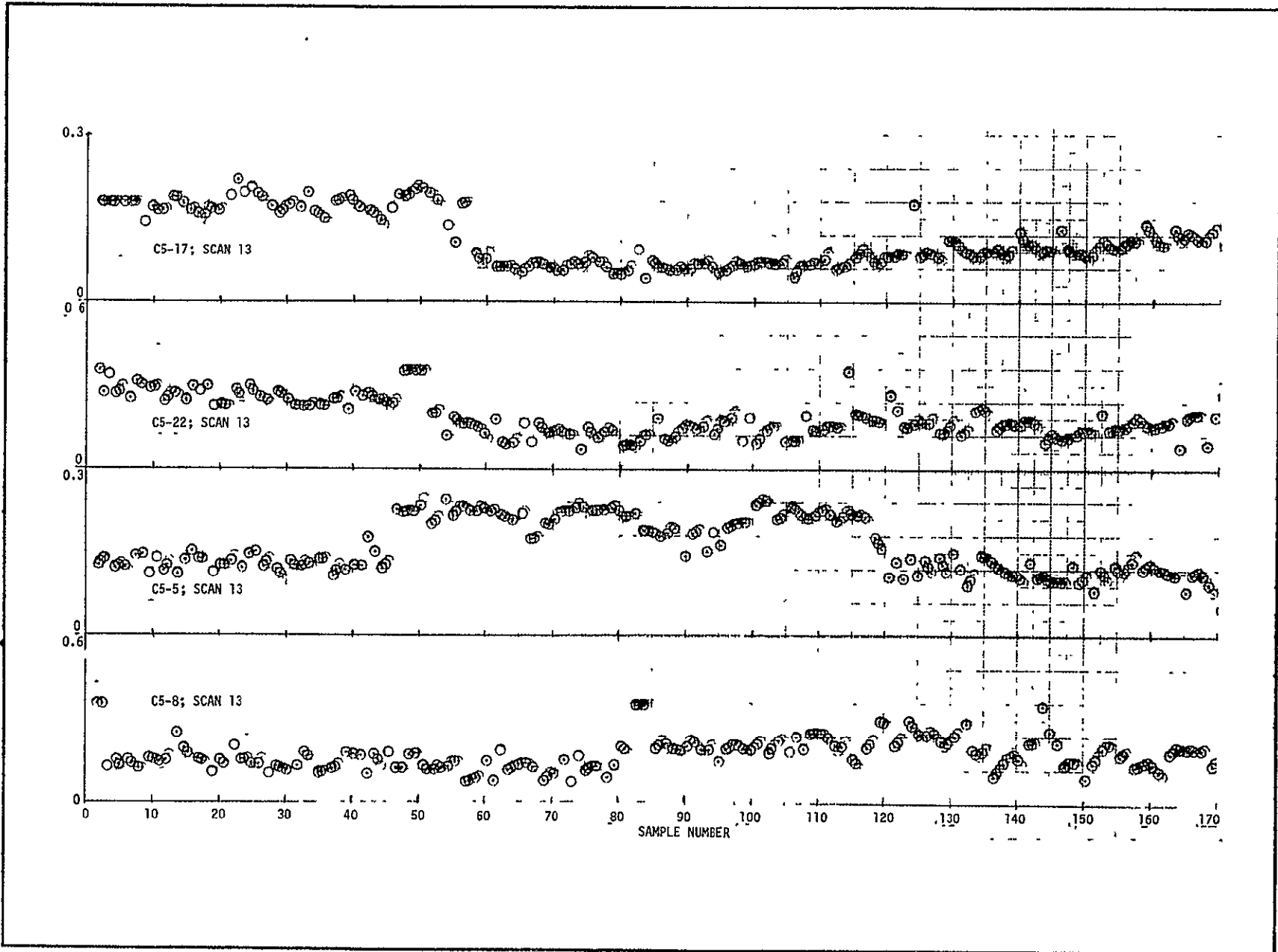


Figure 4-14. ORIGINAL RAW DATA FOR CHANNEL 11 (  $\lambda = 0.72 - 0.80 \mu$  )

4-23

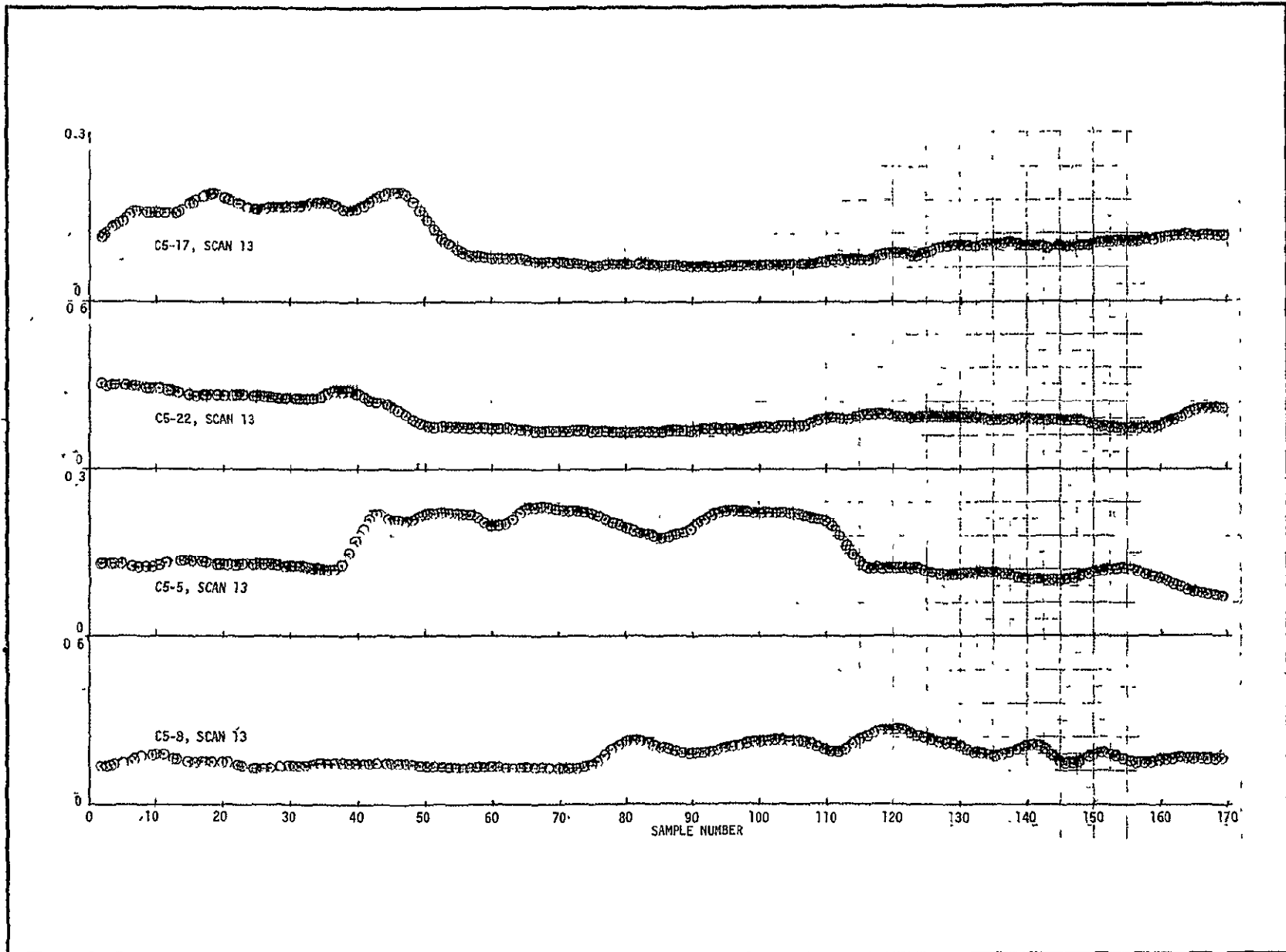


Figure 4-15. SMOOTHED DATA FOR CHANNEL 11 BY AVERAGING OVER 5 x 5 RESOLUTION ELEMENTS

4-24

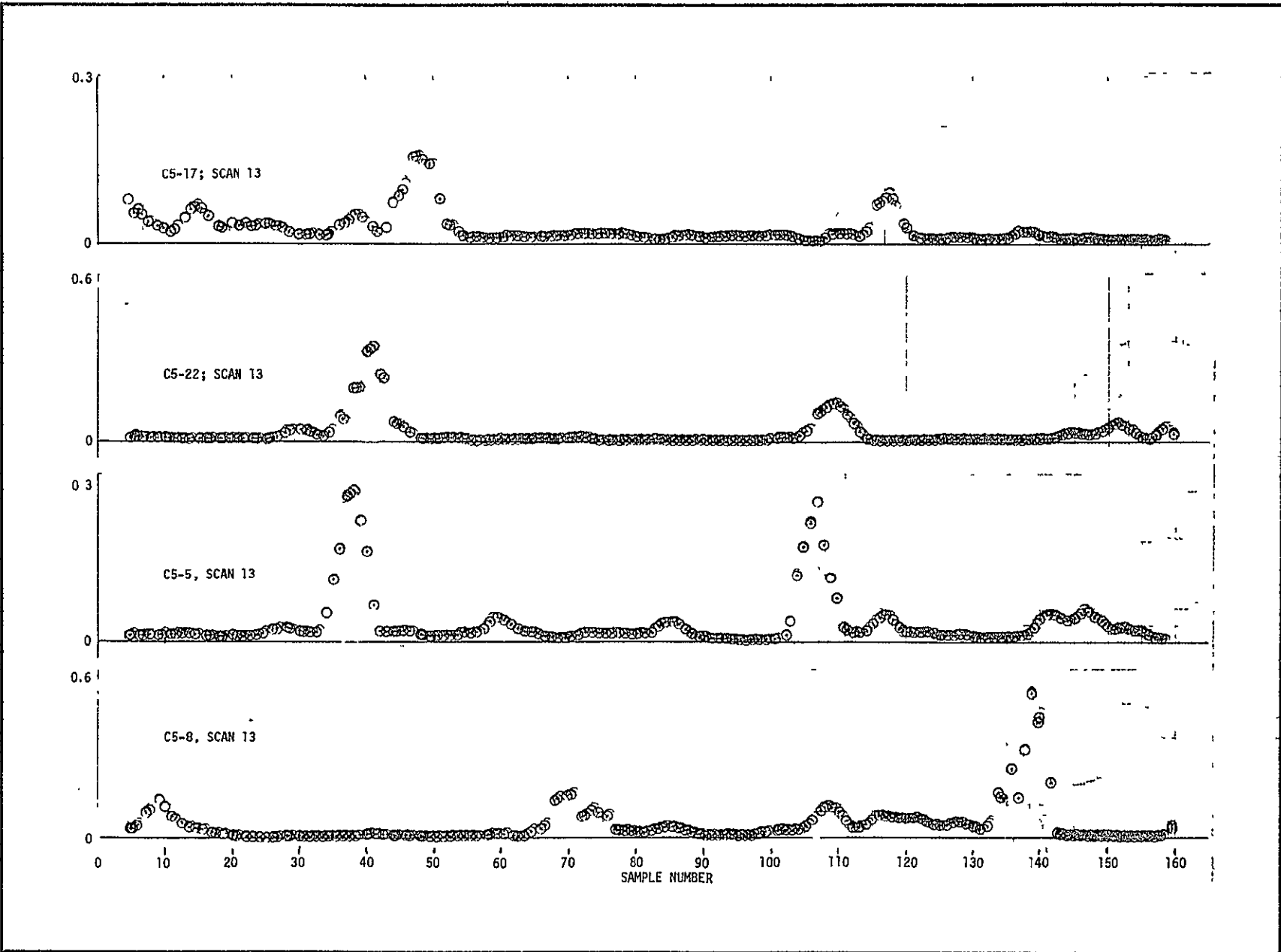


Figure 4-16. ENHANCED DATA USING ALL 12 CHANNELS



INVENTORY BOUNDARY MAP BY BOUNDARY ENHANCEMENT

CROPS C5-17,5-22,5-5,5-8, ALTITUDE 200C FT. DATE RECORDED 6/30/66

CHANNEL	WAVE LENGTH
1	0.40 - 0.44
2	0.44 - 0.46
3	0.46 - 0.48
4	0.48 - 0.50
5	0.50 - 0.52
6	0.52 - 0.55
7	0.55 - 0.58
8	0.58 - 0.62
9	0.62 - 0.66
10	0.66 - 0.72
11	0.72 - 0.80
12	0.80 - 1.00

SYMBOLS . = LESS THAN MEAN . = MEAN-MEAN+1SD . = MEAN+1SD-MEAN+2SD  
2 = MEAN+2SD-MEAN+3SD 3 = GREATER THAN MEAN+3SD

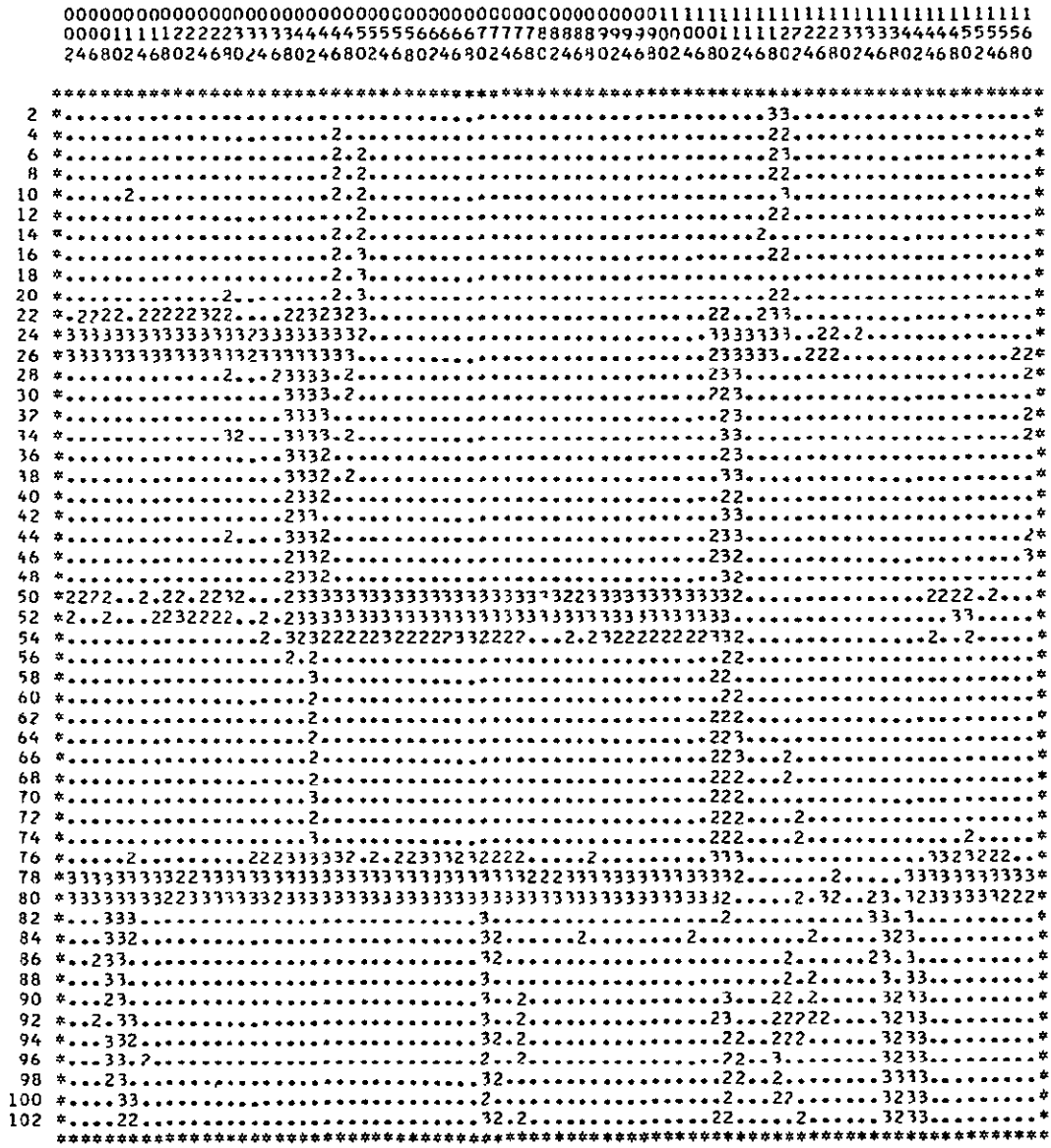


Figure 4-18. INVENTORY BOUNDARY MAP BY BOUNDARY ENHANCEMENT,  
CHANNELS 1-12, USING ABSOLUTE VALUE

INVENTORY BOUNDARY MAP BY BOUNDARY ENHANCEMENT  
CRØPS C5-17,5-22,5-5,5-8, ALTITUDE 2000 FT., DATE RECORDED 6/30/66

CHANNEL	WAVE LENGTH
1	0.40 - 0.44
2	0.44 - 0.46
11	0.72 - 0.80
12	0.80 - 1.00

SYMBOLS     . = LESS THAN MEAN     . = MEAN-MEAN+1SD     . = MEAN+1SD-MEAN+2SD  
                 2 = MEAN+2SD-MEAN+3SD     3 = GREATER THAN MEAN+3SD

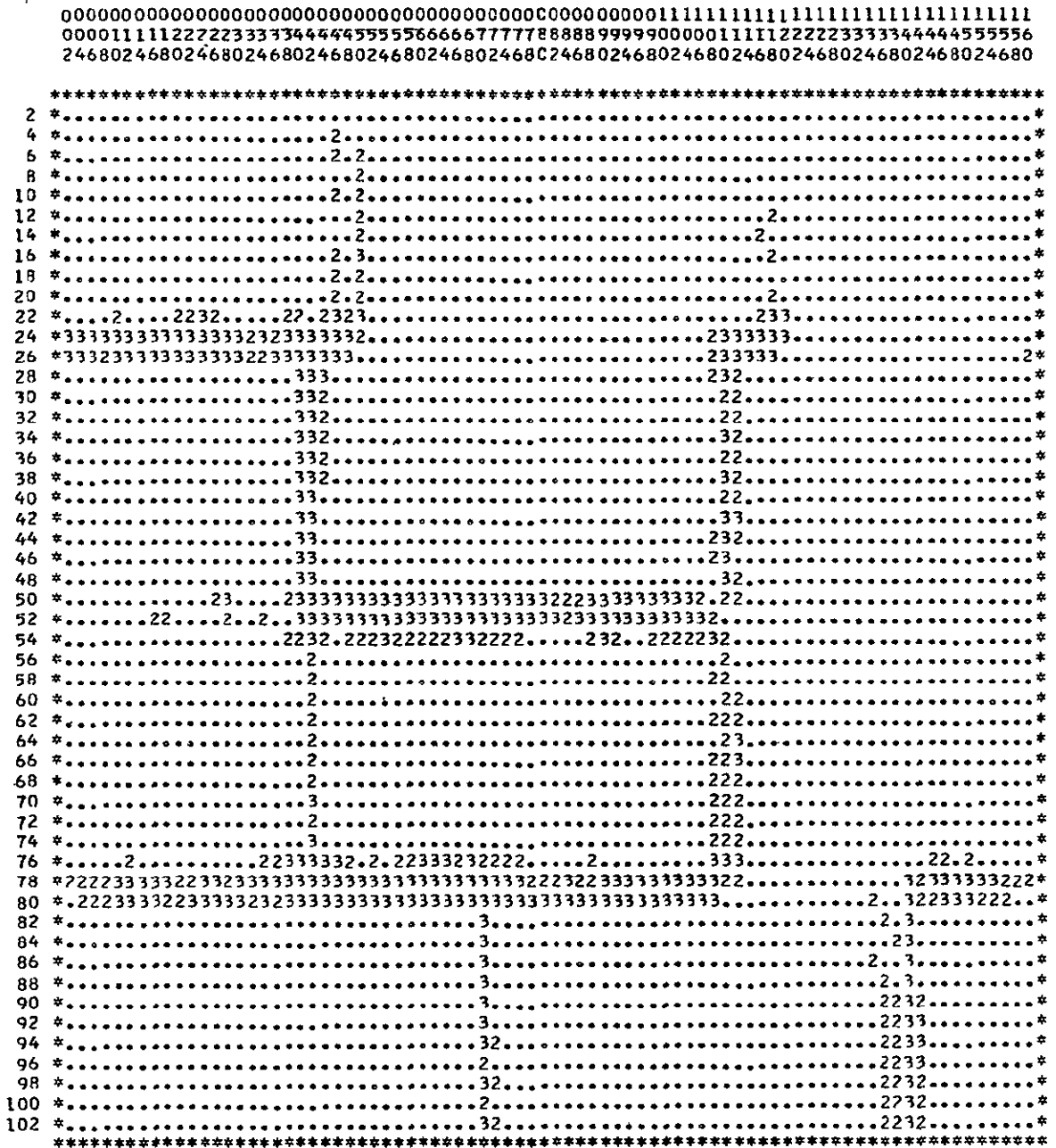


Figure 4-19. INVENTORY BOUNDARY MAP BY BOUNDARY ENHANCEMENT,  
CHANNELS 1, 2, 11, AND 12, USING ABSOLUTE VALUE



INVENTORY BOUNDARY MAP BY BOUNDARY ENHANCEMENT

CORPS C5-17,5-22,5-5,9-8, ALTITUDE 2000 FT. DATE RECORDED 6/30/66

CHANNEL	WAVE LENGTH
1	0.40 - 0.44
2	0.44 - 0.46
3	0.46 - 0.48
4	0.48 - 0.50
5	0.50 - 0.52
6	0.52 - 0.55
7	0.55 - 0.58
8	0.58 - 0.62
9	0.62 - 0.66
10	0.66 - 0.72
11	0.72 - 0.80
12	0.80 - 1.00

NOT REPRODUCIBLE

SYMBOLS . = LESS THAN MEAN . = MEAN-MEAN+1SD . = MEAN+1SD-MEAN+2SD  
 ? = MEAN+2SD-MEAN+3SD 3 = GREATER THAN MEAN+3SD

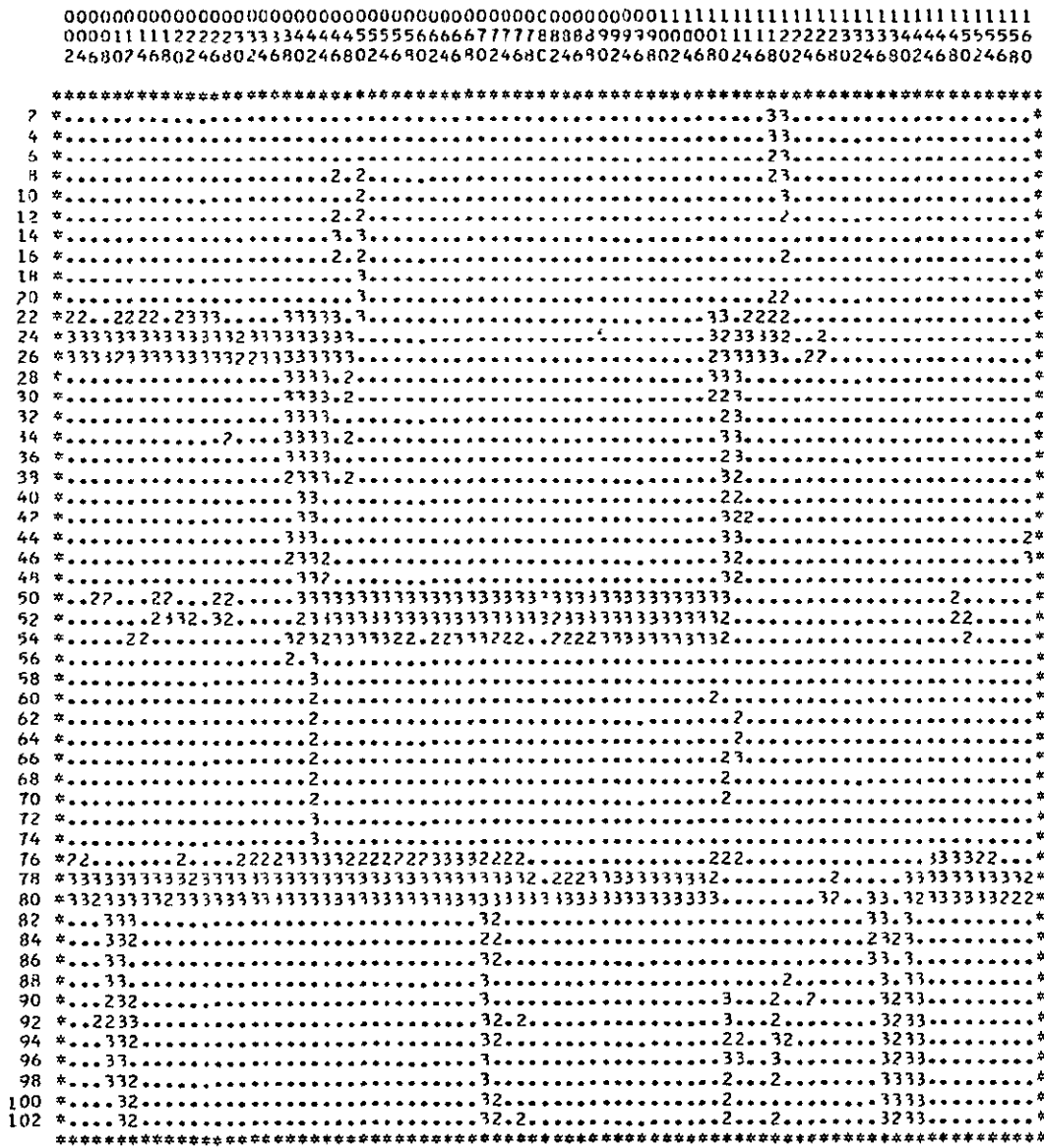


Figure 4-20. INVENTORY BOUNDARY MAP BY BOUNDARY ENHANCEMENT, CHANNELS 1-12, USING SQUARE VALUE



INVENTORY BOUNDARY MAP BY BOUNDARY ENHANCEMENT

CRØPS C5-17,5-22,5-5,5-8, ALTITUDE 200C FT., DATE RECORDED 6/30/66

CHANNEL	WAVE LENGTH
1	0.40 - 0.44
2	0.44 - 0.46
3	0.46 - 0.48
4	0.48 - 0.50
5	0.50 - 0.52
6	0.52 - 0.55
7	0.55 - 0.58
8	0.58 - 0.62
9	0.62 - 0.66
10	0.66 - 0.72
11	0.72 - 0.80
12	0.80 - 1.00

SYMBOLS . = LESS THAN MEAN . = MEAN-MEAN+1SD . = MEAN+1SD-MEAN+2SD  
2 = MEAN+2SD-MEAN+3SD 3 = GREATER THAN MEAN+3SD

0011111111111111111111111111111111111  
000011112222333344445555666677778888999900001111222233334444555566  
24680246802468024680246802468024680246802468024680246802468024680246802468024680246802

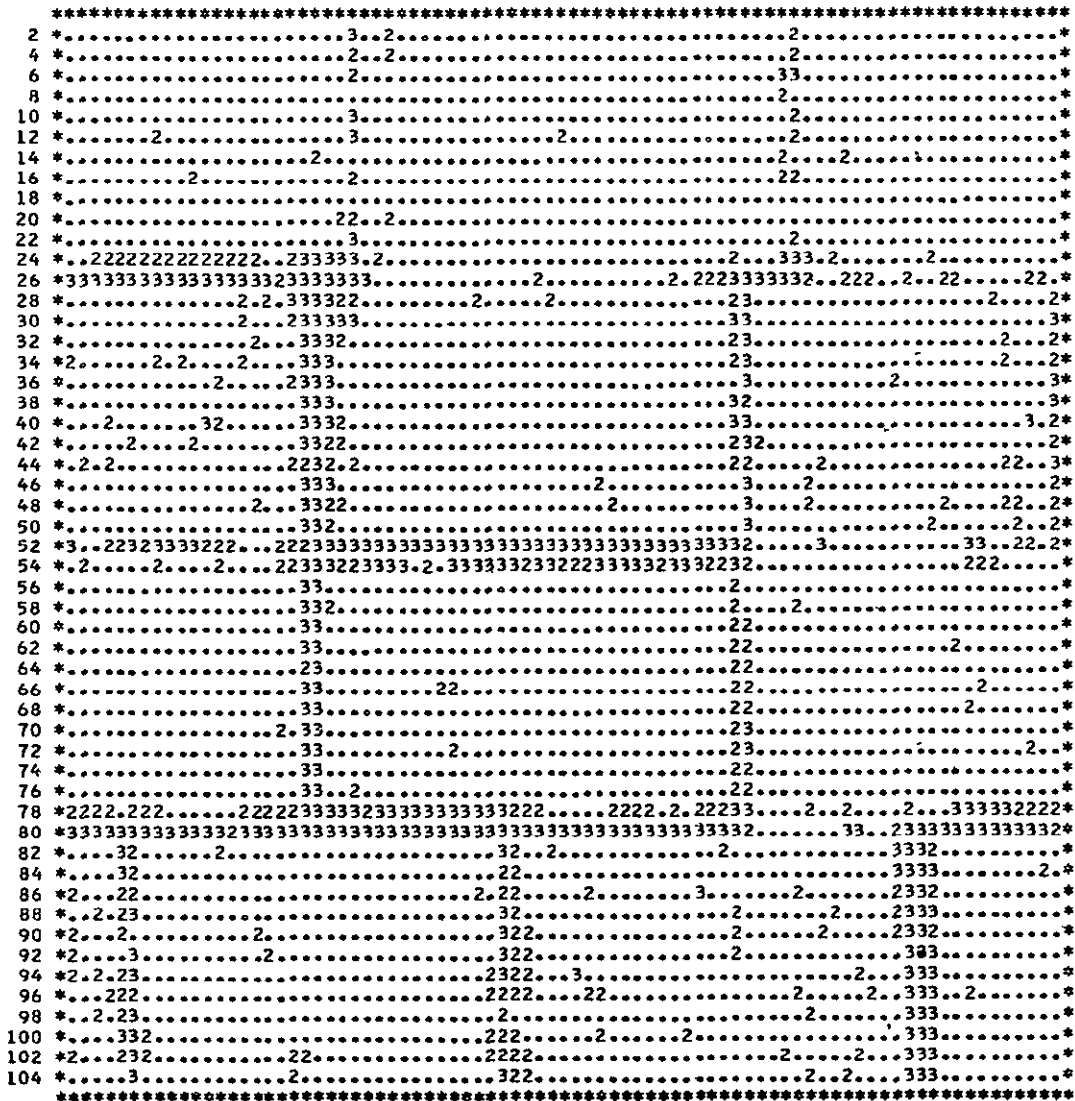
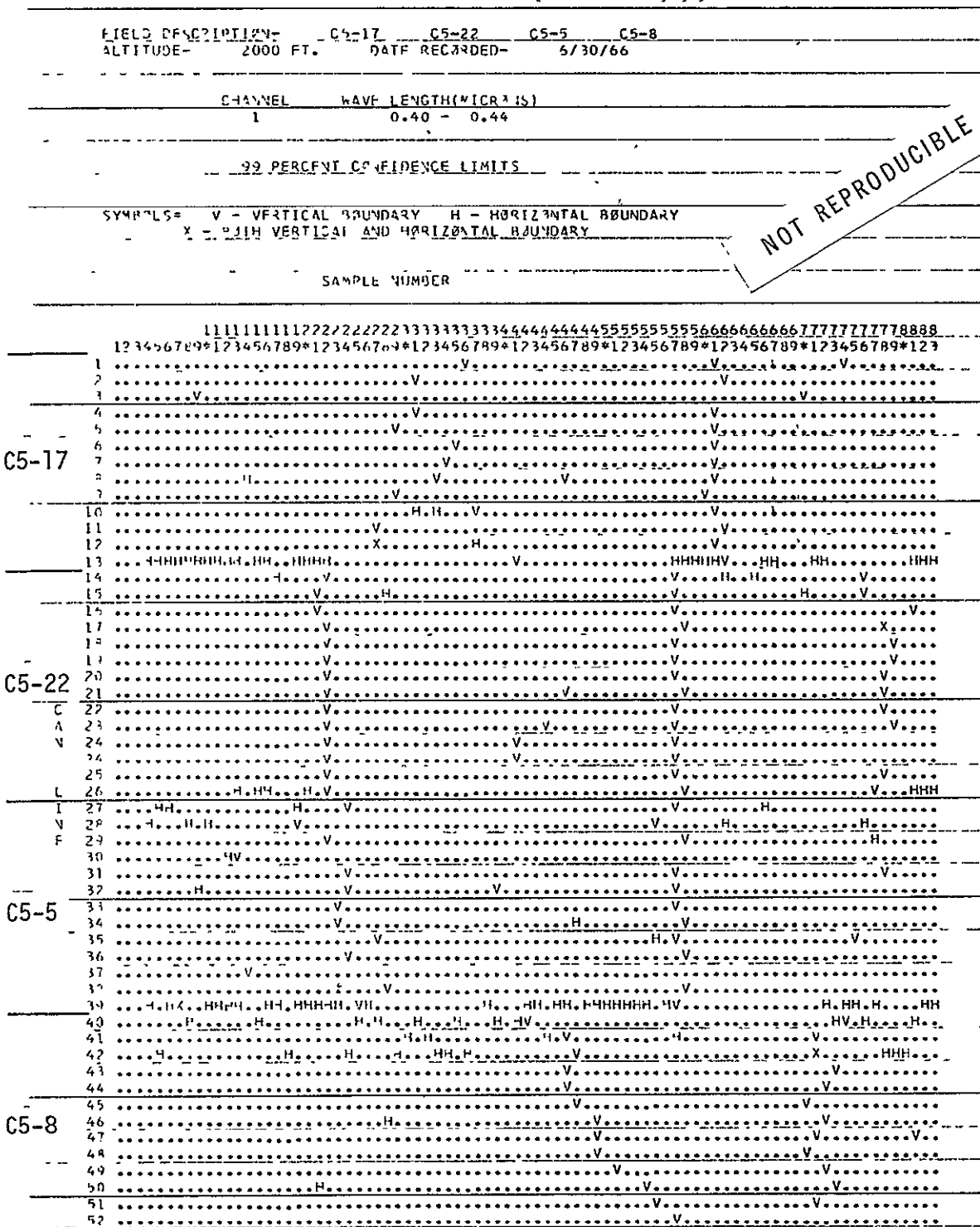


Figure 4-22. INVENTORY BOUNDARY MAP BY BOUNDARY ENHANCEMENT, CHANNELS 1 - 12, USING ABSOLUTE VALUE AND 3 x 3 ELEMENTS FOR MOVING AVERAGE



NOT REPRODUCIBLE

Figure 4-23. MAP OF INVENTORY BOUNDARIES (Channel 1)

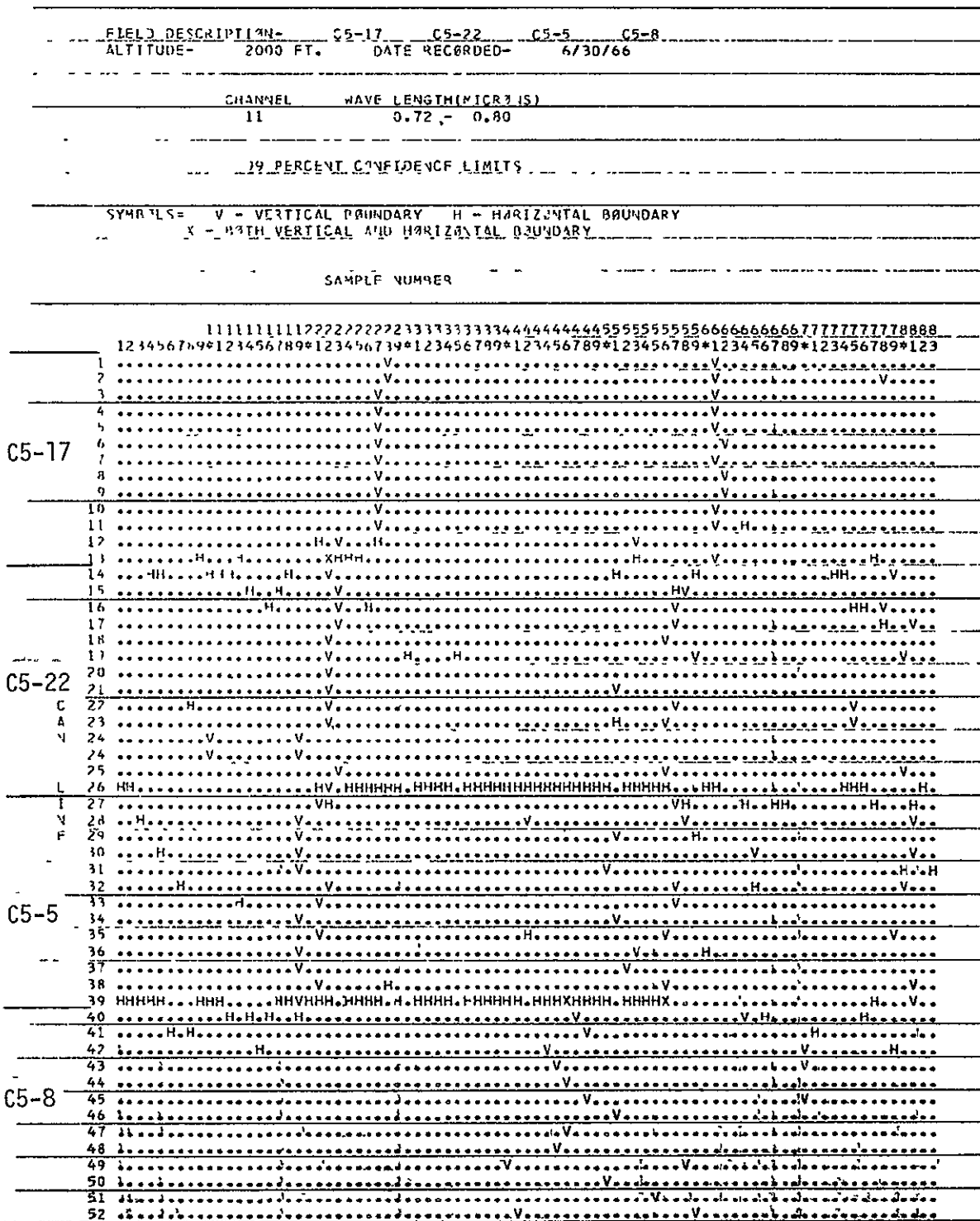


Figure 4-24. MAP OF INVENTORY BOUNDARIES (Channel 11)

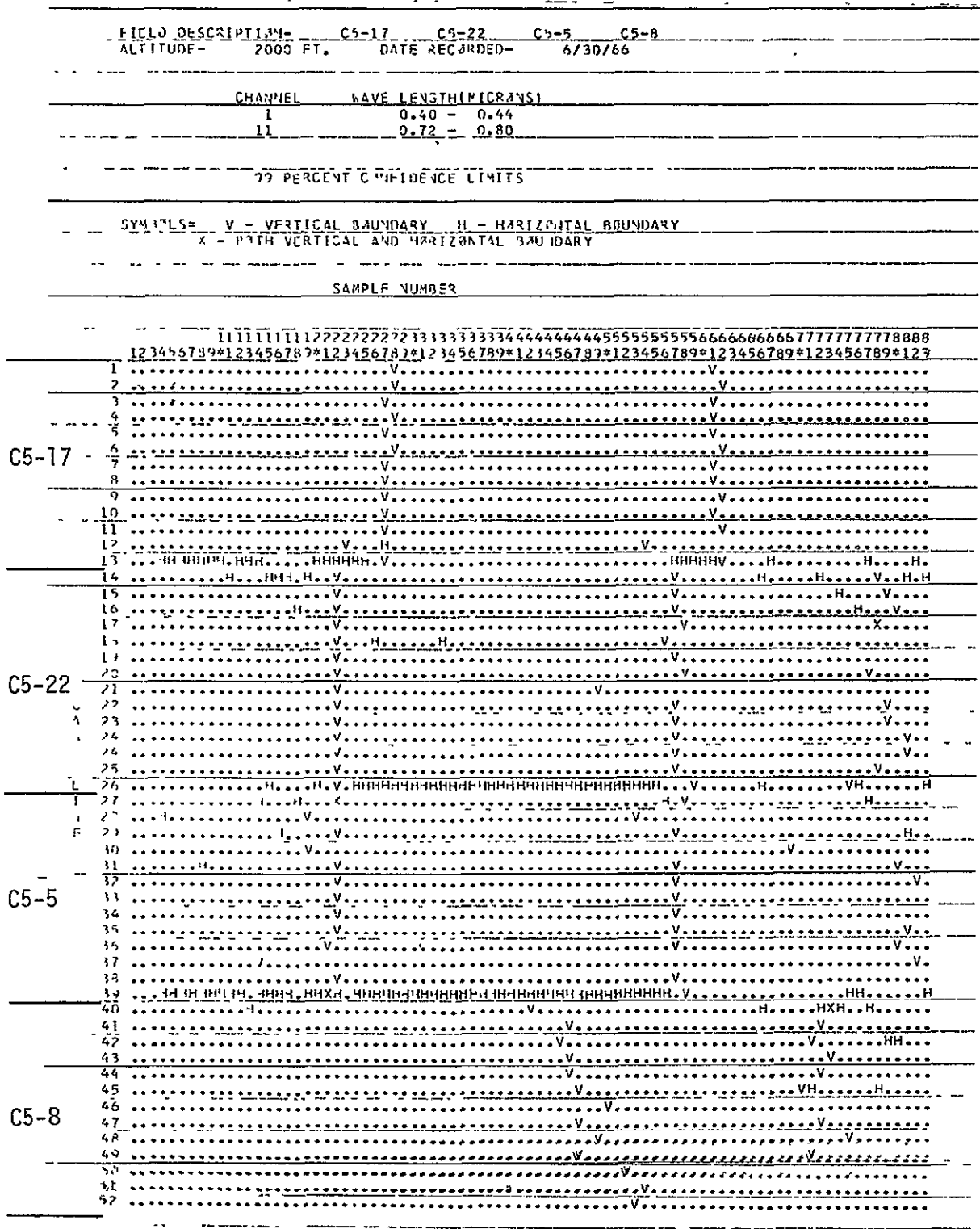
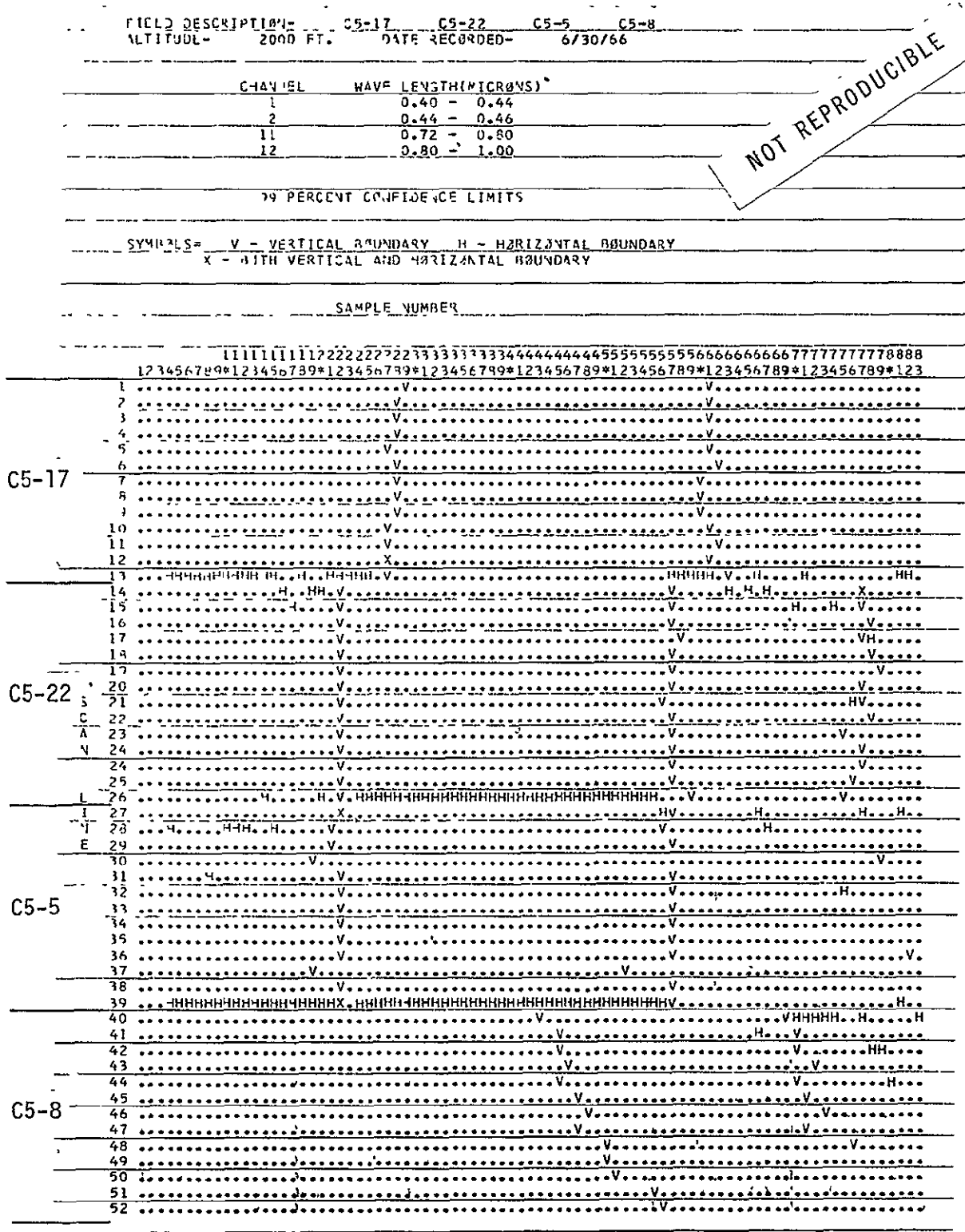


Figure 4-25. MAP OF INVENTORY BOUNDARIES (Channels 1, 11)



NOT REPRODUCIBLE

Figure 4-26. MAP OF INVENTORY BOUNDARIES (Channels 1, 2, 11, 12)

FIELD DESCRIPTION - C5-17 C5-22 C5-5 C5-8  
 ALTITUDE - 2000 FT. DATE RECORDED - 6/30/66

CHANNEL	WAVE LENGTH (MICRONS)
1	0.40 - 0.44
2	0.44 - 0.46
3	0.46 - 0.48
4	0.48 - 0.50
5	0.50 - 0.52
6	0.52 - 0.55
7	0.55 - 0.58
8	0.58 - 0.62
9	0.62 - 0.66
10	0.66 - 0.72
11	0.72 - 0.80
12	0.80 - 1.00

PERCENT CONFIDENCE LIMITS

SYMBOLS - V - VERTICAL BOUNDARY H - HORIZONTAL BOUNDARY  
 X - BOTH VERTICAL AND HORIZONTAL BOUNDARY

SAMPLE NUMBER

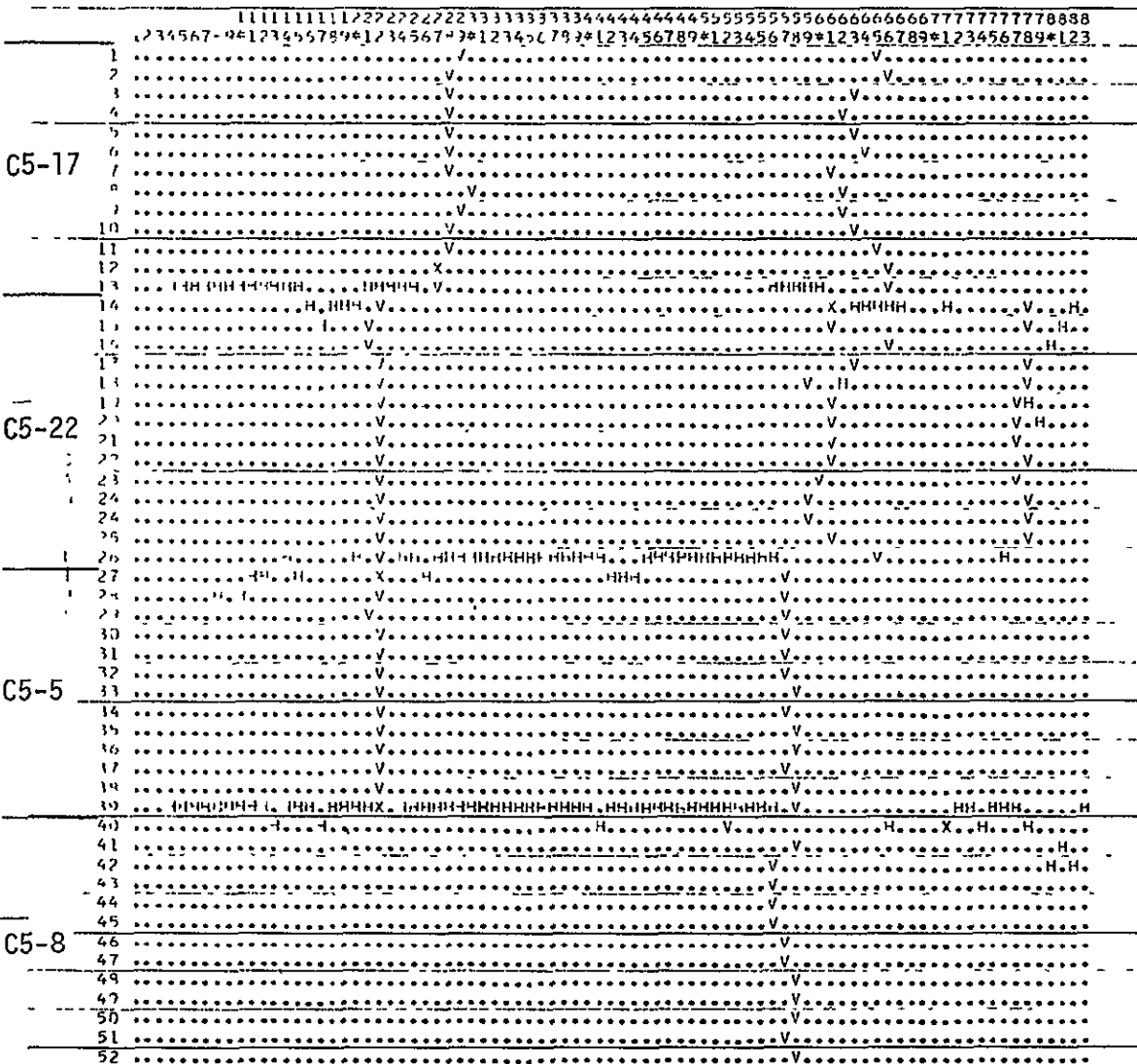


Figure 4-27. MAP OF INVENTORY BOUNDARIES (Channels 1 through 12)



C(5-17) SECTION A

MEAN VECTOR

CH	*	1	2	3	4	5	6	7	8	9	10	11	12
1	*	1.110358	1.60692	1.16319	1.02380	1.04938	.99541	.77604	1.03585	.50232	.63149	.81489	.63113

CORRELATION MATRIX

CH	*	1	2	3	4	5	6	7	8	9	10	11	12
1	*	1.22478	1.78101	1.25326	1.13077	1.16079	1.10460	.85939	1.14047	.54983	.69671	.91284	.70679
2	*	1.78101	2.59407	1.82522	1.64706	1.69035	1.60726	1.25123	1.66202	.80240	1.01498	1.32523	1.02633
3	*	1.25326	1.82522	1.28773	1.16232	1.19157	1.13040	.88122	1.17583	.56993	.71643	.92444	.71622
4	*	1.13077	1.64706	1.16232	1.05096	1.07608	1.01954	.79545	1.06389	.51696	.64740	.82985	.64310
5	*	1.16079	1.69035	1.19157	1.07608	1.10462	1.04809	.81708	1.08921	.52745	.66371	.85847	.66493
6	*	1.10460	1.60726	1.13040	1.01954	1.04809	.99964	.77696	1.02866	.49478	.62905	.82910	.64182
7	*	.85939	1.25123	.88122	.79545	.81708	.77696	.60572	.80445	.38845	.49078	.64001	.49562
8	*	1.14047	1.66202	1.17583	1.06389	1.08921	1.02866	.80445	1.08283	.52864	.65632	.82785	.64146
9	*	.54983	.80240	.56993	.51696	.52745	.49478	.38845	.52864	.26138	.31867	.38920	.30194
10	*	.69671	1.01498	.71643	.64740	.66371	.62905	.49078	.65632	.31867	.39998	.51273	.39713
11	*	.91284	1.32523	.92444	.82985	.85847	.82910	.64001	.82785	.38920	.51273	.72029	.55612
12	*	.70679	1.02633	.71622	.64310	.66493	.64182	.49562	.64146	.30194	.39713	.55612	.43064

COVARIANCE MATRIX

CH	*	1	2	3	4	5	6	7	8	9	10	11	12
1	*	.00688	.00764	.00269	.00093	.00271	.00608	.00297	-0.00268	-0.00451	-0.00019	.01354	.01028
2	*	.00764	.01187	.00428	.00190	.00408	.00771	.00420	-0.00251	-0.00479	.00022	.01576	.01215
3	*	.00269	.00428	.00361	.00216	.00243	.00241	.00182	.00202	.00071	.00083	.00101	.00103
4	*	.00093	.00190	.00216	.00280	.00173	.00045	.00094	.00339	.00269	.00088	-0.00443	-0.00305
5	*	.00271	.00408	.00243	.00173	.00342	.00353	.00272	.00222	.00033	.00104	.00334	.00263
6	*	.00608	.00771	.00241	.00045	.00353	.00880	.00449	-0.00243	-0.00523	.00046	.01795	.01359
7	*	.00297	.00420	.00182	.00094	.00272	.00449	.00349	.00059	.00059	.00072	.00763	.00584
8	*	-0.00268	-0.00251	.00202	.00339	.00222	-0.00243	.00059	.00085	.00831	.00220	-0.01625	-0.01230
9	*	-0.00451	-0.00479	.00071	.00269	.00033	-0.00523	-0.00137	.00831	.00906	.00146	-0.02013	-0.01509
10	*	-0.00019	.00022	.00083	.00088	.00104	.00046	.00072	.00220	.00146	.00121	-0.00187	-0.00142
11	*	.01354	.01576	.00101	-0.00443	.00334	.01795	.00763	-0.01625	-0.02013	-0.00187	.05624	.04182
12	*	.01028	.01215	.00103	-0.00305	.00263	.01359	.00584	-0.01230	-0.01509	-0.00142	.04182	.03231

NORMALIZED COVARIANCE MATRIX

CH	*	1	2	3	4	5	6	7	8	9	10	11	12
1	*	1.00000	.84536	.53920	.21116	.55854	.78158	.60634	-0.32504	-0.57183	-0.06673	.68837	.68978
2	*	.84536	1.00000	.65312	.32905	.63967	.75453	.65303	-0.23192	-0.46187	.05902	.60997	.62060
3	*	.53920	.65312	1.00000	.68002	.69065	.42715	.51383	.33786	.12471	.39806	.07096	.09488
4	*	.21116	.32905	.68002	1.00000	.55795	.09010	.30179	.64602	.53410	.48015	-0.35302	-0.32061
5	*	.55854	.63967	.69065	.55795	1.00000	.64329	.78785	.38161	.05884	.51090	.24111	.25049
6	*	.78158	.75453	.42715	.09010	.64329	1.00000	.80938	-0.26108	-0.58580	.14124	.80655	.80563
7	*	.60634	.65303	.51383	.30179	.78785	.80938	1.00000	.10145	-0.24302	.35027	.54428	.54971
8	*	-0.32504	-0.23192	.33786	.64602	.38161	-0.26108	.10145	1.00000	.87991	.63694	-0.69045	-0.68967
9	*	-0.57183	-0.46187	.12471	.53410	.05884	-0.58580	-0.24302	.87991	1.00000	.44195	-0.89197	-0.88186
10	*	-0.06673	.05902	.39806	.48015	.51090	.14124	.35027	.63694	.44195	1.00000	-0.22646	-0.22794
11	*	.68837	.60997	.07096	-0.35302	.24111	.80655	.54428	-0.69045	-0.89197	-0.22646	1.00000	.98099
12	*	.68978	.62060	.09488	-0.32061	.25049	.80563	.54971	-0.68967	-0.88186	-0.22794	.98099	1.00000

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Figure 4-28. MEAN VECTOR CORRELATION MATRIX, COVARIANCE MATRIX, AND NORMALIZED COVARIANCE MATRIX OF C5-17, SECTION A

Table 4-2. MEAN VECTOR AND COVARIANCE MATRIX OF C5-17 SECTION A

C(5-17) SECTION A													
MEAN VECTOR													
CHANNEL	*	1	2	3	4	5	6	7	8	9	10	11	12
1	*	1.174	1.706	1.177	1.048	1.077	1.062	.806	1.013	.459	.633	.950	.739
COVARIANCE MATRIX													
CHANNEL	*	1	2	3	4	5	6	7	8	9	10	11	12
1	*	.00884	.0057	.00294	.00212	.00197	.00294	.00101	.00213	.00001	.00185	.00022	-.00024
2	*	.00057	.01209	.00287	.00185	.00353	.00202	.00325	.00384	.00198	.00113	-.00017	-.00074
3	*	.00294	.00287	.00731	.00242	.00207	.00264	.00157	.00342	.00184	.00150	-.00011	-.00024
4	*	.00212	.00185	.00242	.00707	.00096	.00145	.00094	.00234	.00176	.00117	-.00022	-.00069
5	*	.00197	.00353	.00207	.00096	.00858	.00115	.00333	.00405	.00168	.00125	-.00075	-.00087
6	*	.00294	.00202	.00264	.00145	.00115	.00733	.00071	.00221	.00085	.00157	-.00067	-.00028
7	*	.00101	.00325	.00157	.00094	.00333	.00071	.00552	.00300	.00148	.00090	-.00027	-.00078
8	*	.00213	.00384	.00342	.00234	.00405	.00221	.00300	.00962	.00310	.00141	-.00014	-.00049
9	*	.00001	.00198	.00184	.00176	.00168	.00085	.00148	.00310	.00533	-.00024	-.00084	-.00034
10	*	.00185	.00113	.00150	.00117	.00125	.00157	.00090	.00141	-.00024	.00480	-.00076	.00002
11	*	.00022	-.00017	-.00011	-.00022	-.00075	-.00067	.00027	-.00014	-.00084	-.00076	.00941	.00375
12	*	-.00024	-.00074	-.00024	-.00069	-.00067	-.00028	.00078	-.00049	-.00034	.00002	.00375	.00763

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Table 4-3. MEAN VECTOR AND COVARIANCE MATRIX OF C5-17 SECTION B

C(5-17) SECTION B

MEAN VECTOR													
CHANNEL	*	1	2	3	4	5	6	7	8	9	10	11	12
2	*	.937	1.380	1.031	.977	.934	.791	.648	1.073	.604	.608	.397	.315
COVARIANCE MATRIX													
CHANNEL	*	1	2	3	4	5	6	7	8	9	10	11	12
1	*	.0526	.0189	.0133	.0141	.0178	.0111	.0142	.0182	.0161	.0083	-.00021	-.0057
2	*	.00189	.00935	.00556	.00464	.00436	.00327	.00289	.00600	.00333	.00375	.00141	.00033
3	*	.00133	.00556	.00978	.00452	.00447	.00352	.00241	.00571	.00305	.00322	.00059	.00060
4	*	.00141	.00464	.00452	.00774	.00448	.00346	.00207	.00456	.00296	.00323	.00152	.00025
5	*	.00178	.00436	.00447	.00448	.01037	.00598	.00269	.00646	.00352	.00452	.00253	.00063
6	*	.00111	.00327	.00352	.00346	.00598	.00836	.00211	.00514	.00292	.00242	.00205	.00101
7	*	.0142	.00289	.00241	.00207	.00269	.00211	.00671	.00532	.00346	.00199	.00139	.00121
8	*	.00182	.00600	.00571	.00456	.00646	.00514	.00532	.01223	.00547	.00435	.00290	.00146
9	*	.00161	.00333	.00305	.00296	.00352	.00292	.00346	.00547	.00655	.00183	.00124	.00089
10	*	.00083	.00375	.00322	.00323	.00452	.00242	.00199	.00435	.00183	.00615	.00280	-.00043
11	*	-.00021	.00141	.00059	.00152	.00253	.00205	.00139	.00290	.00124	.00280	.00615	-.00005
12	*	.00057	.00033	.00060	.00025	.00063	.00101	.00121	.00146	.00089	-.00043	-.00005	.00464

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Table 4-4. DIVERGENCE MATRIX USING ALL 12 CHANNELS

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FIELD	1	2	3	4	5	6	7	8	9	10	11	12
1	0	130.178	53.767	29.861	90.544	53.447	32.300	34.100	98.590	101.669	30.995	111.866
2	0	0	70.901	148.435	3.303	63.591	133.485	201.396	96.357	5.675	69.853	73.353
3	0	0	0	78.715	51.752	18.355	33.987	86.998	10.939	52.859	14.516	51.710
4	0	0	0	0	80.121	22.347	19.341	138.954	31.482	115.938	11.217	58.848
5	0	0	0	0	0	36.430	93.525	191.596	70.361	9.922	46.503	63.304
6	0	0	0	0	0	0	21.782	125.419	14.521	54.010	5.534	32.697
7	0	0	0	0	0	0	0	109.757	10.551	112.519	9.652	89.001
8	0	0	0	0	0	0	0	0	87.246	178.047	84.181	125.607
9	0	0	0	0	0	0	0	0	0	80.602	7.249	36.028
10	0	0	0	0	0	0	0	0	0	0	57.702	76.894
11	0	0	0	0	0	0	0	0	0	0	0	27.584
12	0	0	0	0	0	0	0	0	0	0	0	0

\*\*\*\*\*

FIELDS DESIGNATIONS

\*\*\*\*\*

C(5-17)	SEC-A	IS	FIELD 1
C(5-17)	SEC-B	IS	FIELD 2
C(5-17)	SEC-C	IS	FIELD 3
C(5-21)	SEC-A	IS	FIELD 4
C(5-22)	SEC-B	IS	FIELD 5
C(5-22)	SEC-C	IS	FIELD 6
C(5-3)	SEC-A	IS	FIELD 7
C(5-3)	SEC-B	IS	FIELD 8
C(5-3)	SEC-C	IS	FIELD 9
C(5-8)	SEC-A	IS	FIELD 10
C(5-8)	SEC-B	IS	FIELD 11
C(5-8)	SEC-C	IS	FIELD 12

\*\*\*\*\*

NOT REPRODUCIBLE

Table 4-5. CONTRIBUTION TO THE DIVERGENCE MATRIX FROM COVARIANCE MATRICES

TRACE1 MATRIX USING ALL 12 CHANNELS

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*****
FIELD  *  1      2      3      4      5      6      7      8      9      10     11     12
-----
1  *  0      7.155  16.371  -8.069  -6.352  -5.313  7.609  9.006  6.306  6.636  4.549  21.424
2  *  0      0      24.521  -4.290  3.749  6.504  3.938  7.039  3.562  6.769  27.001
3  *  0      0      0      5.457  21.898  8.483  21.646  23.677  18.420  20.014  15.730  48.868
4  *  0      0      0      0      -7.467  -3.840  -0.763  2.170  -3.113  -5.836  -8.494  -6.049
5  *  0      0      0      0      0      3.751  11.572  16.761  8.320  4.163  4.396  20.624
6  *  0      0      0      0      0      0      7.846  17.761  4.738  2.762  3.176  15.158
7  *  0      0      0      0      0      0      0      9.689  3.449  9.471  7.795  28.289
8  *  0      0      0      0      0      0      0      0      7.728  11.072  13.805  44.448
9  *  0      0      0      0      0      0      0      0      0      6.997  6.082  23.897
10 *  0      0      0      0      0      0      0      0      0      0      5.798  29.554
11 *  0      0      0      0      0      0      0      0      0      0      0      16.269
12 *  0      0      0      0      0      0      0      0      0      0      0      0
-----

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Table 4-6. CONTRIBUTION TO THE DIVERGENCE MATRIX FROM MEAN VECTORS  
TRACE2 MATRIX USING ALL 12 CHANNELS

NOT REPRODUCIBLE

\*\*\*\*\*

FILE	*	1	2	3	4	5	6	7	8	9	10	11	12
1	*		223.201	91.163	67.791	174.732	101.577	56.990	59.194	70.795	196.702	57.441	202.308
2	*		0	117.231	301.160	2,858	120.623	258.033	392.719	185.676	7,787	132.936	119.704
3	*		0	0	151.974	81,506	28.187	46.329	150,318	3.459	85,703	13.302	54.552
4	*		0	0	0	167.710	48.533	39.445	275,737	66.077	267,711	30.928	123.746
5	*		0	0	0	0	69.109	175.479	366.432	132.402	15,680	88.611	185.984
6	*		0	0	0	0	0	35.718	233.077	24.305	105,258	7.892	50.236
7	*		0	0	0	0	0	0	209.825	17.653	215,567	11.508	149.713
8	*		0	0	0	0	0	0	0	166.764	345,021	154.557	206.767
9	*		0	0	0	0	0	0	0	0	154,208	8.417	48.159
10	*		0	0	0	0	0	0	0	0	0	109.605	124.234
11	*		0	0	0	0	0	0	0	0	0	0	38.900
12	*		0	0	0	0	0	0	0	0	0	0	0

\*\*\*\*\*

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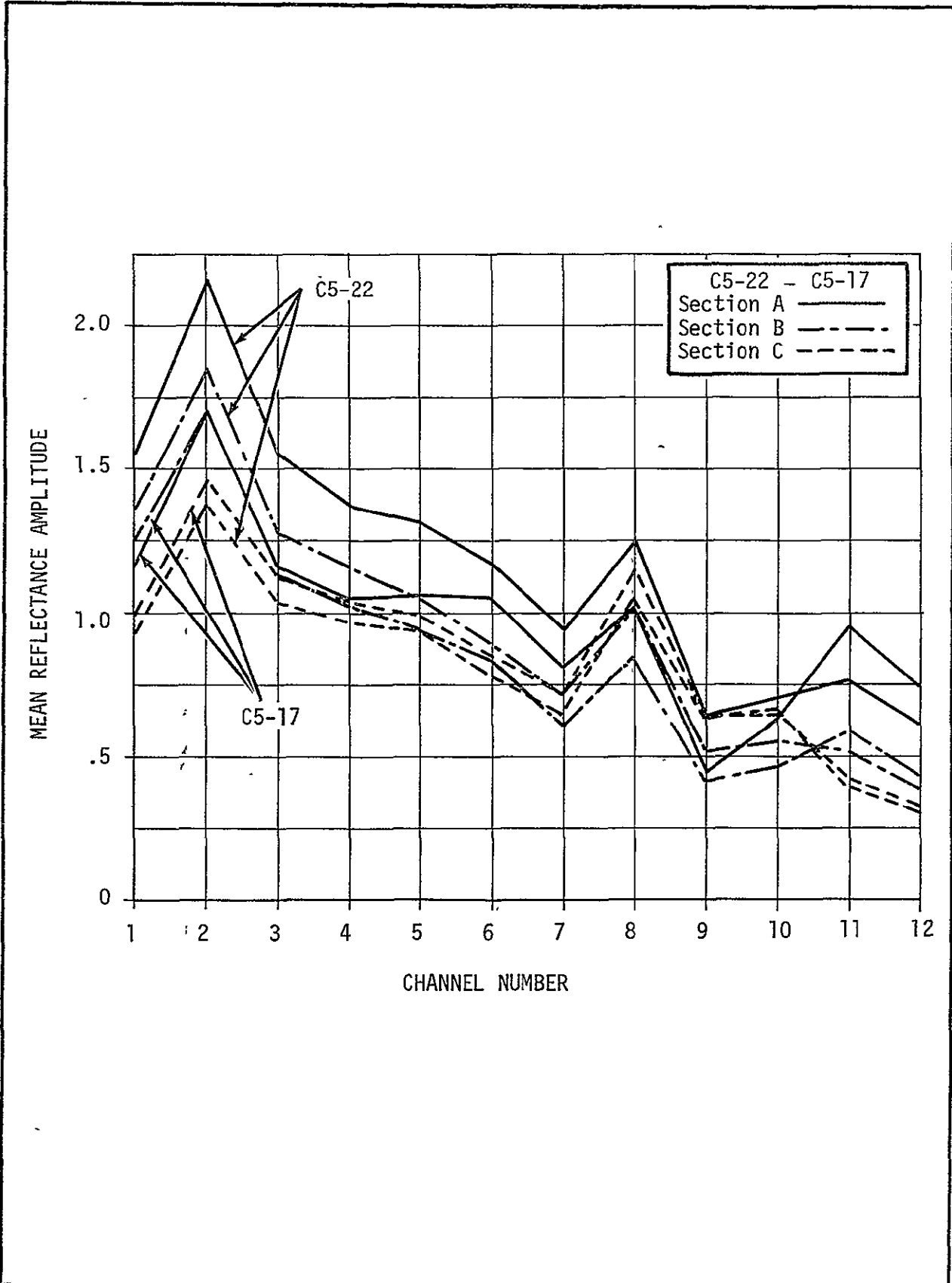


Figure 4-29. MEAN SPECTRAL VECTORS OF THREE HOMOGENEOUS SECTIONS IN FIELDS C5-17 AND C5-22

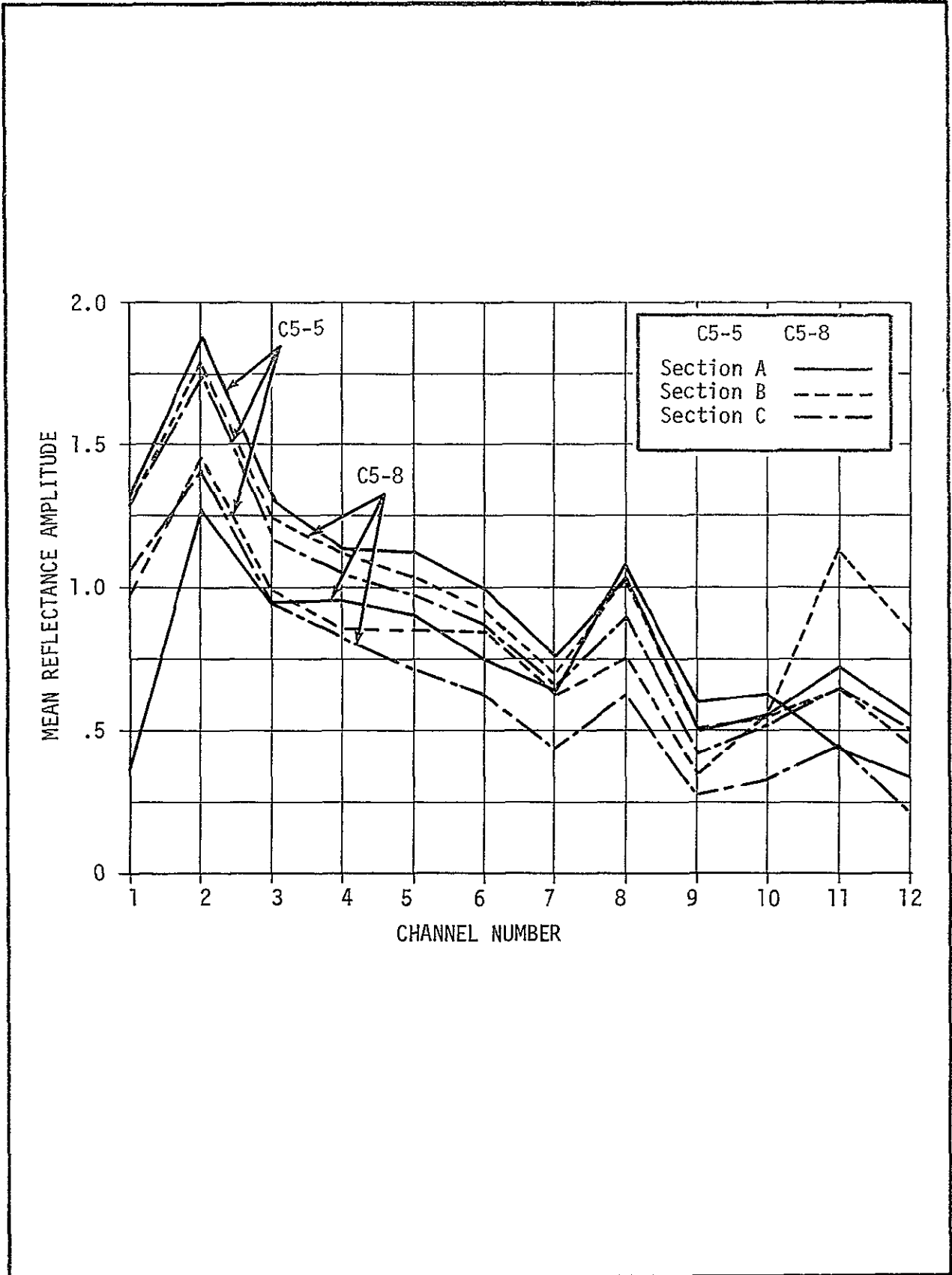


Figure 4-30. MEAN SPECTRAL VECTORS OF THREE HOMOGENEOUS SECTIONS IN FIELDS C5-5 AND C5-8



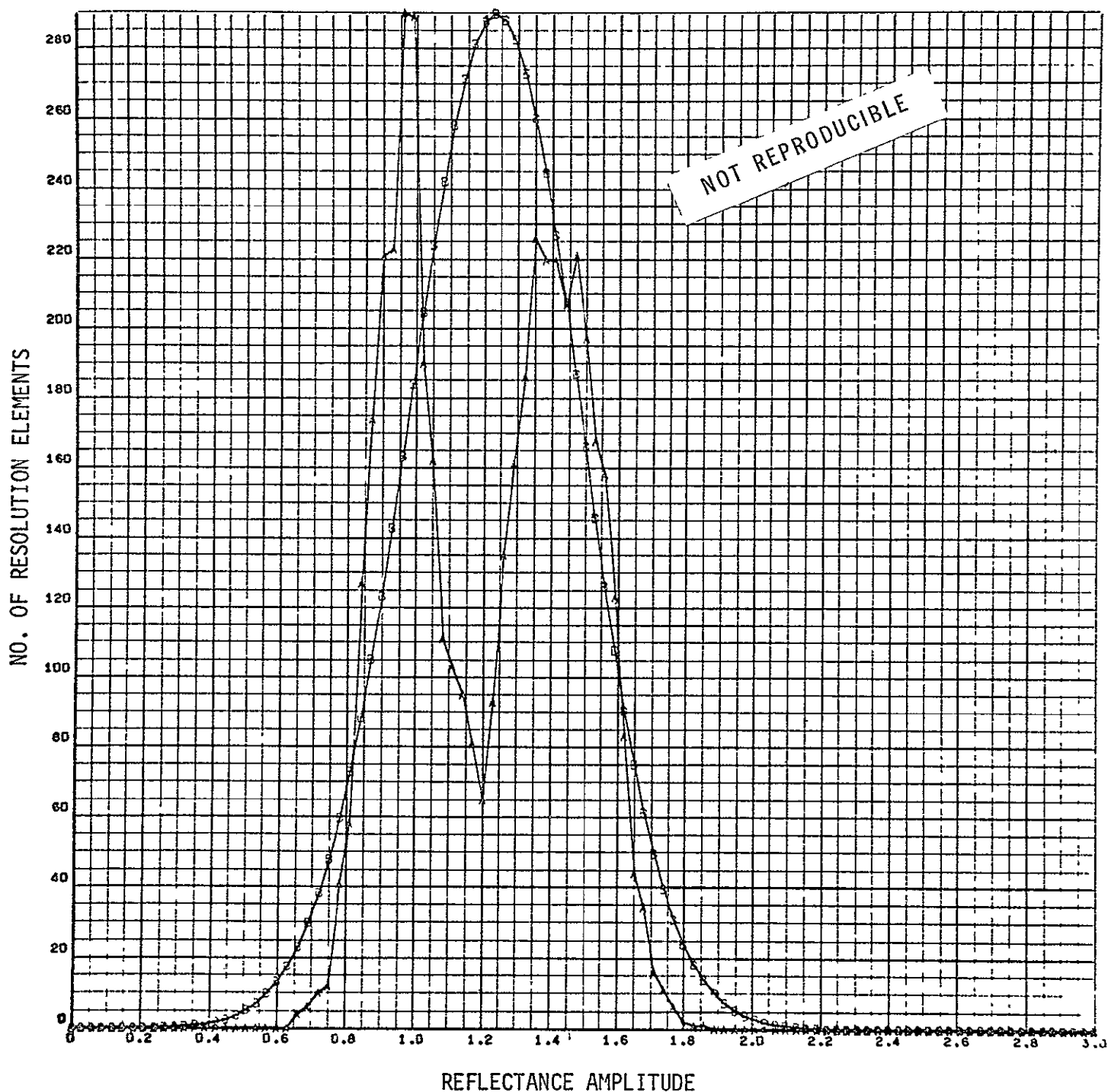


Figure 4-31. UNIVARIATE HISTOGRAM OF CHANNEL 1 OF ENTIRE FIELD C5-22

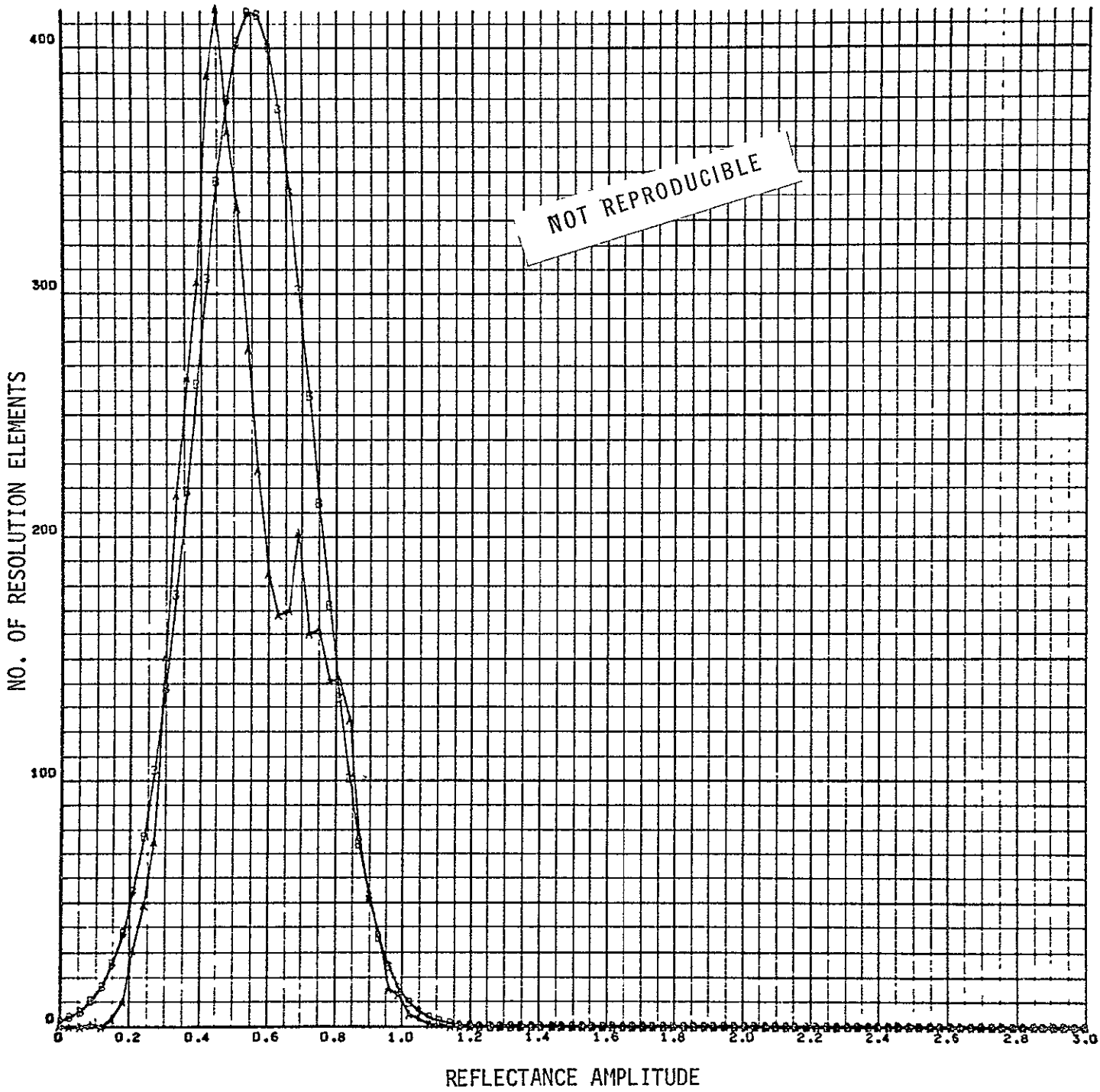


Figure 4-32. UNIVARIATE HISTOGRAM OF CHANNEL 2 OF ENTIRE FIELD C5-22

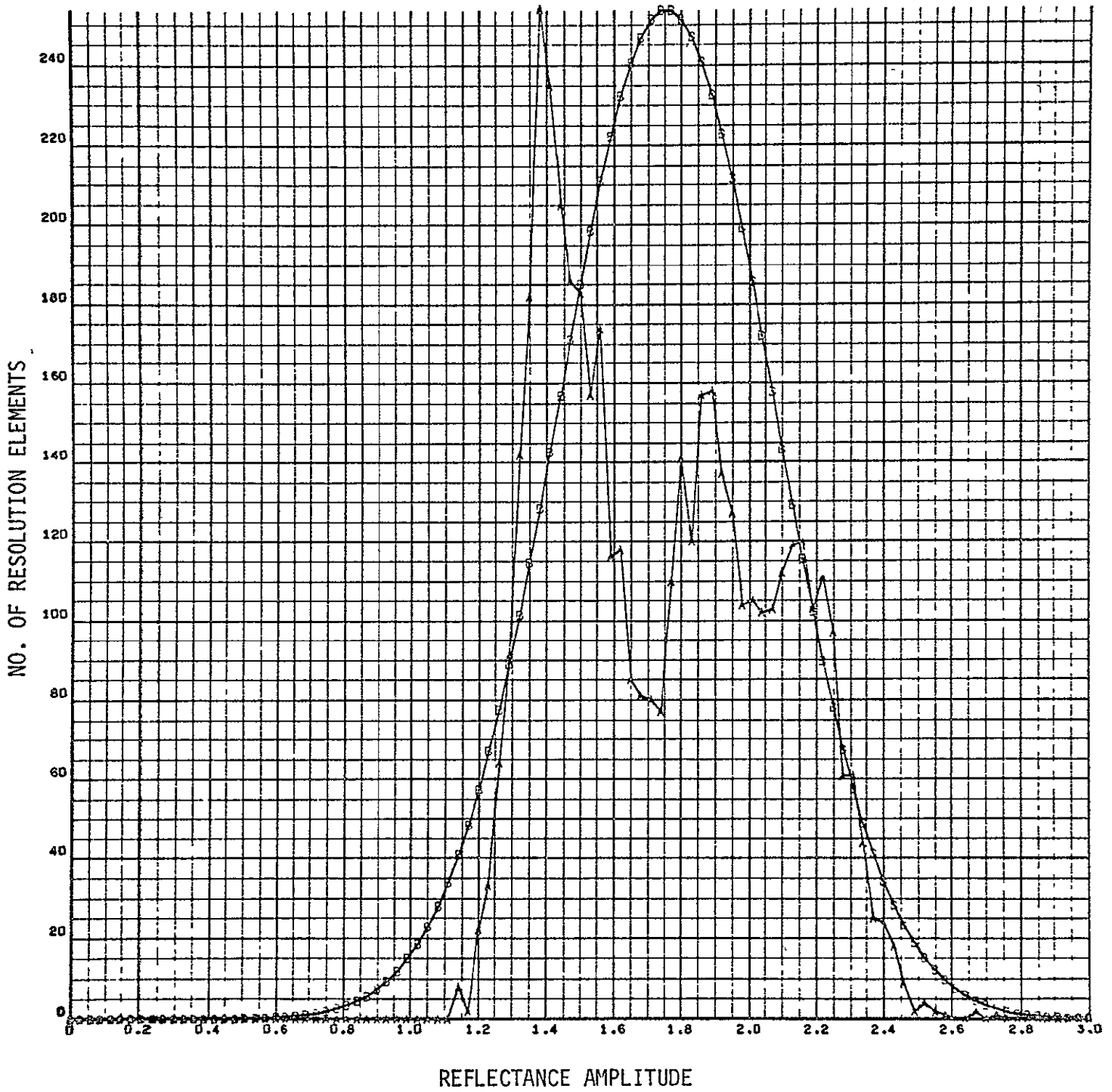


Figure 4-33. UNIVARIATE HISTOGRAM OF CHANNEL 11 OF ENTIRE FIELD C5-22

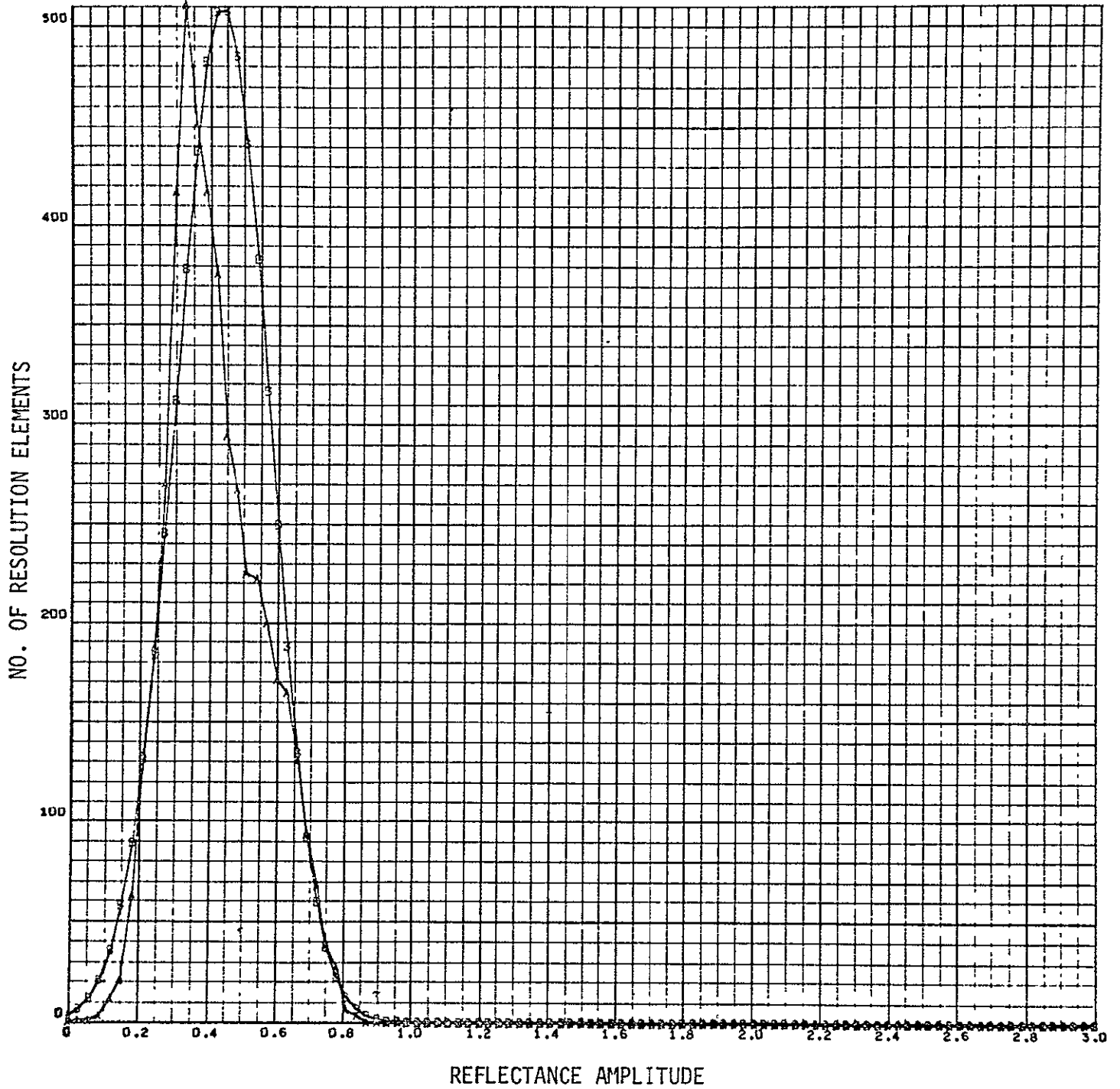


Figure 4-34. UNIVARIATE HISTOGRAM OF CHANNEL 12 OF ENTIRE FIELD C5-22

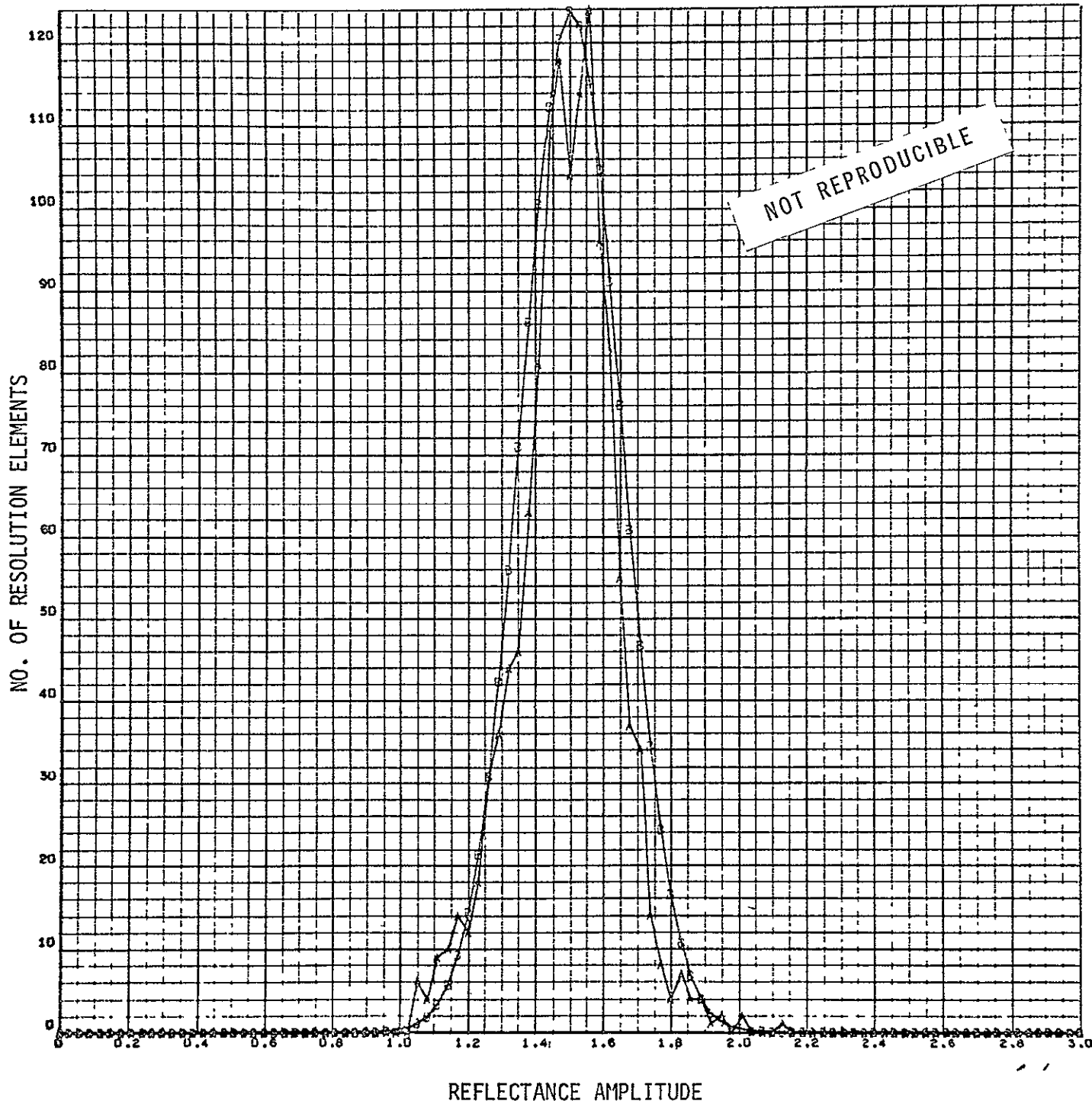


Figure 4-35. UNIVARIATE HISTOGRAM OF CHANNEL 1 OF C5-22, SECTION A

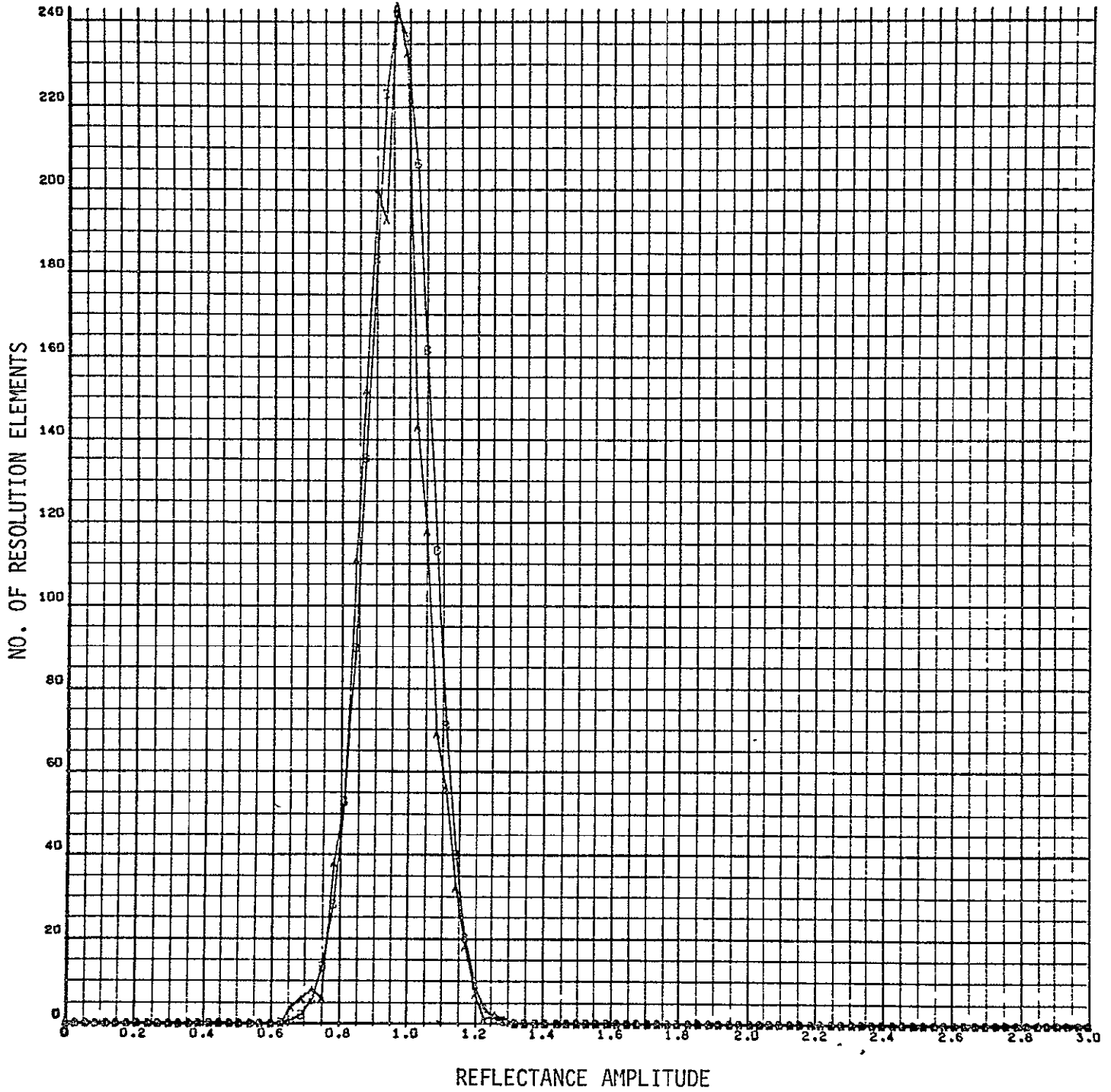


Figure 4-36. UNIVARIATE HISTOGRAM OF CHANNEL 1 OF C5-22, SECTION B

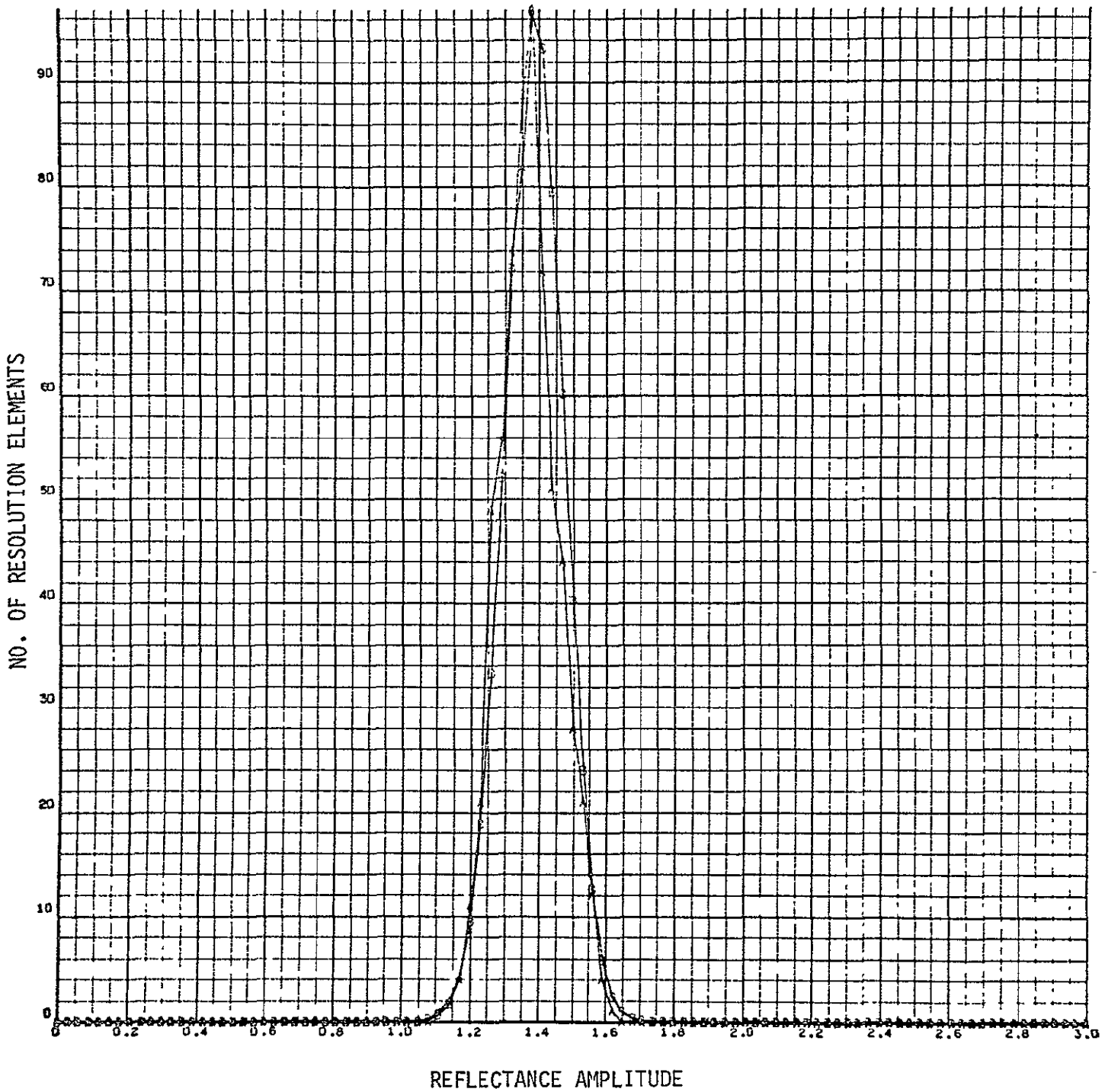


Figure 4-37. UNIVARIATE HISTOGRAM OF CHANNEL 1 OF C5-22, SECTION C

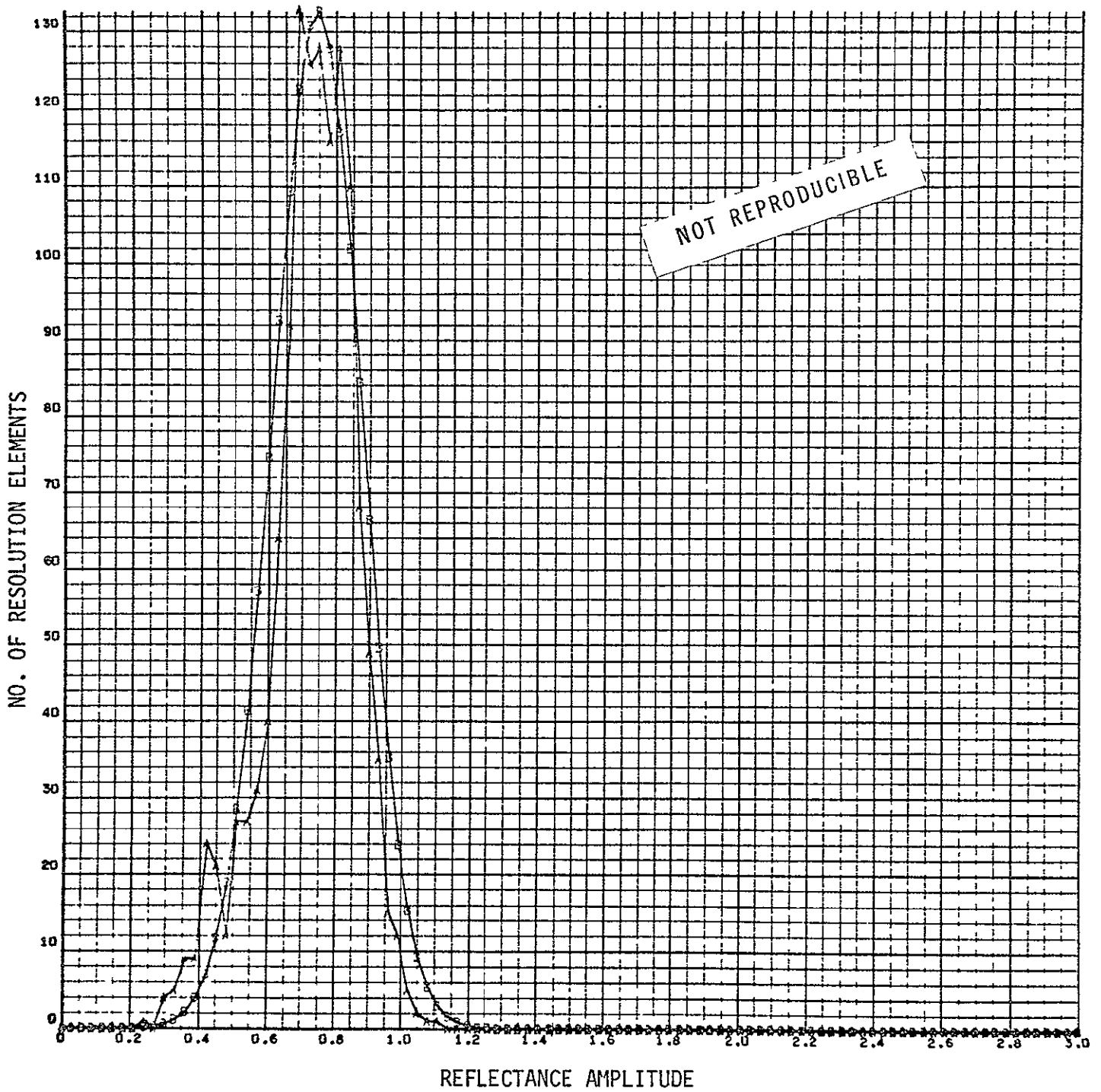


Figure 4-38. UNIVARIATE HISTOGRAM OF CHANNEL 11 OF C5-22, SECTION A



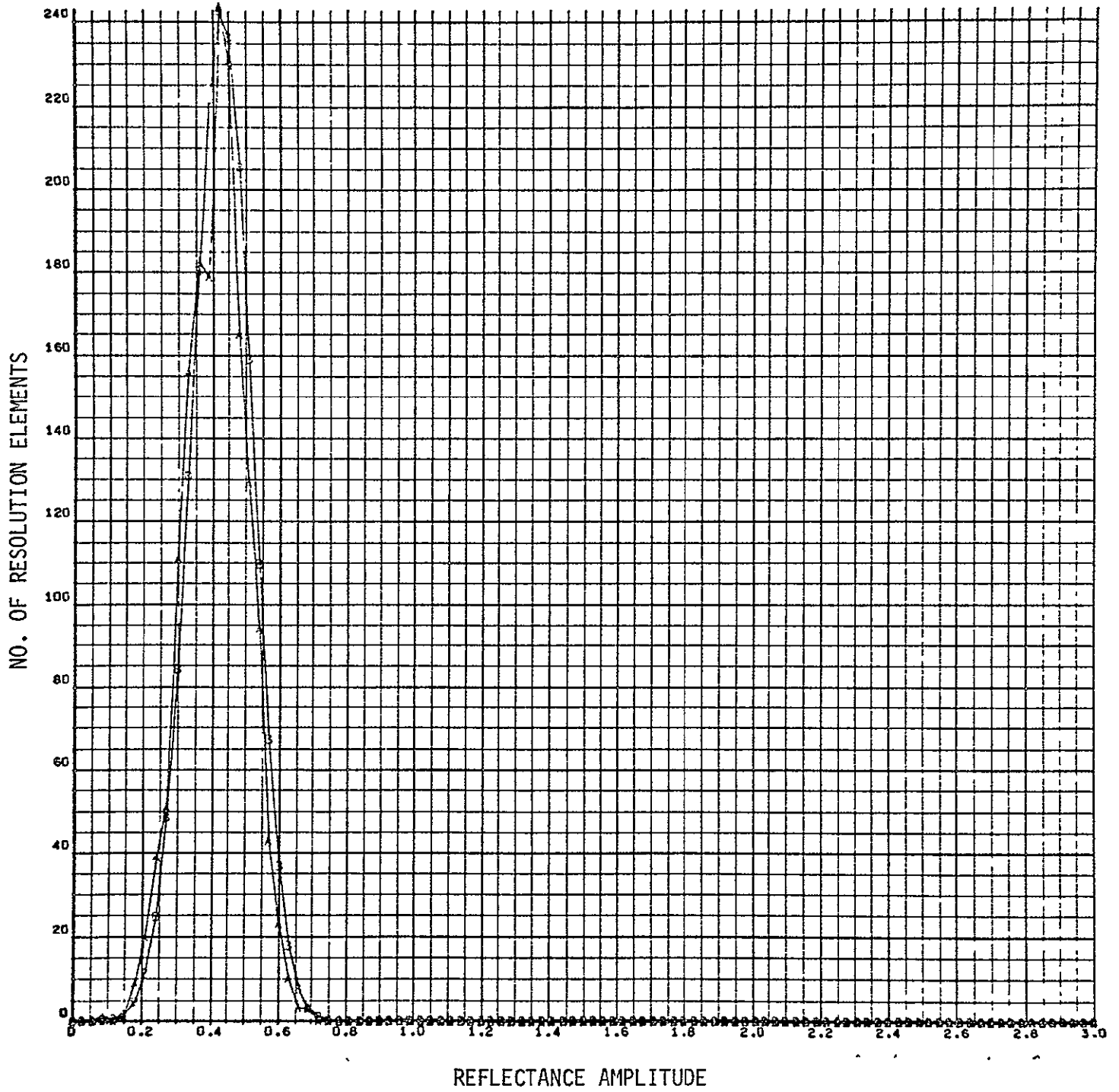


Figure 4-39. UNIVARIATE HISTOGRAM OF CHANNEL 11 OF C5-22, SECTION B

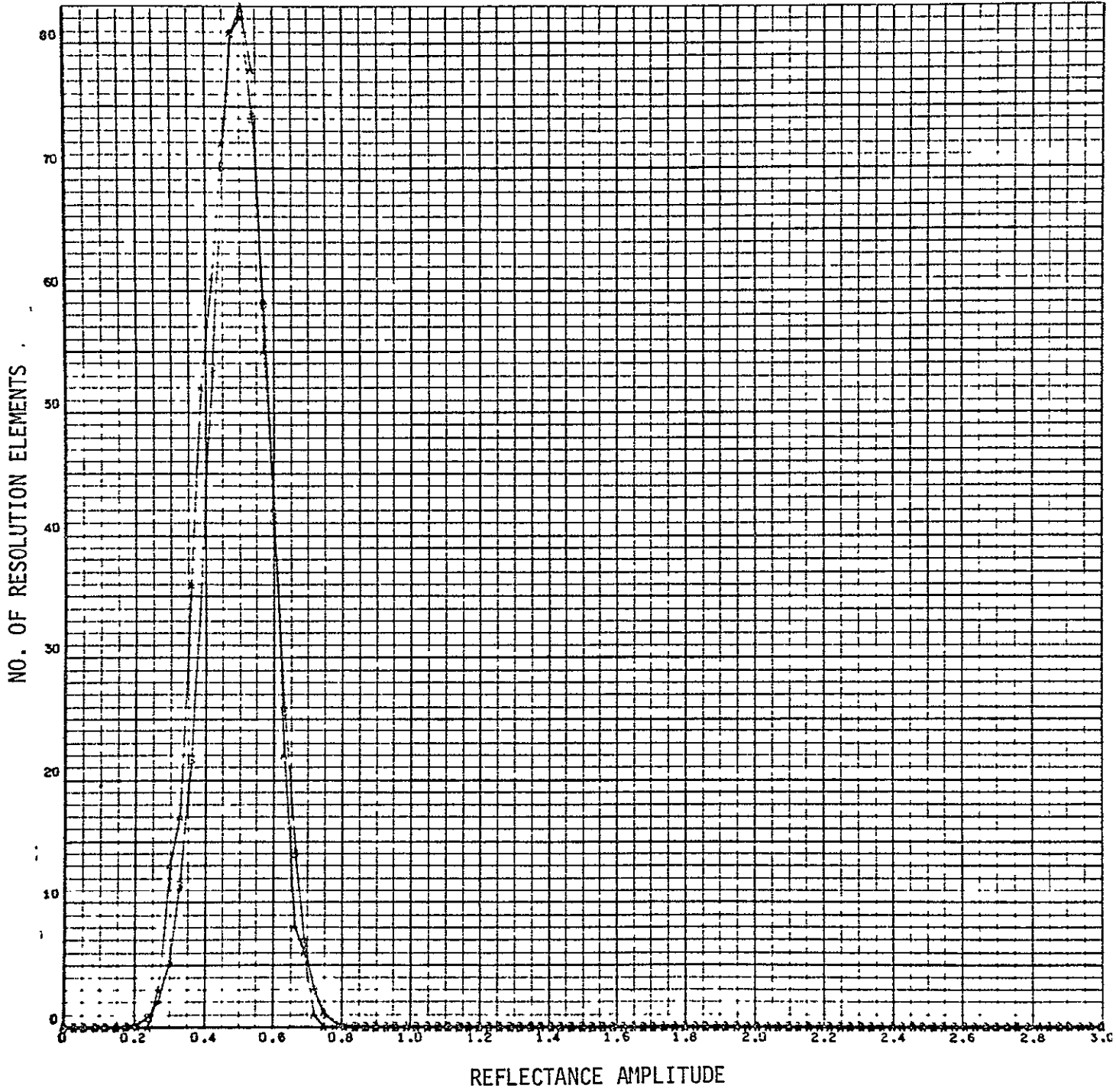


Figure 4-40. UNIVARIATE HISTOGRAM OF CHANNEL 11 OF C5-22, SECTION C

## Section V

### SUMMARY AND CONCLUSIONS

The most significant results of this study are the development of two statistical algorithms for determination of inventory boundaries within a target area from multispectral remotely sensing data without reference to any ground truth or training data. The samples within each individual area bounded by the inventory boundaries, called an inventory area, constitute a homogeneous population. The first algorithm is based on a principle of boundary enhancement which involves area smoothing and taking absolute value of the 2-directional difference of the smoothed data. The second algorithm is based on the statistical variation of the multispectral data and the confidence limit of the statistical estimation. The two algorithms are thus basically opposite in their underlying principles, since the first relies more heavily on the mean of the data; while the second relies more heavily on the variation of the data about the mean. As such, they really compensate each other. These two algorithms have been implemented into digital computer programs.

In addition, several other computer programs have also been developed for general statistical analysis of multispectral data. Specifically, these programs are for calculating the mean vector, correlation matrix, covariance matrix, and univariate probability density distribution from the inventory area, and for calculating the divergence matrix among various inventory areas. The divergence is a statistical measure for separability or dissimilarity between inventory areas. Also developed is a grey level plotting program for 2-dimensional digital display of a single-channel record which may be either raw data or final classified output data.

The capability of the above computer programs for automatic determination of inventory boundaries has been successfully demonstrated on a set of remotely sensed data obtained by the University of Michigan Multispectral Scanner over some agricultural fields at a flight altitude of 2000 feet.

The most important advantage of the data analysis methods is data compression which is accomplished by replacing voluminous raw data samples by the

location of inventory boundaries and associated aerial average over the inventory area. Two to three orders of magnitude of reduction in data flow rate and total computation time may result.

One drawback of the two algorithms for inventory boundary detection is that the boundaries sometimes do not close. To remedy this drawback, a new algorithm for automatic sequential classification of multispectral data into homogeneous populations (without reference to any training set) has been proposed (ref. 13). The performance of the new algorithm will be reported in the future, for it has not yet been implemented.

Section VI  
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## Appendix A

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