

PRACTICAL ASPECTS OF CORRESPONDENCE FACTOR ANALYSIS  
AND RELATED MULTIDIMENSIONAL METHODS

BY

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## A C K N O W L E D G E M E N T S

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## I N T R O D U C T I O N

Correspondence Factor Analysis is a multivariate technique which general aim is to find associations and oppositions between subjects and variables, as in other multivariate methods. Its advantages compared to other methods are related to its more sophisticated mathematics and its simultaneous representation of subjects and variables on the same factorial axes. Theoretically the method is shown to be equivalent to a special case of Hotelling's canonical correlation analysis and also to a scale-free variant of Principal Components Analysis.

Correspondence Factor Analysis is developed by Prof. J.P. Bénézecri at the Mathematical Statistics Laboratory, Faculty of Science, Paris. The name "Correspondence Analysis" is a translation of J.P. Bénézecri's "Analyse Factorielle des Correspondances".

In Chapter 1 we discuss the domain of Correspondence Analysis and give a description of the data tables to which Correspondence Analysis has been applied.

Chapter 2 introduces the formulation of Correspondence Analysis. We present the theory how to compute the factors and explain the computation of the contributions. Furthermore we discuss the input data matrix and some of its restrictions.

Chapter 3 describe the results of the analysis which form the output of the programs in Chapter 4. We explain systematic methods of interpreting the listings produced by the computer, referring to Chapter 4's example on Israeli rainfall. Finally in Chapter 3 we gives a table which explain the differences between Principal Component Analysis and Correspondence Analysis. I would like to mention at this stage that most of the theory given in Chapter 1, Chapter 2 and Chapter 3 is take from Col. 2 of Prof. J.P. Bénézecri's

"L' Analyse des données" which was translated by Michael Greenacre.

Useful ideas were also taken from an article "Correspondence Factor Analysis: An Outline of its Method by H. Teil in the Mathematical Geology, Vol 7, No. 1, 1975 page 3-12.

In Chapter 5 we discuss function plots of High-Dimensional Data. Furthermore we imply Andrew's method on the factors computed by Correspondence Analysis.

Finally in Chapter 6 we explain the theory of Multidimensional Scaling together with an example based on the factors as plotted in Chapter 5.

## C H A P T E R 1.

### 1.1 INTRODUCTION.

In this section we consider the different types of data sets to which correspondence analysis has been applied. Correspondence factor analysis may be applied to any type of data and to any number of data points.

The main types of data are

- (1) Homogeneous data
- (2) Heterogeneous data
- (3) Exhaustive data

The best types of data are finite sets  $I$  and  $J$  with whole positive numbers, e.g., data from questionnaires and surveys because these numbers are independent of any unitary system. Attention must be paid to the unit of measure used in a study of a homogeneous data set so that it has the same meaning throughout the matrix. The best method of handling heterogeneous data is to use a logical code, i.e., divide each variable into classes of similar probability and consider each value as being present or absent in each class. Starting from the treatment of frequency tables, where one can check the validity of the results using a probability model, we shall gradually extend the argument to the treatment of several different kinds of data sets.

### 1.2 FREQUENCY TABLES.

This is the simplest type of data considered suited to correspondence analysis. Let us take two finite sets  $I$  and  $J$ ; a probability distribution  $p_{IJ} = \{p_{ij} | i \in I, j \in J\}$  on the Cartesian product  $I \times J$  may also be considered as a system of nonnegative point masses with total sum equal to 1, each of these masses being assigned to a couple  $(i,j)$  comprising an element  $i$  of  $I$  and an element  $j$  of  $J$ .



The easiest case is met when one logs the occurrences of independent events  $(i,j)$  which are the conjunction of the realization of an element  $i$  of  $I$  and an element  $j$  of  $J$ . If  $k(i,j)$  is the number of times one has observed the outcome of the event  $(i,j)$  and  $k$  is the total number of events observed, an estimate of the probability  $p_{ij}$  is given by the frequency  $f_{ij} = k(i,j)/k$ .

The simplest mathematical structure of the data can be described as follows: first two finite sets  $I$  and  $J$  given "a priori", and secondly an integer-valued nonnegative function  $k(i,j)$  that counts the independent or correlated events defined by simultaneous occurrence of  $i$  and  $j$ .

### 1.3 CONTINGENCY TABLES.

If all the  $k(i,j)$  are quantities of the same nature, for example all mass or all amounts of money, the choice of the units of measurement (e.g. kilogram or rand) does not affect the result of the analysis. This is due to the fact that a change in units is equivalent to the multiplication of all the  $k(i,j)$  by a common coefficient; consequently the  $f_{ij} = k(i,j)/k$  remain unchanged. In fact even if the quantities  $k(i,j)$  are not expressed as rational fractions of some common unit, the particular choice of this unit is of no consequence to the results. We shall thus analyse as contingency tables those composed of homogeneous quantities (e.g. expenditures or income expressed in dollars) and those composed of integers counting population rather than events (e.g. number of persons practising a profession  $i$  in a given area  $j$ ); here  $k(i,j)$  is the weight of  $j$  (or number of  $j$ 's) in  $i$ .

As regards the product set  $I \times J$  used as framework for our observations it will often not appear at first glance as the product of two definite sets. Let us for example think of a study of the expenditures of the

R.S.A. citizens. The first set,  $I$  = the R.S.A. citizens, is too large for a detailed study; the second,  $J$  = the expenditures, is rather a continuum and its division into a finite number of classes presents a tricky problem. Specialists in economics of expenditure usually split the household's budget into a few dozen categories, say 50, and this practice should be accepted at first by the statistician. The advantage of correspondence analysis in such a situation is that, thanks to the principle of distributional equivalence (p. 11 Dis.  $\chi^2$  Corr.), the analysis is only slightly sensitive to the detail of the partition adopted.

For practical considerations it is clear that we cannot consider the complete set of R.S.A. citizens, but merely a sample the size of which does not exceed the capabilities of the available set of investigations. We see the choice of set  $J$  leads to the same kind of problems as those presented by the choice of  $I$ ; in both cases the principle of distributional equivalence favours the stability of the results. Furthermore as in correspondence analysis the value of the computed factors for each individual  $i$  (or  $j$ ) does not depend on the total mass but rather on the profile of each row (or column) describing this individual, elements of different magnitudes can be mixed in an analysis.

Let us discuss contingency table analysis as correspondence analysis is defined algebraically equivalent to Fisher's contingency table analysis. It was first published by Hirschfield(1935), but since that time it has suffered widespread neglect, and has been rediscovered by Guttman(1959). Hirschfield's treatment of the topic is clear and succinct, but was not cited by Fisher(1940). As a result, Fisher has frequently been regarded as the method's first inventor.

Thus, given on  $m \times n$  contingency table  $A = [a_{ij}]$ , specifying the counts of joint occurrences of two discrete variates, let  $K = (I, J)$  be

the bivariate random variable specifying the outcome of each individual observation from which the table was assembled. The count  $a_{ij}$  is then simply the number of times that the random variable  $K$  assumed the value  $(i,j)$  in the observed sample. Fisher's "contingency table analysis" consists of looking for functions  $f,g$  defined on the ranges of  $I,J$ , such that the correlation of the derived random variables  $f(I)$ ,  $g(J)$  is a maximum. Rephrasing the contingency table analysis amounts to looking for scores  $X = (x_1, \dots, x_m)^T$  and  $y = (y_1, \dots, y_n)^T$ , such that when the functions  $f$  and  $g$  are defined by the relations  $f(i) = x_i$  and  $g(j) = y_j$ , then the correlation of the random variables  $f(I)$  and  $g(J)$  is a maximum. Other expositions of this approach are given in Williams(1952), Kendall and Stuart(1961,p.569), Bénzecri(1969) and Lancaster(1969).

#### 1.4 MEASUREMENT TABLES.

For contingency tables we were careful to maintain two important properties regarding the data: homogeneity and exhaustivity. By homogeneity we mean that all the entities presented in the table are of the same nature. By exhaustivity we mean that the sets  $I$  and  $J$  represent a complete investigation of a natural phenomenon.

Suppose we are studying the distribution of commercial activity of Johannesburg. It is possible to follow the existing rule of subdivision of the city into 30 districts, thus defining  $I$ . As regard the commercial activity, the set  $J$ , it is feasible to subdivide it, say, into 10 classes. Now, by defining  $K(i,j) =$  number of shops of type  $j$  in district  $i$ , have we thus satisfied the condition of homogeneity? Probably not, as with our numbering scheme we must want one individual for a large store as well as for a very small tobacconist. Even if one takes care to count the small tobacconists and the stores in different

columns  $j$ , homogeneity is not satisfied because the unit of measurement chosen, the firm, does not have the same meaning in the two cases presented. We should thus replace our simple counting scheme for example, by a measurement  $k(i,j)$  = surface occupied by the firm in the district  $i$ . It is necessary to choose a unit of measurement which bears the same meaning over the entire range of the table. Too large a difference in quantity between the large store and the tobacconist introduces here a qualitative heterogeneity.

We have gradually moved from the study of contingency tables to that of a larger set of measurement tables. The set  $I$  is now a set of individuals supposedly representative of a potentially interesting population which is generally very large and more or less well defined, for the human race. The set  $J$  is a set of measurements constructed in such a way that the vector  $\{k(i,j)|j \in J\}$  (the  $j$ -th row of the table) is a satisfactory description of the individual  $i$  relative to the scope of the study. One may think of  $J$  as a sample of the set of all the variables that could be measured, nevertheless it is certainly true that the concepts of exhaustivity and equal weighting are now met in a very weak sense. The arbitrariness in the choice of the framework of the study (namely the set  $I \times J$ ) has become rather large.

#### 1.5 LOGICAL DESCRIPTION TABLES.

It has been noticed several times that one of the best ways of reducing a heterogeneous data matrix to a common unit is to use a logical coding scheme, i.e. where each measurement scale is replaced by a partition into classes of approximately equal probability, where instead of using a real-valued measurement one simply records whether the value falls into a certain class. For example, we can represent one measurement  $j$  by three columns  $j_1, j_2, j_3$ , so that for an individual  $i$  for

for which the value  $j$  is small and falls into the first class we shall record:

$$k(i, j_1) = 1; \quad k(i, j_2) = 0; \quad k(i, j_3) = 0$$

or where the value is fairly high, in the domain of class 2 and 3:

$$k(i, j_1) = 0; \quad k(i, j_2) = \frac{1}{2}; \quad k(i, j_3) = \frac{1}{2}$$

We can thus substitute a scheme of continuous measurements by a family of classes of logically coded variables.

We talk of a logical description table when the  $k(i, j)$  assume the value 1 or 0 in a Boolean sense:  $k(i, j) = 1$  means that individual  $i$  has property  $j$  and  $k(i, j) = 0$  means that  $i$  does not have property  $j$ . It is possible to code various types of information in this way, for example plant  $j$  grows in area  $i$ , or student  $i$  gives the answer  $j$ .

We say that a logical description table is in complete disjunctive form if the following condition is satisfied: the set of columns (or properties)  $J$  is divided into a family  $Q$  of subsets (or questions)  $q$  such that:

$$\forall i \in I, \forall q \in Q, \exists j \in Q: (k(i, j) = 1 \quad (j' \in q; j' \neq j) \Rightarrow k(i, j') = 0)$$

In other words each individual  $i$  has in each class  $q$  one and only one property  $j$ . One can think of  $Q$  as a "questionnaire"; to each question  $q \in Q$  the subject  $i$  may answer by selecting a set of attitudes in which the abstention can be included; to each of these attitudes is assigned a column  $j$  of the matrix  $k_{I \times J}$ ; if  $i$  gives the answer  $j$  to the question  $q$  then  $k(i, j) = 1$  and for any other  $j' \in q$ ,  $k(i, j') = 0$ . In the particular case where the abstention is

not considered and where all the questions only allow answers yes or no for each question  $q$ , only two attitudes  $q^+$  and  $q^-$  (yes-no) are possible, so that:

$$J = Q^+ \cup Q^- = \cup \{ \{q^+, q^-\} \mid q \in Q \}$$

The person  $i$  who answers yes to  $q$  has  $k(i, q^+) = 1$ ,  $k(i, q^-) = 0$ ; and the one  $i'$  who answers no has  $k(i', q^+) = 0$ ,  $k(i', q^-) = 1$ .

From a mathematical point of view a table  $k_{IJ}$  in complete disjunctive form presents the great advantage that the results of a correspondence analysis are equivalent to those obtained by analyzing a true contingency table. More precisely it can be shown that if  $t_{JJ}$  is the symmetric correspondence matrix with integer values on  $J \times J$  such that,

$$t(j, j'') = \text{Card} \{ i \mid i \in I; k(i, j) = k(i, j'') = 1 \} \quad \text{then the factors}$$

$\phi^J$  (functions on  $J$  of mean 0 and variance 1)

computed from  $t_{JJ}$  are the same as those computed from  $k_{IJ}$ ; the eigenvalues computed from  $t_{JJ}$  are the square of those computed from  $k_{IJ}$ .

#### 1.6 INTENSITY LEVEL TABLE.

Another type of data commonly considered is a table  $k_{IM}$  which gives the following information on a set of individuals  $I$ : for each  $i \in I$ ,  $m \in M$ ,  $k(i, m)$  is an intensity level of each  $i$  between 0 and an upper bound  $\text{Max}_m$  which is usually the same for all the columns of matrix  $k_{IM}$ . A logical description table can be considered as a particular type of intensity level table in which all the intensity levels can take only the values 0 and 1. This analogy suggests a similar doubling of intensity level tables. To table  $k_{IM}$  is associated another table defined as follows:  $J$  is a set of all the couples  $m^+, m^-$

in which each subject under study has been doubled, so that

Card  $J = 2 \times \text{Card } M$ :

$$J = \cup \{ \{m^+, m^-\} \mid m \in M \}$$

In column  $m^+$  is recorded the initial value of the intensity level of subject  $m$ , and in column  $m^-$  is recorded the complement with respect to  $\text{Max}_m$ : We could for example chose  $\text{Max}_m$  as 20.

$$k(i, m^+) = k(i, m); \quad k(i, m^-) = \text{Max}_m - k(i, m)$$

We define  $k(i, m^+)$  as the intensity level and  $k(i, m^-)$  as the deficiency level.

The doubling concept also suggests another coding scheme which enables us to use correspondence analysis on tables with negative values. It is advisable to double each column with numbers of both signs into a positive part column  $m^+$  and a negative part column  $m^-$ . We have:

if  $k(i, m) > 0$  then  $k(i, m^+) = k(i, m)$  and  $k(i, m^-) = 0$ ;

if  $k(i, m) < 0$  then  $k(i, m^+) = 0$  and  $k(i, m^-) = -k(i, m)$

This method has been shown to be useful in practice. It can be very meaningful in certain cases; if for example  $k(i, m^+)$  is an amount of exportation then  $k(i, m^-)$  is the corresponding amount of importation.

### 1.7 MULTIDIMENSIONAL TABLES.

A rectangular table of numbers  $k_{IJ}$  can be considered as values of a two dimensional variable defined on the product  $I \times J$  of two finite sets. More generally a multidimensional table has elements of multidimensional variable defined on the product  $I_1 \times \dots \times I_p$  of several finite sets. For example if  $I$  is a set of countries,  $J$  a set of districts,  $T$  a set of time intervals (e.g. set of months). A ternary table of rainfall  $k_{I \times J \times T}$  may be defined

where  $k(i,j,t)$  is the rainfall in the country  $i$  of the district  $j$  during the month  $t$ .

Several methods have been developed for the analysis of multidimensional tables with a particular reference to those which are time dependant. Correspondence analysis of rectangular tables is applicable to the analysis of ternary tables and usually gives satisfactory results. In the rainfall example the product set  $I \times J \times T$  may be considered in several ways as the product of two sets, one of them being itself the product of two other sets : e.g.

$$I \times J \times T = (I \times T) \times J$$

Consequently the ternary table  $k_{I \times J \times T}$  may be presented as the rectangular table  $k_{(I \times T) \times J}$  with margins  $I \times T$  and  $J$ . A row  $(i,t)$  in this table will give the set of  $\text{Card } J$  elements which are rainfall  $k(i,t),j = k(i,j,t)$  for the country  $i$  during month  $t$  of district  $j$ . To the individual countries  $(I)$  we have substituted the individual countries at given month periods.

But we can equally consider that  $I \times J \times T = I \times (J \times T)$ . Now each line refers to a country  $i$  and gives the rainfall of all the months in the country i.e. the family indexed by  $(j,t) \in J \times T$  of the rainfall by country  $i$  of the district  $t$  at any month.



C H A P T E R 2.

2. FORMULATION OF CORRESPONDENCE ANALYSIS.

2.1 Data matrix (input)

Correspondence analysis takes into account the probabilistic character of a data matrix  $I \times J$  of positive numbers  $\{k(i,j) | i \in I, j \in J\}$ . This matrix could be obtained from the row data after different transformations as described above in section 1. The following notation is commonly used:

$$K = \Sigma\{k(i,j) | i \in I, j \in J\}$$

$k(i) = \Sigma\{k(i,j) | j \in J\}$ ;  $k(j) = \Sigma\{k(i,j) | i \in I\}$  where  $k$  is the total of all values  $i$  and  $j$  in the matrix.

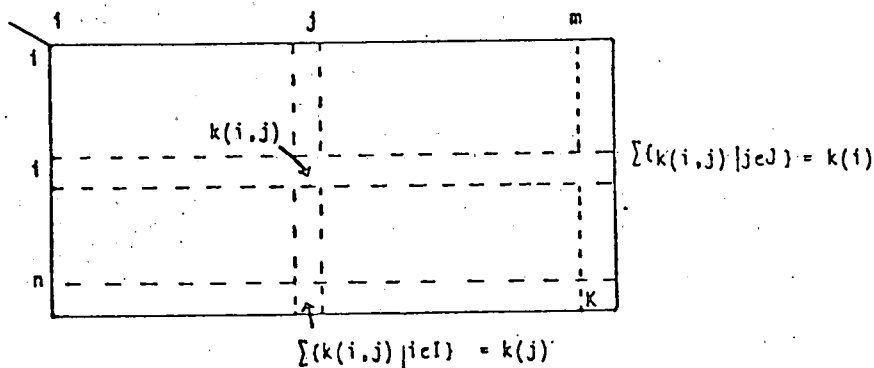


Figure 1. Data matrix  $I \times J$ .

We thus define a probability estimate matrix  $f_{IJ}$  of total sum 1:

$$f_{IJ} = \{f_{ij} | i \in I, j \in J\}; f_{ij} = k(i,j)/k$$

These formulae show that most of our computations will be performed as if  $f_{IJ}$  were a probability distribution on the finite set  $I \times J$  (set of pairs  $(i,j)$ ). Nevertheless one can in any case compute a  $\chi^2$  distance which is a purely algebraic concept. We write:

$$f_I = \{k(i)/k | i \in I\}; f_J = \{k(j)/k | j \in J\}.$$

These distributions are called marginal distributions of the matrix.

Because  $f_{iJ} = \{f_{ij} | j \in J\}$ ;  $f_{iJ} \in K_J$ , a probability law exists such that if we divide  $f_{iJ}$  by the total  $f_i$  of row  $i$  we obtain a distribution denoted by  $f_J^i$ :

$$f_J^i = f_{iJ} / f_i = \{f_{ij} / f_i | j \in J\}$$

$f_J^i$  is called the conditional distribution on  $J$  for a given  $i$ , as  $f_{ij}^i$  is in fact the relative weight of couple  $(i,j)$  amongst all the couples of the form  $(i,j')$  for  $j' \in J$ . If the actual data do not warrant a probabilistic interpretation, then  $f_J^i$  is known as the "profile" of the element  $i$  on  $J$ . The study of the "cloud"  $N(I)$  of profiles  $f_J^i$  with masses  $f_i$  is the aim of correspondence analysis. The cloud is considered in the space  $R_J$  with the  $\chi^2$  distance from the center  $f_J$ .

The  $\chi^2$  distance  $\|f_J^i - f_J^{i'}\|_{f_j}$  is called the distributional distance between  $i$  and  $i'$ . Simultaneously we consider in  $R_I$ , structured by the  $\chi^2$  distance centred at  $f_I$ , the cloud  $N(J)$  of the profiles  $f_I^j$  (or column profiles):

$f_I^j = \{f_{ij} | i \in I\}$  to which are respectively attached the masses  $f_j$ .

The  $\chi^2$  distance  $\|f_I^j - f_I^{j'}\|$  is given by

$$D^2(i, i') = \sum_{j=1}^P \{(f_J^i - f_J^{i'})\}^2$$

In order to eliminate the influence of certain variables which may have large absolute values compared to the rest, and therefore would give unbalanced results, each difference is divided by  $f_j$

(the sum of the column corresponding to the variables  $j$ ). The new formula is thus:

$$D^2(i, i') = \sum_{j=1}^m \{f_J^i - f_J^{i'}\}^2 / f_j$$

Also the cloud  $N(J)$  of profiles  $f_J^i$  with masses  $f_j$  is considered in the space  $R_I$  which has the  $\chi^2$  distance from the center  $f_I$ .

The principle of distributional equivalence is one of the advantages existing in correspondence analysis because it gives stability to the results. It is explained as follows: if  $j'$  and  $j''$  are two elements of  $J$  such that their corresponding column have the same profile i.e.,

$f_I^{j'} = f_I^{j''}$ , or  $f_I^{j'}$  is proportional to  $f_I^{j''}$ , then a column  $j^s$  equal to their sum can be substituted in their place without modifying the elements of  $I$ . The cloud  $N(J)$  is evidently not modified because one unique point  $f_I^{j^s}$  with mass  $f_j^I + f_j^{II}$  replace the two points.

## 2.2 Factorial axes and factors.

The cloud  $N(I)$  of  $f_J^i$  in  $R_J$  has for its center of gravity  $G$  the marginal profile  $f_J$  itself. Around this center, there are principal axes of inertia.

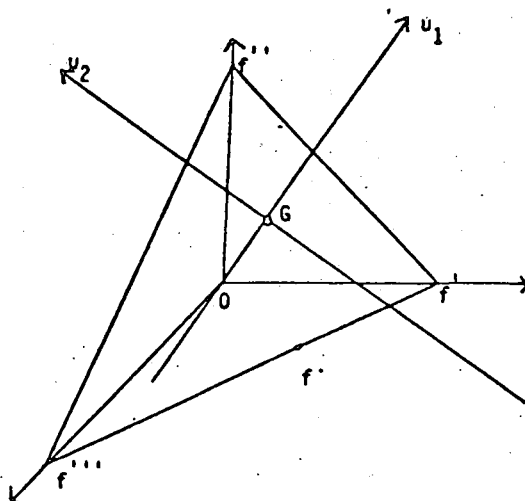


Figure 2. Set of factorial axes  $u_1$  and  $u_2$ .

It may be compared to the situation met with in mechanics where the axes of inertia for a system of weighted points need to be found. In a similar manner, axes are extracted by decreasing inertia in correspondence analysis.

In  $R_J$  the factorial axis of order  $\alpha$  is a unit vector  $u_{\alpha J}$  in the sense of the  $\chi^2$  metric. We denote by  $\phi_{\alpha}^J = (u_{\alpha J}/f_J)$  the density of this measure. The function  $\phi_{\alpha}^J$  has zero mean and owing to the unitary property has a variance of 1:

$$\Sigma\{\phi_{\alpha}^J f_j | j \in J\} = 0 : \Sigma\{(\phi_{\alpha}^J)^2 f_j | j \in J\} = 1$$

The successive factorial axes are mutually orthogonal in the sense of the  $\chi^2$  metric. For the functions  $\phi_{\alpha}^J$  this property is expressed by:

$$\Sigma\{\phi_{\alpha}^J \phi_{\beta}^J f_j | j \in J\} = \delta_{\alpha\beta}$$

In this formula  $\delta_{\alpha\beta} = 0$  if  $\alpha \neq \beta$  and 1 if  $\alpha = \beta$ ; the two conditions of orthogonality and normalization (i.e. orthonormality) are thus expressed in a single formula. In the language of probability we would say that the functions  $\phi_{\alpha}^J$  are mutually independent on  $J$  with probability distribution  $f_J$ .

The cloud  $N(I)$  can be referenced relative to the system with origin at  $f_J$  and orthogonal axes  $u_{\alpha J}$ ; we shall denote by  $A$  the index set, indexed by  $\alpha$ , of the family of these axes. We have for each  $f_J^i$  coordinates denoted by  $F_{\alpha}(i)$ :

$$f_J^i = f_J + \Sigma\{F_{\alpha}(i) u_{\alpha J} | \alpha \in A\};$$

$$f_J^i = f_J(1 + \Sigma\{F_{\alpha}(i) \phi_{\alpha}^J | \alpha \in A\});$$

so that keeping in mind that  $f_j^i = f_{ij}/f_i$  we have:

$$\forall i, j : f_{ij} = f_i f_j (1 + \sum \{F_\alpha(i) \phi_\alpha^j | \alpha \in A\})$$

Because the origin has been placed at the centre of gravity  $f_J$  of the cloud  $N(I)$  the function  $F_\alpha(i)$  of  $i$  is of zero mean on  $I$  relative to the system of masses  $f_I : \sum \{F_\alpha(i) f_i | i \in I\} = 0$ . The moment of inertia of the cloud  $N(I)$  in the direction of the axis  $U_{\alpha J}$  is by definition the sum of the  $F_\alpha(i)^2$  weighted by  $f_i$  (i.e. the variance of  $F_\alpha$ ):

$$\lambda_\alpha = \sum \{(F_\alpha(i))^2 f_i | i \in I\}$$

It can be shown that in correspondence analysis the  $\lambda_\alpha$  are necessarily positive numbers lying between 0 and 1. To the function  $F_\alpha$  is related a function  $\phi_\alpha^I$ :

$$\phi_\alpha^I = \lambda_\alpha^{-\frac{1}{2}} F_\alpha(i); F_\alpha(i) = \lambda_\alpha^{\frac{1}{2}} \phi_\alpha^I$$

From the definition of the principal axes of inertia we know that the  $F_\alpha$  (or the  $\phi_\alpha^I$ ) are mutually uncorrelated:

$$\sum \{\phi_\alpha \phi_\beta f_i | i \in I\} = \delta_{\alpha\beta}$$

The sum of the moments of inertia  $\sum \{\lambda_\alpha | \alpha \in A\}$  is simply the sum  $\sum \{f_i \|f_J^i - f_J\|^2 | i \in I\}$ , i.e. the total inertia of the cloud (the sum of the point masses  $f_i$ ). To each moment of inertia  $\lambda_\alpha$  corresponds a part of the total inertia:

$$\lambda_\alpha / \sum \{\lambda_\alpha | \alpha \in A\}, \text{ usually coded } \tau_\alpha \text{ (proportion of inertia).}$$

The cloud  $N(J) = R_I$  is investigated in the same manner as for the cloud  $N(I) \in R_J$ , and it is noted that the functions  $\phi_\alpha$  and the values  $\lambda_\alpha$  are the same for both clouds. Therefore, the function  $\phi_\alpha^J = \lambda_\alpha^{-\frac{1}{2}} G_\alpha(j)$  has a complete symmetry with the function

$\phi_\alpha^I$ .  $F_\alpha$  and  $G_\alpha$  are known as the factors and the  $\lambda_\alpha$  as the characteristic values of the matrix as defined above. The sum of the  $\lambda_\alpha$  gives the total inertia for  $N(I)$  and  $N(J)$  and is called the trace. Each factor  $F_\alpha, G_\alpha$  relative to the characteristic value  $\lambda_\alpha$  extracts a part of inertia.

### 2.3 Computation of the eigenvalue $\lambda_\alpha$ with the aid of the transition formula.

When the factors are known on one of the sets it is possible to determine their value on the other set by using only the simple linear computations of the transition formula. If  $\phi_\alpha$  is one of the factors we have:

$$\begin{aligned}\Sigma\{f_j^i \phi_\alpha^j | j \in J\} &= \Sigma\{f_{ij}/f_i\} \phi_\alpha^j | j \in J\} = \lambda_\alpha^{\frac{1}{2}} \phi_\alpha^i \\ \Sigma\{f_i^j \phi_\alpha^i | i \in I\} &= \Sigma\{f_{ij}/f_j\} \phi_\alpha^i | i \in I\} = \lambda_\alpha^{\frac{1}{2}} \phi_\alpha^j\end{aligned}$$

The transition formulae enables us to go from set  $I$  to set  $J$  and vice versa. In the above we can replace the  $\phi_\alpha^I, \phi_\alpha^J$  by the  $F_\alpha, G_\alpha$  because they are proportional.

The transition formula allows us to compute  $F_\alpha(i) = \lambda_\alpha^{\frac{1}{2}} \phi_\alpha^i$ , coordinate of the point  $f_j^i$  of the cloud, by orthogonal projection on the factorial axis  $u_{\alpha J}$ . The transition formula provide a new definition of the factors. If we start from a function  $\phi^I$  on  $I$  we obtain by transition a function  $\chi^J$  on  $J$ ; and again by transition we return to a  $\beta^I$  on  $I$ :

$$\Sigma\{\phi^i f_j^i | i \in I\} = \chi^j; \quad \Sigma\{\chi^j f_j^i | j \in J\} = \beta^i;$$

$\phi^I$  is a factor relative to the eigenvalue  $\lambda$  if and only if we have  $\beta^I = \lambda \phi^I$ . The use of this formula gives not only the usual factors

$\phi_\alpha^I$  with zero mean but also the constant function equal to 1 which is often called the trivial factor relative to the eigenvalue  $\lambda = 1$ .

Using the transition formula we can show why the eigenvalue  $\lambda_\alpha$  lies between 0 and 1. Let us consider the set  $I \times J$  with distribution  $f_{IJ}$  (system of point masses with total mass 1);  $\phi_\alpha^I$  and  $\phi_\alpha^J$  can be considered as functions on  $I \times J$ , each one being the function of only one of the two variables  $i$  or  $j$  thus:  $\phi_\alpha^I(i,j) = \phi_\alpha^i$ ;  $\phi_\alpha^J(i,j) = \phi_\alpha^j$ . On  $I \times J$  the  $\phi_\alpha^I$  and  $\phi_\alpha^J$  are functions with zero mean and variance 1 (as on  $I$  and  $J$  respectively). The correlation coefficient between these two functions can be expressed by:

$$\begin{aligned} \text{cor}(\phi_\alpha^I, \phi_\alpha^J) &= \Sigma\{\phi_\alpha^i \phi_\alpha^j f_{ij} \mid i \in I, j \in J\} \\ &= \Sigma\{\phi_\alpha^i f_i \Sigma\{\phi_\alpha^j (f_{ij}/f_i) \mid j \in J\} \mid i \in I\} \\ &= \Sigma\{\phi_\alpha^i f_i \phi_\alpha^i \lambda_\alpha^{\frac{1}{2}} \mid i \in I\} \\ &= \lambda_\alpha^{\frac{1}{2}} \end{aligned}$$

where a double summation has been performed. We have thus shown, with the aid of the transition formula, that  $\lambda_\alpha^{\frac{1}{2}}$  is a correlation coefficient, hence  $\lambda_\alpha^{\frac{1}{2}} \in (0,1)$ . In this way we have another interpretation of the factors computed from correspondence analysis, namely they are the couples  $(\phi_\alpha^I, \phi_\alpha^J)$  of a function on  $I$  and a function on  $J$  which when considered as functions on  $I \times J$  (with distribution  $f_{IJ}$ ) are the most correlated.

#### 2.4 Computation of the contributions.

In order to shorten the formulae in the following expressions we denote the  $\chi^2$  distance between an element of the cloud and the centre of gravity as a polar radius  $\rho(i)$  (or  $\rho(j)$ ):

$$\rho(i) = \|f_J^i - f_J\|_{f_J} ; \quad \rho(j) = \|f_I^j - f_I\|_{f_I}$$

The total inertia of the cloud  $N(I)$ , as that of the cloud  $N(J)$ , is equal to the trace (or total sum of the eigenvalues), so that we have the formula

$$\Sigma\{\lambda_\alpha | \alpha \in A\} = \Sigma\{\rho(i)^2 f_i | i \in I\} = \Sigma\{\rho(j)^2 f_j | j \in J\} = \text{Trace}$$

We also know that each of the eigenvalues  $\lambda_\alpha$  is a moment of inertia which can be expressed as a sum indexed by  $I$  or  $J$ :

$$\lambda_\alpha = \Sigma\{F_\alpha(i)^2 f_i | i \in I\} = \Sigma\{G_\alpha(j)^2 f_j | j \in J\}$$

As the square of a  $\chi^2$  distance is, according to the usual Euclidian formula, equal to the sum of the squares of the coordinate relative to an orthonormal system of axes (this condition is essential) we have:

$$\rho(i)^2 = \Sigma\{F_\alpha(i)^2 | \alpha \in A\}; \quad \rho(j)^2 = \Sigma\{G_\alpha(j)^2 | \alpha \in A\}$$

This is based on the condition that a squared distance (in the sense of  $\chi^2$ ) is the sum of the squares of the coordinates in a system of orthogonal axes.

$\rho(i)^2 f_i$  is known as the absolute contribution of the element  $i$  to the trace;  $F_\alpha(i)^2 f_i$  the absolute contribution of the element  $i$  to the moment of inertia  $\lambda_\alpha$ ;  $F(i)^2$  the absolute contribution of the factor  $\alpha$  to  $i$ . The relative contribution is the contribution of the factor to the element -  $F_\alpha(i)^2 / \rho(i)^2$ , equal to the cosine



squared.

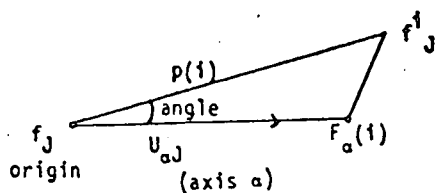


Figure 3. Relative contribution of factor to element is  $F_\alpha(i)^2/p(i)^2$ , equal to cosine squared.

$$\cos(u_{\alpha J}, (f_J^i - f_J)) = F_\alpha(i)/\rho(i)$$

The usage of these terms will be discussed later.

## 2.5 Simultaneous Representation of I and J.

In order to represent the set J, the cloud  $N(J)$  is projected in the space  $E_p$  with  $p$  axes of inertia. We have already seen that the cloud  $N(J)$  is the set of points  $f_I^j$  of  $R_I$ , where the distances are those given by the  $\chi^2$  metric centred at  $f_I$  ( $f_I$  is the centre of gravity of the cloud  $N(J)$ ).

For a factor  $\phi$ , there is an axis with vector  $(\phi^I f_I)_I$  (measure with function  $\phi^I$  as density relative to  $f_I$ ).

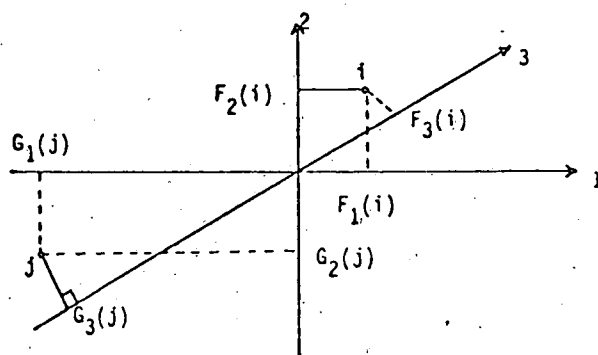
A vector  $x_I$  of  $R_I$  has for its coordinate on the axis  $\phi^I \circ x_I = \sum_i \phi^i x_i$ . In particular, the vector  $\delta_I^i$  (representing the unit mass placed at  $i$ ) has a coordinate  $\phi^i$  in the system of axes of  $N(J)$  whereas the coordinates of the representative point  $i$  are  $\lambda_i(\phi)^{\frac{1}{2}} \phi^i$ . We can say that we pass from the system of the  $\delta_I^i$  to the system of points representing the element  $i$  by means of a linear transformation  $r$  the eigenvalues of which are the principal axes of inertia of the cloud  $N(J)$  relative to the eigenvalues  $\lambda_\alpha^{\frac{1}{2}}$ .

The point  $f_I^j$ , representing  $j$  in  $R$ , is exactly the barycenter

of the  $\delta_I^i$  weighted with the point masses  $f_i^j$ :  $f_I^j = \sum_i f_i^j \delta_I^i$

In certain problems (especially when the cardinal of the set  $I$ , say, is small compared to the cardinal of  $J$ ) it may be of interest to destroy the symmetric situation between  $I$  and  $J$  by presenting the cloud  $N(J)$  with the set  $\{\delta_I^i\}$  representing the set  $I$ . Using the usual coding of the output listings this is equivalent to assigning to each  $i$  the coordinate  $F(i)\lambda^{-\frac{1}{2}}$  instead of the usual  $F(i)$ . In this way the point  $i$  is represented as a point  $j$  for which  $\delta_I^i = f_I^j$  (the limiting case of a  $j$  associated with  $i$  only); hence  $j$  is exactly at the centre of gravity of the  $i$  (the  $\delta_I^i$ ) weighted by the masses  $f_i^j$ . It is then by a coefficient  $\lambda$  rather than  $\lambda^{\frac{1}{2}}$  that  $i$  can be made to coincide with the barycentre of the  $j$  weighted by the masses  $f_j^i$ .

The clouds may be considered graphically on the same plan.



Graphs show the distribution of the points  $i$  and  $j$  with respect to the chosen axes.

## 2.6 Correspondence Analysis as a Method of Scaling.

Guttman(1941), Torgerson(1958, p.538) and Hill(1973) introduced

correspondence analysis as a method of scaling. Let's consider a simpler method of scaling namely "gradient analysis" which was developed by R.H. Whittaker(1967).

The data (for example floristic data) of gradient analysis consists of a table of the incidences of a number of species at a number of sites. A particular species of grass indicate wet conditions, while another may indicate dry conditions. We can scale the species accordingly to their suspected preferences along a known physical gradient. For example, a grass with a score of 1 may be wet-loving, and a grass with a score of 10 may be dry-loving. It is clear that a grass of score 5 may be intermediate. The site scores are the averages of the scores of the species which occur in them. If one considers the various environmental gradients and obtain scores along the corresponding axes of variation, we could derive a multidimensional scaling as described in Chapter 6.

The problem arise that the user has to guess the important physical gradients in advance, and his results are therefore highly subjective. An experienced person may interpret the gradients correctly, but a novice is less trustworthy. We could take the data as basic, ignoring physical factors, and use standard multivariate methods to reveal the gradients. The revealed gradients are then related to such physical factors as are thought to be relevant.

Corresponding analysis can be regarded as a generalization of gradient analysis using the method of successive approximation. There are a few definitions and propositions related to Correspondence analysis and we would like to formulate them by looking at an example. Let  $A$  be an  $m \times n$  data matrix of elements  $a_{ij}$  specifying the occurencies of  $m$  species (rows) at  $n$  sites (columns). If we

apply the method of gradient analysis, we can calibrate the sites along a presumed physical gradient by assigning scores  $y_j$  ( $j = 1, \dots, n$ ) to the sites so as to conform with the physical gradient. The species scores

$$x_i = \sum_j a_{ij} y_j / a_{.i}$$

are the mean site scores of the sites at which they occur. The derived species scores can now be used to derive a new calibration

$$y'_j = \sum_i a_{ij} x_i / a_{.j}$$

The scores  $y'_j$  are a gradient analysis of the sites. We could iterate the process with the new scores  $y'_j$  in place of the old ones  $y_j$ . Hill(1973) has called this process "reciprocal averaging".

The following two definitions and three propositions as mentioned above are taken from Applied Statist.(1974), 23, No.3, p.342, M.O. Hill.

DEFINITION 1.

Let  $A$  be an  $m \times n$  table of non-negative numbers  $a_{ij}$ , and let  $R \equiv \text{diag}(\alpha_{.i})$  and  $C \equiv \text{diag}(\alpha_{.j})$  be the diagonal matrices of row and column totals. It is assumed that none of the totals is zero. The sequence of operations

$$y = C^{-1} A^T x; x' = R^{-1} A y; y' = C^{-1} A^T x'; \dots$$

in which new sets of scores  $y, x', y', \dots$  are successively derived from an initial set of scores  $x$  is referred to here as the "two-way averaging algorithm" corresponding to the matrix  $A$ .

The two-way averaging algorithm is simply the process of cross-calibration outlined above; its eigenvectors are the solutions of the correspondence analysis problem defined by the matrix  $A$ .

DEFINITION 2.

Using the same notation as above, a triple  $(\rho, x, y)$  is a solution of the zero-order correspondence analysis of  $A, C_0(A)$ , if

$$\rho x = R^{-1}Ay; \quad \rho y = C^{-1}A^T x.$$

The elements of the vector  $x$  are called "row scores" and the elements of the vector  $y$  are called "column scores". The number  $\rho$  is, as explained below, the correlation of  $x$  and  $y$  with respect to the matrix  $A$ .

Before much can be said about the method, three simple propositions should be noted.

PROPOSITION 1. The correspondence analysis problem is equivalent to a singular value decomposition problem, and is therefore solved by extracting the eigenvectors of a positive semi-definite symmetric matrix.

PROOF: Defining  $R^{\frac{1}{2}} \equiv \text{diag}(\sqrt{a_{i.}})$ , and defining  $C^{\frac{1}{2}}$  similarly, then  $(\rho, x, y)$  is a solution of  $C_0(A)$  if and only if

$$\begin{aligned} \rho(R^{\frac{1}{2}}x) &= (R^{-\frac{1}{2}}AC^{-\frac{1}{2}})(C^{\frac{1}{2}}y) \\ \rho(C^{\frac{1}{2}}y) &= (R^{-\frac{1}{2}}AC^{-\frac{1}{2}})^T(R^{\frac{1}{2}}x). \end{aligned}$$

This establishes that the solutions are equivalent to a singular value decomposition. Looking at the matter from the point of view of  $x$ , we see that

$$\rho^2(R^{\frac{1}{2}}x) = (R^{-\frac{1}{2}}AC^{-\frac{1}{2}})(R^{-\frac{1}{2}}AC^{-\frac{1}{2}})^T(R^{\frac{1}{2}}x).$$

The matrix preceding  $(R^{\frac{1}{2}}x)$  on the right-hand side of the equation is of the form  $BB^T$  and is therefore positive semi-definite;  $\rho^2$  is the eigenvalue of the solution. The solutions or "axes" are deemed to be ordered by their eigenvalues.

PROPOSITION 2. The maximal solution of the correspondence analysis problem is  $(1, \mathbf{1}_m, \mathbf{1}_n)$ , where  $\mathbf{1}_m$  is  $(1, \dots, 1)^T$ , the  $m$ -vector of 1's and  $\mathbf{1}_n$  is defined similarly.

PROOF: Recalling the two-way averaging algorithm of Definition 1, and the informal discussion which preceded it, it is clear that the range (i.e. maximum minus the minimum) of the column scores  $y_j$  - which are averages - cannot exceed that of the row scores  $x_i$  from which they were derived. Similarly the new row scores  $x'_i$  must have a range less than that of the column scores  $y_j$ . Therefore the range of the scores  $x'_i$  is less than that of the scores  $x_i$ , so that the eigenvalue  $\rho^2$  of a solution cannot exceed 1. The triple  $(1, \mathbf{1}_m, \mathbf{1}_n)$  is a solution, as the average of a set of 1's is 1. It must be maximal. as  $\rho^2 = 1$ .

PROPOSITION 3. Solutions other than the first satisfy the relation

$$\sum_i x_i \cdot x_i = \sum_j y_j \cdot y_j = 0.$$

PROOF: By Propositions 1 and 2 the condition of orthogonality to the trivial first axis is

$$(R^{\frac{1}{2}}\mathbf{1}_m)^T (R^{\frac{1}{2}}x) = 0.$$

An analogous result holds for the column scores  $y$ .

C H A P T E R 3.

3. INTERPRETATION OF THE NUMERICAL AND GRAPHICAL OUTPUT OF THE ANALYSIS.

3.1 Number of interpreted factors, eigenvalues and proportions of inertia.

The computer program provides a listing of the values on I and J of the first extracted factors F, G, with associated eigenvalues  $\lambda_{\alpha}$  and proportions of inertia  $\tau_{\alpha}(\lambda_{\alpha}/\Sigma\lambda_{\alpha})$ . In the past it was the practice to compute only the first five factors. The motive for this choice was that of convenience - printing the label of F(i) (generally three lettered), the numerical values relevant to the five factors and the total mass k(i) usually fills up the available space on a line of listing. In the early days the computation of the factors was a costly process and up to the fourth factor was sufficient, but today with highly development computers it allows us to go beyond the five factors. The question is now to know at which number to stop the examination.

In the case of a true frequency table the  $\chi^2$  test approximately indicates until which factor the explained part of the inertia dominates sampling fluctuations. The case of tables generated by independent events is rather difficult. The interpretation of the factors proceeds according to the meaning of associations and analogies which become opponent, according to typical shapes of the projections, governed by the computed contributions.

The set of eigenvalues and corresponding percentages must be examined even though they do not give strong indications. Usually we regard as highly meaningful a first factor which represents more than 50% of the total inertia. An eigenvalue greater than 0,6 indicates a possible dichotomy in the data itself, usually because a small number

of elements oppose all the others. Therefore, the factor is not meaningful for the set as a whole. If the characteristic value is around 0, 2, the factor becomes interesting. A low value of  $\lambda_\alpha$  indicates that the profile  $f_J$  of the individuals is similar to the mean profile  $f_J$ . The associated factor could be of significance.

### 3.2 Geometrical configurations of the planar representations.

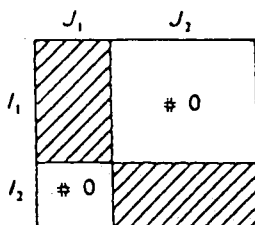
To give a visual idea of the values of the factors for the different elements it is most convenient to use two dimensional diagrams considering firstly the one which represents simultaneously the clouds I and J with respect to factorial axes 1 and 2. The plot produced by the computer examines the results for a particular factor. The planar representation according to factorial axes 1 and 2 the projections i have  $F_1(i)$  for abscissa and  $F_2(i)$  for ordinate, the projections j have  $G_1(j)$  for abscissa and  $G_2(j)$  for ordinate. These sorted lists are particularly helpful when used in examining the contributions.

We know that if I is weighted by the system of masses  $f_i$ , the two factors  $F_1(i)$  and  $F_2(i)$  are functions of zero mean and respective variance  $\lambda_1$  and  $\lambda_2$ , and they are also uncorrelated. A statistician acquainted with Gaussian variables instantly imagines in the plane 1-2, an elliptic cloud centred at the origin, with primary axis  $\lambda_1^{\frac{1}{2}}$  (standard deviation) in the direction of the first and  $\lambda_2^{\frac{1}{2}}$  in the direction of the second axis. Other shapes can also be observed and their occurrence is rather meaningful: in fact there exists no special reason for the factors to be Gaussian or even unimodal; and furthermore, two uncorrelated variables are not necessarily independent - there may indeed be a relationship between them which is compatible with ortho-



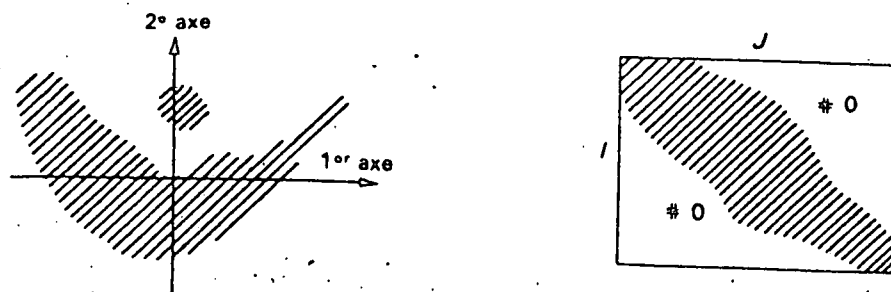
ganality properties (e.g. one is a second degree polynomial of the other). Let us look at three typical shapes.

FIRST TYPICAL SHAPE: the cloud is divided into two separate clusters:  $I = I_1 \cup I_2$ ,  $J = J_1 \cup J_2$ , where  $I_1$  is associated with  $J_1$  and  $I_2$  with  $J_2$ . If one reorganizes the data table by grouping together the rows (the columns)  $I_1$  the  $I_2$  ( $J_1$  then  $J_2$ ) we have approximately the following situation; outside of the diagonal blocks  $I_1 \times J_1$  and  $I_2 \times J_2$  the two blocks  $I_1 \times J_2$  and  $I_2 \times J_1$  are close to zero.



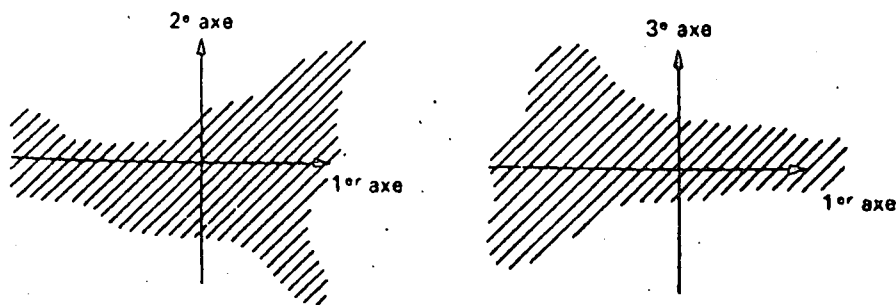
Sometimes one of the diagonal blocks ( $I_2 \times J_2$  for example) is composed of a few elements only (e.g. Card  $I_2 = 2$ , Card  $J_2 = 3$ ); in such a case it may be possible that the few isolated elements strongly disturb the analysis. Here it is advisable to repeat the analysis without these elements, that is analyse the table  $k_{I_1 \times J_1}$ . Correspondence analysis often reveals strong dichotomies on a few axes (division and subdivision of the cloud) and continuous spreadings on other axis.

SECOND TYPICAL SHAPE: Cloud in the shape of a parabolic cresent:



Let us suppose (the common case) that the two extremities of the crescent project onto the first axis on opposite sides of the origin. If the table is rearranged in such a way that the rows (set I) and the columns (set J) are in the same order as they project onto the first axis, there clearly appears a diagonal zone with rather heavy elements ( $f_i \times f_j < f_{ij}$ ) between two rather light corner zones ( $f_{ij} < f_i \times f_j$ ). The second axis contributes to the same general classification, but reveals some meaningful complementary nuances; to a point located on the graph inside the crescent (near the positive part of the second axis as seen in the above figure) corresponds in the table a row (or column) with a rather flat profile (i.e. with relatively high values outside of the diagonal of the table). Such a point does not have a well-defined rank in the general classification but is likely to be mixture of the two extremes (this is due to the barycentric principle, the geometrical expression of the transition formula).

THIRD TYPICAL SHAPE: Cloud in the shape of a triangle (or tetrahedron).



We see in the above illustration that if the first factor is negative the second shows little dispersion around zero, while for positive values of factor 1, the factor 2 is most dispersed (between its extreme negative and positive values). On the other hand it is possible that on a third axis we find dispersion if the factor 1 is negative and concentration around zero if factor 1 is positive. In this case the cloud will have the shape of a tetrahedron in the vector space generated by the three axes; this tetrahedron has two opposite vertices perpendicular to the axis 1, one parallel to axis 2 (on the positive axis 1), the other parallel to axis 3 (on the negative side of axis 1). We seldom obtain perfect triangular or tetrahedric shapes but even an approximate configuration is worth noting.

### 3.3 Guidelines to understand the meaning of the results.

If an interval of relative importance separates two factors  $x$  and  $y$  the most important one, say  $x$ , has a definite significance. If the percentage of  $y$  is low and the interval large, the factor  $y$  has relatively little importance. If  $x$  and  $y$  have similar percentages, they have equally significant, independent meanings.

To interpret an axis, the opposition between the negative and the

positive sides of the axis needs to be explained. Its understanding may be clarified by considering the other axis which are not only different but uncorrelated.

Each factor is studied using the absolute contributions for all the elements, unless its characteristic value is high, in which case the relative contributions are used. If the value of an absolute contribution is greater than  $\lambda_q/4$  then the corresponding element should be placed as a supplementary element (i.e., it is not used in the calculation of the axes, but may be projected onto the factorial plan). This avoids the distortion of the axes resulting from an element with a high contribution. More detailed guidelines could be seen at the end of Chapter 4.

### 3.4 Difference between principal Component analysis and Correspondence Analysis.

The following table is given by H. Teil in the Mathematical Geology, Vol. 7, No. 1, 1975 page 11.

Main differences between Principal Component Analysis and Correspondence Analysis.

<u>Principal component analysis</u>	<u>Correspondence analysis</u>
1. Euclidean distance between two points.	1. $x$ distance (eq 1)
2. Individuals have equal weights	2. Individuals have proportional weights $f_i = k_i/k$ .
3. The individual $k(i,j)$ itself is considered	3. The "profile" of the individual is described by the vector $\{k(i,j)/k_i   j \in J\}$
4. Diagonalization of variance matrix (euclidean distance) or the correlation matrix (weighted euclidean distance)	4. Diagonalization of the matrix of vector $j$ profiles
5. Characteristic values of $I$ and $J$ not equal, and so no representation of $I$ and $J$ on the same axes. Correlation coefficients calculated between a variable and the set of projections of individuals on the factorial axis	5. Simultaneous representation of $I$ and $J$ because their matrices have the same characteristic values. Associations between $I$ and $J$ seen from the factorial plans

Principal component analysis

6. Rotation of the principal axes of inertia

Correspondence analysis

6. No rotation

## C H A P T E R 4.

### 4.1 ILLUSTRATIONS OF CORRESPONDENCE FACTOR ANALYSIS ON DATA.

Data of monthly rainfall averages in the rainy season were compiled by Katznelson(1968-69) for 55 stations in Israel. For each month the average rainfall (mm) was computed in the selected 55 stations (1921-50). The table taken from the Journal of Applied Meteorology Vol. 11. No. 7, October, 1972, pp. 1071-1077 is Table 1 as given on page 48.

A computer program (page 46) produces for each  $i$  and  $j$  their coordinates relative to  $m$  factors  $F_{\beta}(\beta=1, \dots, 55), G_{\alpha}(\alpha=1, \dots, 9)$  together with their absolute and relative contributions (Table 2, page 51, and Table 3, page 52). For each factor, the characteristic value  $\lambda_{\alpha}$  and the percentage variability explained by the factor is given.

A program (page 46) was written to produce two dimensional diagrams to give a visual idea of the values of the factors for the different elements. We considered the one which represents simultaneously the clouds  $I$  and  $J$  (3.1, in our case months and stations) with respect to factorial axes 1 and 2 (page 55).

### 4.2 PROGRAMS.

Before we look at the listings of the programs, it may be useful to summarize the method of Correspondence analysis and describe some of the variables used in the main program.

Input matrix:  $K : p \times m$

All elements of  $K$  must be positive. Computation is reduced if  $p \geq m$

Results are the same whether  $K$  or  $K'$  is input.

Calculations:

$$k_{..} = \sum_{i=1}^p \sum_{j=1}^m k_{ij} \quad : \text{Sum of all the elements of } K.$$

$$a_{ij} = \frac{k_{ij}}{k_{..}} \quad : \text{A : } p \times m \text{ consists of elements of } K$$

scaled so that the sum of all the elements  
of  $A$  is 1.

$$D_r : p \times p \quad \text{Diagonal matrix of row sums of } A. r_{ii} = \sum_{j=1}^m a_{ij}$$

$$D_c : m \times m \quad \text{Diagonal matrix of columns sums of } A. c_{jj} = \sum_{i=1}^p a_{ij}$$

$$B = D_r^{-\frac{1}{2}} A D_c^{-\frac{1}{2}}$$

The largest characteristic root of  $B'B$  is equal to 1.

$V : m \times (m - 1)$  Matrix of unit length characteristic vectors corresponding to the  $p - 1$  characteristic roots of  $B'B$  which are less than 1.

$D_\gamma : (m - 1) \times (m - 1)$  Diagonal matrix of the  $p$  characteristic roots of  $B'B$  which are  $\leq 1$ .

( $\therefore B'B = V D_\gamma V' + \underline{r}^{\frac{1}{2}} \underline{1} \underline{c}^{\frac{1}{2}}$  where  $\underline{r}^{\frac{1}{2}}$  and  $\underline{c}^{\frac{1}{2}}$  are vectors of diagonals of  $D_r^{\frac{1}{2}}$  and  $D_c^{\frac{1}{2}}$ ).

$$V'V = I_{m-1}$$

$$U = B V D_\gamma^{-\frac{1}{2}}$$

$$F = D_r^{-\frac{1}{2}} U D_\gamma^{\frac{1}{2}} = D_r^{-\frac{1}{2}} B V \quad p \times (m - 1) \text{ matrix of row factor loadings.}$$

$$G = D_c^{-\frac{1}{2}} V D_\alpha^{\frac{1}{2}} \quad m \times (m - 1) \text{ matrix of column factor loadings.}$$

Check:  $A = D_r (1_p 1'_m + F D_Y^{-\frac{1}{2}} G') D_c$  where  $1_p, 1_m$  are unit vectors.

The program prints out the first few columns of F and G.



#### 4.3 EXTENDED GUIDELINES TO UNDERSTAND THE MEANING OF THE RESULTS.

First we consider the graph on page 55 and look at the shape of the first two factors compared to the three typical shapes described on page 26. The two-dimensional diagrams are composed of labelled points. In order to go beyond an interpretation of the geometric shape of the clusters, one must take into account the significance of the labels. This significance is usually at hand for at least one of the two sets I or J, say J, which is called set of characteristics (or measurements). On the other hand the set of individuals I can be unknown or difficult to know in all its details.

The relations between the two sets I and J are ruled by the barycentric principle. However we should emphasize that two points  $i$  and  $j$  which are near one another on a plane graph ( $\alpha \beta$ ) do not necessarily have a high level of association (i.e. a high  $f_{ij}/(f_i \times f_j)$ ). This is due to the fact that the location of  $i$  is determined according to the barycentric principle.

The interpretation of an axis involves trying to express the analogies between the points on one side of the origin and similar between those on the other side of the origin, and then explaining as concisely and exactly as possible the opposition between the two extremes. Such an interpretation is usually difficult to find because one has to take into account not only the relative locations of the points the most distant to the right and to the left, but also the location of the points which bring large absolute contributions ( $F_\alpha(i)^2 f_i$  or  $G_\alpha(j)^2$ ) to the factor of interest. It is also to be feared that one might stop, once an explanation more or less compatible with the geometric repartition of the points on the axis is found, without trying to discover the basic causes.

It is therefore necessary to handle each case carefully, if possible with a statistician, to balance the interpretation with the amount of information available. Very often the interpretation of a factor is improved by keeping in mind those which follow it. One has to remember that the successive factors are not only different but also mutually uncorrelated. If an interpretation given to axis 1 seems to be equally good for interpreting axis 3, for example, this is certainly a sign that one should review the analysis with more care.

Let us look at the table given on page 53. We could group the factor column according to their scores for the different subjects. Similarly for the objects. The importance in the interpretation of the factors has already become apparent and could be described the same as the factors of Principal Component analysis. We shall end this section by describing the format of the contributions and by giving some details of their use.

For an analysis involving, say 5 factors, the listing usually gives for each factor 3 contributions namely, the absolute, relative and cumulative contributions. The absolute contribution on page 53 is  $F_{\alpha}(i)^2 f_i / \lambda_{\alpha} \times 100$ . The relative contribution is  $F(i)^2 / (i) \times 100$ . The cumulative contribution is the absolute of the relative contribution. It is important to point out that the absolute contributive elements are not necessarily those which have the most extreme position on the axis of interest. Another interesting factor is that the sum of the absolute contributions to  $\lambda_{\alpha}$  is equal to  $4 \lambda_{\alpha} / 5$ . Further interpretation of the relative and absolute contribution has already become apparent if one only looks at their definition given in §2.4.

One could use the Multidimensional technique to plot the different 55 stations by using the  $\chi^2$  distance,  $D^2(i, i')$  as given on page 11.

The result is shown on page 57. The virtual image of this graph is nearly the same as the two dimensional graph of the Correspondence factors on page 55.

#### 4.4 Interpretation of Correspondence Analysis tables and graph.

H. Teil(1975) suggested a Correspondence Analysis table which look like the computer printout on page 53. Each  $i$  and  $j$  coordinates, relative to  $m$  factors  $F_{\alpha}, G_{\alpha}$  ( $\alpha=1, \dots, m$ ) together with their absolute and relative contributions, are printed in this table. For each factor, the characteristic value  $\lambda_{\alpha}$  and the percentage variability explained by the factor are given. Let us look at the example of Israeli rainfall at 55 stations and 9 months given on page 53.

On the top lefthand side of the table is printed 'Factor 1'. This was really the fifth factor as computed by Correspondence Analysis, but is now treated as Factor 1 because its characteristic value was the highest compared (ignoring the characteristic value 1). The characteristic value is .0153315 and the percentage of inertia is 54.567. One should add the percentage of inertia of Factor 1 and Factor 2 and this sum should be 60% or more to make the two dimensional graph on page 55 significant.

We could now divide this table into the objects and subjects. The nine different months and the 55 different stations are printed under the heading 'Object' and 'Subject' respectively. Consider the object table; under the heading 'Mass' for object 1 is printed; 29.5. This figure is the sum of all the actual rainfall values corresponding to the first month (i.e. object 1).

The distance .8302 (in the sense of  $\chi^2$ ) is the distance from the center of gravity. The next column gives the Correspondence Analysis factor loadings of the first factor. One could group these factors in the

same manner as Principal Component analysis. It is clear that the first 4 objects 1,2,3 and 4 (i.e. -.3158, -.1666, -.1422, and -.1348 respectively) could be classified as group 1. It follows from the table that object 5,6,7,8 and 9 form the next group. The same interpretation on the subjects (i.e. stations) could be concluded.

The next three columns gives the contributions namely; absolute, relative and cumulative. The absolute contribution -.7834 is the contribution of object 1 to the  $\lambda_{\alpha}$  - characteristic value .0153315. The sum of all the absolute contributions of the 9 objects must be equal to 100. The relative contribution -12.0154 is the contribution of the object 1 relative to the other factors to  $\lambda_{\alpha}$ . The sum of all the relative contributions of object 1 must be equal to 100. The cumulative contribution is the absolute of the relative contribution.

Consider the two dimensional graph of factor 1 and factor 2 given on page 55. The objects and subjects are plotted on the same graph. M1 is associated to month 1 and 'S01' to station 1. One immediately sees that there exists a great variation in rainfall during month 1 and month 9 as these two points are extreme to the origin. The least variation is in months 5 and 6. One could also see that station 6 and 9 are positively correlated to month 1, while station 43 and 38 are negatively correlated to month 1. This discussion on correlation could be extended to all the months and stations. Furthermore one could group the stations and months together to form certain areas, page 56. The stations almost coincide with the factual graphical notation predetermined on an existing map of Israel (page 100).

REFERENCE TO PROGRAMS AND CORRESPONDING EXECUTION EXAMPLES.

	<u>PAGE</u>
1. Main Correspondence analysis program.	39
2. Subroutine to calculate eigenvalues and eigenvectors used in the main program of Correspondence analysis.	45
3. Program which plot the first two factors on the same graph.	46
4. Average monthly rainfall (mm) in selected stations 1921-50. (Journal of Applied Meteorology, Vol. 11, No. 7, P.107) (Table 1).	48
5. First output of Correspondence analysis. After inspection of the eigenvalues and factors one could produce tables as described in 5. (Table 2)	49
6. Tables which contain the factors, characteristic values and contributions. (Table 3).	52
7. Precise output from program as described in 3.	55
8. Graph divided into different areas.	56
9. Distance graph as obtain from the Multidimensional Scaling Program.	57

```

1 C *****
2 C D.BESTER. CORRESPONDENCE FACTOR ANALYSIS
3 C
4 C REFERENCE: MATHEMATICAL GEOLOGY, VOL. 7, NO. 1, 1975. - H. TEIL.
5 C HILL- APPL. STATIST. (1974), 23, 340-354.
6 C
7 C EXECUTE CARDS NEEDED :
8 C 1. TITLE CARD (80 CHARACTERS ALFANUMERIC)
9 C
10 C 2. PROBLEM CARD.
11 C COLUMN 1-4 OBJECTS (MAXIMUM OF 80)
12 C COLUMN 5-8 FACTORS TO BE TREATED BY CORRESPONDENCE
13 C ANALYSIS. (MAXIMUM OF 10)
14 C COLUMN 9-12 SUBJECTS (MAXIMUM OF 330)
15 C COLUMN 13-16 0= NO PRINTING OF TABLES
16 C 1= PRINT TABLES FOR SPECIFIED FACTORS AS
17 C GIVEN ON PAGE 8 OF H. TEIL.
18 C COLUMN 17-18 FACTORS TO BE PRINTED AS DESCRIBED IN
19 C COLUMN 13-16 (NUMBER)
20 C COLUMN 19-20 FACTOR 1
21 C COLUMN 21-22 FACTOR 2
22 C COLUMN 23-24 FACTOR 3
23 C .....
24 C .....
25 C .....
26 C COLUMN 37-38 FACTOR 10
27 C THE ANALYSER MUST BE CAREFUL THAT ALL THE DATA IS POSITIVE
28 C AND THE OBJECTS MUST BE < OR = THAN THE SUBJECTS.
29 C *****
30 C DIMENSION KP(2), A(330,80), F(330,10), DC(330), DV(80),
31 C * DG(80), OPS(20), FOR(60), V(80,60), G(80,10), B(80,80)
32 C *, SUBM(330), OBJM(80), NPF(10), V1(330,80)
33 C NWTR=6
34 C -----
35 C READ HEADING CARD FROM CARD-READER (TITLE CARD)
36 C -----
37 C READ (5,2) OPS
38 C 2 FORMAT (20A4)
39 C -----
40 C WRITE HEADING AND TITLE ON PRINTER
41 C -----
42 C WRITE (6,10) OPS
43 C 10 FORMAT(1H1,40X,39(1H*),/41X,* CORRESPONDENCE FACTOR ANALYSIS
44 C * *,/41X,39(1H*),//41X,20A4)
45 C -----
46 C READ THE PROBLEM CARD
47 C -----
48 C READ (5,12) NUMFAC, NOB, NSUB, NT, NP, (NPF(I), I=1, NP)
49 C 12 FORMAT(4I4,12I2)
50 C IND=1
51 C -----
52 C READ THE FORMAT CARD WHICH MUST BE SMALLER THAN 60 CHARACTERS
53 C AND WRITE THE FORMAT ON THE PRINTER
54 C -----
55 C READ (5,14) FOR
56 C 14 FORMAT (60A1)
57 C WRITE (6,16) FOR
58 C 16 FORMAT (/1X,'YOUR FORMAT IS : ',60A1)
59 C -----

```

```

60 C      COMPUTE IF SUBJECTS,OBJECTS AND FACTORS ARE WITHIN LIMITS
61 C      -----
62      IF (NOB.LE.80) GO TO 17
63      WRITE (6,3) NOB
64      3 FORMAT (//1X,'YOUR OBJECTS ',I3,' IS OUT OF RANGE')
65      GO TO 99
66      17 IF (NSUB.LT.NOB) GO TO 4
67      IF (NSUB.LE.330) GO TO 7
68      4 WRITE (6,5) NSUB,NOB
69      5 FORMAT (1X,'YOUR SUBJECTS ',I3,' IS EITHER TOO BIG OR SMALLER
70      *THAN YOUR OBJECTS',I3)
71      GO TO 99
72      7 WRITE (6,18) NOB,NSUB
73      18 FORMAT (//1X,'YOUR OBJECTS = ',I3,//1X,
74      *          ' SUBJECTS = ',I3)
75 C      -----
76 C      READ THE INPUT DATA MATRIX FROM CARD-READER.
77 C      WRITE OBSERVATION MATRIX ON PRINTER
78 C      -----
79      WRITE(6,66)
80      66 FORMAT (///37X,20(1H-),/37X,'- OBSERVATIONS -',/37X,20(1H-))
81      DO 77 I=1,NSUB
82      READ (5,FOR) (A(I,J),J=1,NOB)
83      77 WRITE (6,88) (A(I,J),J=1,NOB)
84      88 FORMAT (1X,10F10.5)
85      DO 41 I=1,NSUB
86      41 SUBM(I)=0.0
87      DO 42 J=1,NOB
88      42 OBJM(J)=0.0
89      DO 43 I=1,NSUB
90      DO 43 J=1,NOB
91      SUBM(I)=SUBM(I) + A(I,J)
92      43 OBJM(J)=OBJM(J) + A(I,J)
93      SK=0.
94 C      -----
95 C      COMPUTE THE DIAGONAL MATRIX OF ROW AND COLUMN SUMS
96 C      -----
97      DO 121 I=1,NSUB
98      DO 121 J=1,NOB
99      121 SK = SK + A(I,J)
100      DO 122 I=1,NOB
101      122 DV(I) = 0.0
102      DO 123 I=1,NSUB
103      DC(I)=0.0
104      DO 123 J=1,NOB
105      A(I,J)= A(I,J)/SK
106      DV(J)=DV(J) + A(I,J)
107      123 DC(I)=DC(I) + A(I,J)
108 C      -----
109 C      WRITE THE ROW- AND COLUMN TOTALS.
110 C      -----
111      WRITE (NWTR,120)
112      120 FORMAT (1H1,36X,21(1H-),/37X,'- ROW-TOTALS -',/37X,21(1H-),/
113      *31X,'ROW NUMBER',15X,'TOTAL',/31X,10(1H-),15X,5(1H-))
114      WRITE (NWTR,221)( I,DC(I) ,I=1,NSUB)
115      221 FORMAT (31X,I3,18X,F10.5)
116      WRITE (NWTR,230)
117      230 FORMAT (1H1,36X,21(1H-),/37X,'- COLUMN-TOTALS -',/37X,21(1H-),/
118      *31X,'COLUMN NUMBER',12X,'TOTAL',/31X,13(1H-),12X,5(1H-))
119      WRITE (NWTR,231) ( J,DV(J) ,J=1,NOB)

```

```

120 231 FORMAT (35X,I3,14X,F10.5)
121 IF (IND.NE.0)GO TO 127
122 DO 125 I=1,NSUB
123 DO 125 J=1,NOB
124 125 V1(I,J)= A(I,J)/DC(I)
125 WRITE (NWTR,150) (( V1(I,J),J=1,NOB),I=1,NSUB)
126 150 FORMAT ('1',19X,24(1H-),/20X,'THE COLUMN PROFILE MATIX',/20X,24(1H
127 *-),//100(1X,12F10.5,/) )
128 127 DO 128 I=1,NOB
129 128 DV(I)= 1./SQRT(DV(I))
130 DO 129 J=1,NSUB
131 129 DC(J)= 1./SQRT(DC(J))
132 DO 211 I=1,NSUB
133 DO 211 J=1,NOB
134 211 A(I,J) = A(I,J)* DV(J)* DC(I)
135 DO 212 I=1,NOB
136 DO 212 J=1,I
137 G(I,J)=0.
138 DO 133 K=1,NSUB
139 133 G(I,J)=G(I,J)+A(K,I)*A(K,J)
140 G(J,I)=G(I,J)
141 B(J,I)=G(J,I)
142 212 B(I,J)=G(I,J)
143 C -----
144 C COMPUTE THE EIGENVALUES AND VECTORS OF THE MATRIX G BY MAKING USE
145 C OF THE SUBROUTINE EIEW. THIS PROGRAM MUST BE CHANGED IF YOU HAVE
146 C ANY STANDARD SUBROUTINES AVAILABLE.
147 C -----
148 EPS = 5.E-8
149 CALL EIEW(B,V,80,NOB,EPS,888,132,1)
150 GO TO 333
151 132 WRITE (NWTR,134)
152 134 FORMAT ('U','ERROR WITH COMPUTATION OF EIGENVALUES ---- IT MAY BE
153 USEFUL TO ENLARGE THE VALUE OF 888 IN THE CALL STATEMENT ',/1X,'
154 *OF THE SUBROUTINE EIEW.')
```

---

```

155 C -----
156 C COMPUTE THE FACTORS F AND G AS DESCRIBED
157 C IN THE THEORY OF CORRESPONDENCE ANALYSIS
158 C -----
159 333 DO 135 I=1,NOB
160 135 DG(I)= B(I,I)
161 DO 144 I=1,NSUB
162 DO 144 J=1,NUMFAC
163 F(I,J)=0.0
164 DO 144 K=1,NOB
165 144 F(I,J)= F(I,J) + V(K,J) * A(I,K)
166 DO 155 I=1,NSUB
167 DO 155 J=1,NUMFAC
168 155 F(I,J)=F(I,J) * DC(I)
169 DO 166 J=1,NUMFAC
170 DGS = SQRT (ABS(DG(J)))
171 DO 166 I=1,NOB
172 166 G(I,J)= V(I,J) *DV(I) *DGS
173 C -----
174 C WRITE EIGENVALUES AND EIGENVECTORS.
175 C -----
176 WRITE (NWTR,20)
177 20 FORMAT ('1',20X,'EIGENVALUES',/21X,11(1H-),//)
178 WRITE (NWTR,21)(DG(I),I=1,NOB)
179 21 FORMAT (1X,12F10.5)
```



```

180      WRITE (NWTR,22)
181      22 FORMAT (///,21X,'EIGENVECTORS',/21X,12(1H-),//)
182      DO 23 I=1,NOB
183      23 WRITE (NWTR,21) (V(I,J),J=1,NOB)
184      TR= 0.0
185      DO 11I=2,NOB
186      TR= TR + DG(I)
187      11 DV(I-1)= SQRT( ABS(DG(I)))
188      WRITE (NWTR,30)
189      30 FORMAT (///21X,'CORRELATIONS',/21X,12(1H-),//)
190      WRITE (NWTR,31)(DV(I),I=1,NOB-1)
191      31 FORMAT (1X,12F10.6)
192      DO 13 I=2,NOB
193      13 DV(I-1)=DG(I)/TR
194      WRITE (NWTR,40) TR
195      40 FORMAT (//,21X,'TRACE = ',F12.6)
196      WRITE (NWTR,50)
197      50 FORMAT (//,21X,'PROPORTION OF TRACE',/21X,19(1H-),/ )
198      WRITE (NWTR,55)(DV(I),I=1,NOB-1)
199      55 FORMAT (1X,10F12.6)
200      WRITE (NWTR,60) (I,I=1,NUMFAC)
201      C -----
202      C WRITE THE ROW AND COLUMN LOADINGS
203      C -----
204      60 FORMAT (1H1,20X,'ROW LOADINGS',/21X,12(1H-),/3X,'VARIABLE ',*FACT
205      *OR', 8(I2,' FACTOR'),I2)
206      DO 61 I=1,NSUB
207      61 WRITE(NWTR,62) I,(F(I,J),J=1,NUMFAC)
208      62 FORMAT (4X,I3,3X,10F12.8)
209      WRITE (NWTR,70) (I,I=1,NUMFAC)
210      70 FORMAT (1H1,20X,'COLUMN LOADINGS',/21X,12(1H-),/3X,'VARIABLE ',*F
211      *ACTOR', 8(I2,' FACTOR'),I2)
212      DO 71 I=1,NOB
213      71 WRITE (NWTR,62) I,(G(I,J),J=1,NUMFAC)
214      IF (NT.EQ.0) GO TO 99
215      TOM=0.0
216      TSM=0.0
217      C -----
218      C COMPUTE AND PRINT TABLES AS DESCRIBED ON PAGE 8 OF H.TEIL
219      C -----
220      DO 72 I=1,NOB
221      72 TOM=TOM +OBJM(I)
222      DO 73 J=1,NSUB
223      73 TSM=TSM + SUBM(J)
224      SOM=0.0
225      DO 76 I=1,NP
226      KK=NPF(I)
227      76 SOM=SOM +DG(KK)
228      DO 89 K=1,NP
229      KK=NPF(K)
230      PER = DG(KK)/ SOM * 100.0
231      WRITE (6,100)
232      WRITE (6,101)
233      WRITE (6,103)
234      WRITE (6,102)
235      WRITE (6,104) K,DG(KK),PER
236      WRITE (6,103)
237      WRITE (6,101)
238      WRITE (6,103)
239      WRITE (6,105)

```

```

240     WRITE (6,103)
241     WRITE (6,101)
242     DO 74 I=1,NUMFAC
243     RHO= 0.0
244     DO 75 J =1,NP
245     JJ=NPF(J)
246     75 RHO=RHO + ((ABS(G(I,JJ))) ** 2.0)
247     ACO =((ABS(G(I,KK))**2.0)*(OBJM(I)/TOM))/DG(KK)*100.0
248     IF (G(I,KK).LT.0.0) ACO=ACO* (-1.0)
249     RCO=((ABS(G(I,KK)))**2.0/RHO) * 100.
250     IF (G(I,KK).LT.0.0) RCO=RCO * (-1.0)
251     CCO =ABS(RCO)
252     74 WRITE (6,106)I,OBJM(I),RHO,G(I,KK),ACO,RCO,CCO
253     WRITE (6,101)
254     WRITE (6,100)
255     WRITE (6,101)
256     WRITE (6,103)
257     WRITE (6,102)
258     WRITE (6,104) K,DG(KK),PER
259     WRITE (6,103)
260     WRITE (6,101)
261     WRITE (6,103)
262     WRITE (6,107)
263     WRITE (6,103)
264     WRITE (6,101)
265     DO 78 I=1,NSUB
266     RHS=0.0
267     DO 79 J=1,NP
268     JJ=NPF(J)
269     79 RHS=RHS + ((ABS(F(I,JJ))) ** 2.0)
270     ACS =((ABS(F(I,KK))**2.0)*(SUBM(I)/TSM))/DG(KK)*100.0
271     IF (F(I,KK).LT.0.0) ACS=ACS* (-1.0)
272     RCS=((ABS(F(I,KK)))**2.0/RHS) * 100.
273     IF (F(I,KK).LT.0.0) RCS=RCS * (-1.0)
274     CCS =ABS(RCS)
275     78 WRITE(6,106)I,SUBM(I),RHS,F(I,KK),ACS,RCS,CCS
276     WRITE (6,101)
277     89 CONTINUE
278     100 FORMAT(1H1)
279     101 FORMAT( 1X,119(1H*))
280     102 FORMAT(1X,'*',15X,'FACTOR',26X,'CHARACTERISTIC VALUE :',17X,'PERCE
281     *NTAGE OF INERTIA :',8X,'*')
282     103 FORMAT (1X,'*',117X,'*')
283     104. FORMAT(1X,'*',17X,I2,34X,F9.7,33X,F6.3,16X,'*')
284     105 FORMAT(1X,'*',92X,'CONTRIBUTIONS :',10X,'**/ 1X,'*',5X,'OBJECT',
285     *15X,'MASS',16X,'RHO',15X,'FACTOR', 47X,'**/1X,'*',78X,'ABSOLUTE',
286     *7X,'RELATIVE',6X,'CUMULATIVE*')
287     107 FORMAT(1X,'*',92X,'CONTRIBUTIONS :',10X,'**/ 1X,'*',4X,'SUBJECT',
288     *15X,'MASS',16X,'RHO',15X,'FACTOR', 47X,'**/1X,'*',78X,'ABSOLUTE',
289     *7X,'RELATIVE',6X,'CUMULATIVE*')
290     106 FORMAT(1X,'*',7X,I2,6X,'*',6X, F10.4,5X,'*',5X, F10.4,
291     *4X,'*',4X,F10.4,2X,'*',2(2X,F10.4,2X,'*'),2X,F10.4,'*')
292 C -----
293 C     WRITE THE FIRST TWO FACTORS TO DISC.
294 C     THESE FACTORS ARE USED BY ANDREW'S METHOD.
295 C -----
296     WRITE (3,112) NOB,NSUB
297     112 FORMAT (2I3)
298     K= NPF(1)
299     L= NPF(2)

```

```
300      DO 113 I=1,NOB
301      113 WRITE (3,114) G(I,K),G(I,L)
302      114 FORMAT (2F10.7)
303      DO 115 J=1,NSUB
304      115 WRITE (3,114) F(J,K),F(J,L)
305      99 STOP
306      END
```

```

1      SUBROUTINE EIEW(A,E,NM,N,ACC,IT,S,L)
2      DIMENSION A(NM,NM),E(NM,NM)
3      GO TO (1,2),L
4      1   DO 6 I=1,N
5          DO 5 J=1,N
6          5   E(I,J)=0.
7          6   E(I,I)=1.
8          2   NI=0
9          IND=0
10         VF=ACC
11         VI=0.
12         DO 10J=2,N
13         K=J-1
14         DO 10 M=1,K
15         10  VI=VI+2.*A(M,J)*A(M,J)
16         VI=SQRT(VI)
17         IF(L.EQ.1) VF=VI*ACC/N
18         IF(L.EQ.1) V=VI
19         14  V=V/N
20         IF(V-VF) 110,15,15
21         15  DO 100 J=2,N
22         K=J-1
23         DO 90 M=1,K
24         IF(ABS(A(M,J))-V) 90,20,20
25         20  IND=1
26         NI=NI+1
27         Y=-A(M,J)
28         U=0.5*(A(M,M)-A(J,J))
29         IF(A(M,M)-A(J,J)) 22,21,22
30         21  U=ABS(U)
31         22  W=Y*SIGN(1,U)/SQRT(Y*Y+U*U)
32         S=W/SQRT(2.*(1.+SQRT(1.-W*W)))
33         C=SQRT(1.-S*S)
34         DO 50 I=1,N
35         IF(I.EQ.M.OR.I.EQ.J) GO TO 45
36         A(I,M)=A(I,M)*C-A(I,J)*S
37         A(I,J)=A(M,I)*S+A(I,J)*C
38         A(M,I)=A(I,M)
39         A(J,I)=A(I,J)
40         45  SS=E(I,M)
41         E(I,M)=E(I,M)*C - E(I,J)*S
42         50  E(I,J)=SS*S+E(I,J)*C
43         SAM=A(M,M)
44         A(M,M)=A(M,M)*C*C+A(J,J)*S*S-2.*A(M,J)*S*C
45         A(J,J)=SAM*S*S+A(J,J)*C*C+2.*A(M,J)*S*C
46         A(M,J)=0.
47         A(J,M)=A(M,J)
48         IF(NI.EQ.IT) GO TO 109
49         90  CONTINUE
50         100 CONTINUE
51         IF(IND.EQ.0) GO TO 14
52         IND=0
53         GO TO 15
54         109 ACC=VF
55         RETURN 1
56         110 IT=NI
57         ACC=VF
58         RETURN
59         END

```

```

1 C -----
2 C THIS PROGRAM COULD BE INCLUDED IN THE MAIN PROGRAM AS A
3 C SUBROUTINE. IT IS HOWEVER NOT POSSIBLE AT THE U.O.V.S.
4 C AS THE PLOTTER PROGRAMS ARE WRITTEN IN A DIFFERENT LANGUAGE.
5 C -----
6 DIMENSION IBUF(1000),X(330),Y(330),IBYS(5),SIM(55),R(9)
7 DATA IBYS /6HGRAPH ,6HOF 2 F,6HACTORI,6HAL AXI,6HS /
8 DATA SIM /'S01','S02','S03','S04','S05','S06','S07','S08','S09','S
9 *10','S11','S12','S13','S14','S15','S16','S17','S18','S19','S20','S
10 *21','S22','S23','S24','S25','S26','S27','S28','S29','S30','S31','S
11 *32','S33','S34','S35','S36','S37','S38','S39','S40','S41','S42','S
12 *43','S44','S45','S46','S47','S48','S49','S50','S51','S52','S53','S
13 *54','S55'/
14 DATA R /'M1','M2','M3','M4','M5','M6','M7','M8','M9'/
15 CALL PLTIME (50)
16 CALL PLOTS(IBUF(1),1000,9)
17 CALL PLOT (0.0,0.5,-3)
18 CALL FACTOR (0.6)
19 CALL SYMBOL (7.0,20.5,0.3,IBYS(1),0.0,28)
20 C -----
21 C READ THE FACTORS AS COMPUTED IN THE MAIN PROGRAM OF
22 C CORRESPONDENCE ANALYSIS
23 C -----
24 READ (5,3) K,L
25 3 FORMAT (2I3)
26 J=0
27 DO 2 I=1,K
28 J=J+1
29 2 READ(5,4) X(J),Y(J)
30 4 FORMAT(2F10.7)
31 DO 6 I=1,L
32 J=J+1
33 6 READ(5,4) X(J),Y(J)
34 J=K+L
35 C -----
36 C AMX,AMY IS THE MINIMUM OF THE TWO FACTORS
37 C AX,XY IS THE MAXIMUM OF THE TWO FACTORS
38 C -----
39 AMY= 999.
40 AMX= 999.
41 AY =-999.
42 AX =-999.
43 DO 8 I=1,J
44 IF (X(I).LT.AMX) AMX= X(I)
45 IF (X(I).GT.AX) AX=X(I)
46 IF (Y(I).LT.AMY) AMY= Y(I)
47 IF (Y(I).GT.AY) AY=Y(I)
48 8 CONTINUE
49 C -----
50 C DX,DY INCREMENT ALONG THE X-AND Y-AXIS EXACTLY
51 C -----
52 DX = ((2* AX) - (1.0- ABS(AMX)))/20.0
53 DY = ((2* AY) - (1.0 - ABS(AMY)))/20.0
54 CALL AXIS (0.0,10.0,1H , -1,20.0,0.0,-0.4,.04)
55 CALL AXIS (10.0,0.0,1H , 1,20.0,90.0,-0.2,.02)
56 C -----
57 C COMPUTE ORDINATES AND PLOT FACTORS
58 C -----
59 DO 12 I=1,K

```

```
      IF (X(I)) 21,23,22
21  X(I) = (0.4 - ABS(X(I)))
      GO TO 23
22  X(I) = .4 + X(I)
23  CONTINUE
      IF (Y(I)) 24,27,26
24  Y(I) = (0.2 - ABS(Y(I)))
      GO TO 27
26  Y(I) = 0.2 + Y(I)
27  CONTINUE
      S = R(I)
      X(I) = X(I)/0.4 * 10.0
      Y(I) = Y(I)/.2 * 10.0
      CALL SYMBOL (X(I),Y(I),0.14,S,0.0,3)
12  CONTINUE
      KK=K + 1
      DO 14 I =KK,J
      IF (X(I)) 31,33,32
31  X(I) = (0.4 - ABS(X(I)))
      GO TO 33
32  X(I) = .4 + X(I)
33  CONTINUE
      IF (Y(I)) 34,36,35
34  Y(I) = (0.2 -ABS(Y(I)))
      GO TO 36
35  Y(I) = 0.2 + Y(I)
36  CONTINUE
      II = I - K
      S = SIM(II)
      X(I) = X(I)/.4 * 10.0
      Y(I) = Y(I)/.2 * 10.0
14  CALL SYMBOL (X(I),Y(I),0.14,S,0.0,3)
-----
C   CLOSE OUTPUT PLOTTER
-----
      CALL PLOT (32.0,0.0,999)
      STOP
      END
```

Area	Station	Altitude (m)	IX	X	XI	XII	I	II	III	IV	V
<b>A. Coast</b>											
1. North coast area	1. Rosh Hanikra	60	0.4	20.7	95.9	122.6	176.3	117.4	50.0	30.3	9.4
	2. Acre	10	1.4	21.7	81.7	126.0	154.2	122.2	44.7	19.7	5.4
2. Carmel area	3. Haifa, Carmel Blvd.	10	1.2	18.7	88.1	145.4	160.8	113.5	39.7	18.4	4.2
	4. Haifa, Mt. Carmel	300	0.4	22.8	94.9	161.3	182.5	123.1	44.5	23.5	8.0
	5. Yagur	30	0.3	18.8	99.8	165.7	220.3	155.1	58.5	23.0	7.5
	6. Atlit, Salt Co.	10	1.0	17.5	88.1	177.2	124.6	84.4	26.8	18.8	3.6
	7. Zichron Ya'akov	150	0.5	17.5	89.3	154.4	161.4	117.5	40.4	19.2	3.8
3. Central coastal plain	8. Hedera	20	0.9	15.3	83.5	165.9	153.0	105.2	37.9	14.1	4.2
	9. Tel-Aviv, Reading	3	3.3	17.8	83.1	150.4	124.0	89.9	34.4	13.8	2.3
	10. Lod Airport	40	1.9	17.4	61.9	120.7	121.8	112.0	42.4	15.8	2.1
4. Southern coastal plain	11. Masketet Batya	60	1.1	13.2	68.4	104.3	130.2	98.5	43.8	15.0	2.5
	12. Be'er Tuvia	55	0.6	11.4	72.0	114.1	123.2	82.2	43.0	12.0	1.5
	13. Gvar'am	100	0.4	7.9	61.1	99.2	93.7	69.4	37.4	8.5	1.4
	14. Gara	45	0.3	14.4	60.7	90.5	90.9	70.2	32.9	12.6	3.5
	15. Han-Yunes	45	0.2	8.8	51.2	58.0	60.4	49.7	19.8	12.3	2.6
<b>B. Mountains</b>											
1. Upper Galilee	16. Kfar Giladi	340	0.2	18.7	79.4	137.3	207.9	192.8	88.4	48.4	13.9
	17. Rehovya	660	0.4	15.5	75.3	93.1	165.3	155.5	54.5	26.9	6.5
	18. Ma'anya	500	0.6	25.2	89.9	134.3	218.8	179.0	70.5	36.8	7.9
	19. Mt. Con'an	935	2.1	15.5	80.4	139.0	195.3	172.2	72.0	35.6	15.9
2. Lower Galilee	20. Mitzepe	75	0.1	12.0	58.1	97.1	122.7	111.6	43.4	18.8	10.2
	21. Nazaret, Moshelot Haye'ur	445	0.6	11.8	71.9	139.1	172.2	146.2	61.3	27.5	6.4
	22. Tavor, Agricultural School	145	0.2	8.7	54.7	102.6	130.6	120.7	49.0	22.4	4.1
3. Yezze'el Valley	23. Ramat David Airport	50	0.1	12.7	59.4	109.8	138.6	110.1	41.0	17.4	4.9
	24. Mishmar Haemek	100	0.3	16.1	74.0	137.4	172.7	137.0	48.9	19.4	5.2
	25. Atula South-West	65	0.3	13.3	59.5	108.4	143.7	112.7	41.4	21.5	5.2
4. Beisan Valley	26. Tel-Josef	5	0.4	12.4	50.7	83.5	114.0	91.7	39.6	16.7	5.0
	27. Be'elba, Gilboa	-80	0.4	10.8	53.5	86.5	118.8	94.8	40.3	17.7	4.2
	28. Beisan	-120	0.6	10.9	37.4	68.4	84.4	67.8	33.2	14.2	3.2
5. Samarian hills	29. Jenin	140	0.2	12.3	53.3	95.9	135.4	111.2	42.9	22.4	4.4
	30. Tul-Carem	80	0.3	12.2	75.5	127.1	149.9	128.2	37.4	19.7	3.7
	31. Nablus	490	0.5	14.9	61.5	127.0	176.6	152.4	66.3	31.9	4.9
6. Judean hills	32. Bir-Zayit	780	1.2	11.2	58.4	132.4	194.1	174.6	88.9	38.1	3.1
	33. Latrun Monastery	200	0.8	15.2	69.3	90.1	129.5	99.0	56.3	20.0	3.8
	34. Kiryat Anavim	700	1.2	15.6	75.1	112.5	177.3	158.0	82.2	28.6	2.5
	35. Jerusalem, Hanvel'in Street	810	0.6	9.2	59.0	91.7	143.2	142.9	69.6	24.8	4.0
	36. Be't-Jamal	360	0.1	13.4	63.4	88.3	126.1	108.6	54.3	19.1	2.7
7. Negev	37. Be'er-sheva	90	0.3	7.3	53.5	76.1	127.2	109.9	68.4	22.6	2.7
	38. Zohar'ya	640	0.3	4.8	33.4	57.8	97.3	82.1	57.6	14.0	2.7
	39. Ruchama	180	0.3	3.7	39.8	67.3	103.2	64.0	38.0	11.5	1.2
	40. Dim	90	0.2	5.0	38.9	42.2	51.5	43.0	21.0	5.8	1.4
	41. Be'er Sheva	270	0.3	4.0	25.2	39.6	47.9	40.8	30.5	7.4	4.3
	42. Mamshit	450	0.3	1.0	13.0	20.4	34.1	25.4	15.6	5.3	4.9
	43. Mosh'avy Sede	350	0.2	1.7	12.2	18.3	22.4	22.9	19.3	5.0	3.0
	44. Nirana	250	0.1	2.1	10.9	12.4	19.8	18.1	15.1	7.7	3.8
<b>C. Jordan Valley</b>											
1. Hula region	45. Dafna	150	0.1	11.1	61.2	103.9	154.0	129.0	62.7	35.8	11.2
	46. Kfar Blum	75	0.2	5.6	56.3	93.3	127.5	115.1	53.9	25.4	11.7
	47. Ayelet Hashahar	175	0.8	8.5	57.4	93.1	132.6	109.8	46.7	24.4	8.7
2. Central Jordan valley	48. Dganya A	-200	0.4	8.3	42.4	76.1	100.9	88.9	38.3	22.8	5.9
	49. Naharayim	-220	0.3	13.1	46.8	80.7	108.7	90.8	42.8	22.3	5.5
	50. Tirat Zvi	-220	0.5	10.3	37.2	62.5	65.6	61.9	27.5	12.7	9.8
3. Dead Sea region	51. Jerico	-260	0.0	3.0	18.6	27.5	35.5	31.1	17.0	7.1	3.2
	52. Ashlag North	-385	0.0	2.6	14.1	17.7	19.5	16.2	11.1	4.5	1.3
	53. Ashlag South	-380	0.0	1.5	4.4	9.3	11.3	8.7	6.8	3.2	1.8
4. Arava	54. Ein Hazeva	-140	0.1	1.5	6.3	17.0	15.3	12.6	11.5	2.3	4.4
	55. Eilat	12	0.0	1.3	1.7	6.9	3.7	4.3	4.0	4.3	1.4

TEST RUN ON ISRAELI RAINFALL

YOUR FORMAT IS : (9F5.1)

YOUR OBJECTS = 9

SUBJECTS = 55

-----  
 - OBSERVATIONS -  
 -----

.40000	20.70000	95.90000	122.60000	176.30000	117.40000	50.00000	30.30000	9.40000
1.40000	21.70000	81.70000	126.00000	154.20000	122.20000	44.70000	19.70000	5.40000
1.20000	18.70000	88.10000	145.40000	160.80000	113.50000	39.70000	18.40000	4.20000
.40000	22.80000	94.90000	161.30000	182.50000	123.10000	44.50000	23.50000	8.00000
.30000	18.80000	99.80000	165.70000	220.30000	155.10000	58.50000	23.00000	7.50000
1.00000	17.50000	88.10000	127.20000	124.60000	84.40000	26.80000	18.80000	3.60000
.50000	17.50000	89.30000	154.40000	161.40000	117.50000	40.40000	19.20000	3.80000
.90000	15.30000	83.50000	165.90000	153.00000	105.20000	37.90000	14.10000	4.20000
3.30000	17.80000	83.10000	150.40000	124.00000	89.90000	34.40000	13.80000	2.30000
1.90000	17.40000	61.90000	120.70000	121.80000	112.00000	42.40000	15.80000	2.10000
1.10000	13.20000	68.40000	104.30000	130.20000	93.50000	43.80000	15.00000	2.50000
.60000	11.40000	72.00000	114.10000	123.20000	89.20000	43.00000	12.00000	1.50000
.40000	7.90000	61.10000	99.20000	93.70000	69.40000	37.40000	8.50000	1.40000
.30000	14.40000	60.70000	90.50000	90.90000	70.20000	32.90000	12.60000	3.50000
.20000	8.80000	51.20000	58.00000	60.40000	49.70000	19.80000	12.30000	2.60000
.20000	18.70000	79.40000	137.30000	207.90000	192.80000	88.40000	48.40000	13.90000
.40000	15.50000	75.30000	93.10000	165.30000	155.50000	54.50000	26.90000	6.50000
.60000	25.50000	89.90000	134.30000	218.60000	179.00000	70.50000	36.80000	7.90000
2.10000	15.50000	80.40000	139.00000	195.30000	172.20000	72.00000	35.60000	15.90000
.10000	12.00000	58.10000	97.10000	122.70000	111.60000	43.40000	18.80000	10.20000
.60000	11.80000	71.90000	139.10000	172.20000	146.20000	63.30000	27.50000	6.40000
.20000	8.70000	54.70000	102.60000	130.60000	120.70000	49.00000	22.40000	4.10000
.10000	12.70000	59.40000	109.80000	138.60000	110.10000	41.00000	17.40000	4.90000
.30000	16.10000	74.00000	137.40000	172.70000	137.00000	48.90000	19.40000	5.20000
.30000	13.30000	59.50000	108.40000	143.70000	112.70000	41.40000	21.50000	5.20000
.40000	12.40000	50.70000	83.50000	114.00000	91.70000	39.60000	16.70000	5.00000
.40000	10.80000	53.50000	86.50000	118.80000	93.80000	40.30000	17.70000	4.20000
.60000	10.90000	37.40000	68.40000	84.30000	67.80000	33.20000	14.20000	3.20000
.20000	12.30000	53.30000	95.90000	135.40000	111.20000	42.90000	22.40000	4.40000
.30000	12.20000	75.50000	127.10000	149.90000	128.20000	37.40000	19.70000	3.70000
.50000	14.90000	63.50000	127.00000	176.60000	152.40000	66.30000	31.90000	4.90000
1.20000	11.20000	58.40000	132.40000	194.10000	174.60000	88.90000	38.10000	3.10000
.80000	15.20000	69.30000	90.10000	129.50000	99.00000	56.30000	20.00000	3.80000
1.20000	15.60000	75.10000	112.50000	177.30000	158.00000	82.20000	28.60000	2.50000
.60000	9.20000	59.00000	91.70000	143.20000	142.90000	69.60000	24.80000	4.00000
.10000	13.40000	63.40000	88.30000	126.10000	108.60000	54.30000	19.10000	2.70000
.30000	7.30000	53.50000	76.10000	127.20000	109.90000	68.40000	22.60000	2.70000
.30000	4.80000	33.40000	57.80000	97.30000	82.10000	57.60000	14.60000	2.70000
.30000	3.70000	39.80000	67.30000	103.20000	64.00000	38.00000	11.50000	1.20000
.20000	5.60000	38.90000	42.20000	51.50000	43.00000	21.00000	5.80000	1.20000
.30000	4.00000	25.20000	39.60000	47.90000	40.80000	30.50000	7.40000	4.30000
.30000	1.00000	13.00000	20.40000	34.10000	25.40000	15.60000	5.30000	4.90000
.20000	1.70000	12.20000	18.30000	22.40000	22.90000	19.30000	5.00000	3.00000
.10000	2.10000	10.90000	12.40000	19.80000	18.10000	15.10000	7.70000	3.80000
.10000	11.10000	61.20000	103.90000	154.00000	129.00000	62.70000	35.80000	11.20000
.20000	5.60000	56.30000	93.30000	127.50000	115.10000	53.90000	25.40000	11.70000
.80000	8.50000	57.40000	93.10000	132.60000	109.80000	46.70000	24.40000	8.70000
.40000	8.30000	42.40000	76.10000	100.90000	88.90000	38.30000	22.80000	5.90000
.30000	13.10000	46.80000	80.70000	108.70000	90.80000	42.80000	22.30000	5.50000
.50000	10.30000	37.20000	62.50000	65.60000	61.90000	27.50000	12.70000	9.80000
.00000	3.00000	18.60000	27.50000	35.50000	31.10000	17.00000	7.10000	3.20000
.00000	2.60000	14.10000	17.70000	19.50000	16.20000	11.10000	4.50000	1.30000
.00000	1.50000	4.40000	9.30000	11.30000	8.70000	6.80000	3.20000	1.80000
.10000	1.50000	6.30000	17.00000	15.30000	12.60000	11.50000	2.30000	4.40000
.00000	1.30000	1.70000	6.90000	3.70000	4.30000	4.00000	4.30000	1.40000



----- ROW-TOTALS -----		----- COLUMN-TOTALS -----	
ROW NUMBER	TOTAL	COLUMN NUMBER	TOTAL
1	.02543	1	.00120
2	.02355	2	.02566
3	.02408	3	.12712
4	.02698	4	.20934
5	.03057	5	.26824
6	.02008	6	.21867
7	.02465	7	.09662
8	.02367	8	.04202
9	.02118	9	.01112
10	.02024		
11	.01947		
12	.01906		
13	.01547		
14	.01535		
15	.01073		
16	.03212		
17	.02420		
18	.03115		
19	.02971		
20	.01935		
21	.02608		
22	.02012		
23	.02016		
24	.02494		
25	.02065		
26	.01690		
27	.01739		
28	.01306		
29	.01951		
30	.02261		
31	.02604		
32	.02865		
33	.01975		
34	.02665		
35	.02224		
36	.01943		
37	.01910		
38	.01431		
39	.01343		
40	.00855		
41	.00816		
42	.00490		
43	.00429		
44	.00367		
45	.02322		
46	.01996		
47	.01967		
48	.01567		
49	.01677		
50	.01175		
51	.00584		
52	.00355		
53	.00192		
54	.00290		
55	.00113		

EIGENVALUES

.00088	.00065	.00190	1.00000	.01533	.00052	.00265	.00129	.00487
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EIGENVECTORS

.47282	-.05425	-.13730	.03470	-.08851	-.68780	.18364	.48846	.01499
.22958	.53695	.45591	.16020	-.21553	.35486	-.13387	.46047	.15210
.02920	-.38954	.58071	.35654	-.40955	-.13419	.28785	-.30924	.13723
-.26410	-.05497	-.58702	.45754	-.49819	.21543	.12826	.21290	.13006
-.07532	.51066	-.04127	.51792	.02744	-.41536	-.30671	-.37618	-.23401
.45185	-.44796	-.05029	.46762	.30792	.29971	-.34471	.08069	-.25295
-.04311	.20417	.01596	.31084	.51401	.13317	.75268	.04738	-.09422
-.61944	-.21792	.24580	.20499	.32805	-.23728	-.24993	.44279	.20957
.24028	.05796	-.16305	.10544	.24979	-.01412	-.08464	-.24918	.87713

CORRELATIONS

.029729	.025438	.043624	1.000000	.123820	.022803	.051511	.035904	.069776
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TRACE = 1.028096

PROPORTION OF TRACE

.000860	.000629	.001851	.972671	.014913	.000506	.002581	.001254	.004736
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ROW LOADINGS

VARIABLE	FACTOR 1	FACTOR 2	FACTOR 3	FACTOR 4	FACTOR 5	FACTOR 6	FACTOR 7	FACTOR 8	FACTOR 9
1	-.02740035	.02634675	.08654794	.99999935	-.05206452	-.03451231	-.02849357	-.02878722	.06813180
2	.04569522	.02167823	.03425666	.99999936	-.09867733	-.00143495	-.01898723	.02693910	.00729985
3	.00201498	.00969955	-.00338410	.99999935	-.16853558	-.01377761	-.01009500	.00093600	.00200566
4	-.02080829	.03539458	.00187166	.99999937	-.14442173	.00927708	-.03213638	-.01325390	.04877555
5	.00115489	.02714403	-.01732370	.99999937	-.07477388	-.00491431	-.03244638	-.05816613	-.01570936
6	-.03331551	-.02610697	.05180620	.99999934	-.24529887	-.02219513	.00108270	.01505290	.05326967
7	-.02452689	-.00570868	-.01837499	.99999934	.17062590	.01388174	-.01230055	-.01087657	-.00396467
8	-.02348852	.00173816	-.08278171	.99999937	-.21874149	.01174543	.01543383	-.00904227	-.01042400
9	.03462197	-.01739331	-.04779560	.99999936	-.27244527	-.05745125	.07083781	.09748186	.02162540
10	.05623873	-.00356901	-.03208013	.99999936	-.10122466	.01635170	.01280953	.09219011	-.03904779
11	.02063245	.00728776	.01300912	.99999938	-.08089668	.01974935	-.03207805	-.00370517	-.04249220
12	-.01281283	-.00591987	-.00895672	.99999937	-.13850987	.00573870	.07138524	-.02848265	-.04490856
13	-.02568232	-.02800975	-.03123637	.99999937	-.15941861	.02272375	.11894256	-.03647498	-.03030695
14	-.00689257	.00830405	.05090624	.99999936	-.14495706	.04481475	.05277654	.01364287	.04221377
15	-.03307375	-.07765152	.13238619	.99999936	-.15134590	.00333876	.03709257	-.00441167	.07096483
16	-.01779363	-.00804869	.01191206	.99999936	-.16284770	.01149244	-.04235269	.02417658	.03497422
17	.05442393	-.02922860	.06886203	.99999938	.08428172	.00056626	-.07168404	-.02357873	-.03947603
18	.01667266	.03401582	.05654486	.99999937	.05019007	-.000227550	-.06540935	.01283488	.00368895
19	.04648388	-.01384877	-.03278241	.99999937	.09275101	-.04238676	-.03074439	.00991911	.07078813
20	.03729240	-.01451000	-.01893094	.99999939	.03615809	.03594945	-.03443196	-.03386591	.07702962
21	-.01625205	-.01730622	-.05205773	.99999938	.02762888	.00243955	-.00748346	-.00186386	-.02510371
22	-.01431100	-.03949550	-.03838866	.99999940	.05318772	.02061437	-.02343973	.00051895	-.04782244
23	.00036288	.01343133	-.03212473	.99999937	-.03650750	.02362415	-.04140911	-.02415074	-.01999719
24	.01247030	.01560091	-.03581975	.99999935	-.05474237	.02235664	-.04302449	-.02368728	-.03422436
25	-.01069152	.01383247	-.01819675	.99999937	-.01586368	.00256873	-.05813938	-.00627666	-.01329396
26	.01604122	.02675345	.01095436	.99999937	.00873407	.00986292	-.01811391	-.00128247	.00181092
27	-.00179591	.00932268	.00600221	.99999939	.00419113	-.00553131	-.01486651	-.01204035	-.01875226
28	.00127859	.04111406	.00493652	.99999938	.00213606	.01120662	.01263843	.05565008	.00236833
29	-.01358033	.01029551	-.00523554	.99999938	-.03117962	.00610429	-.05946372	.00404982	-.03198148
30	.00032750	-.04817463	-.02251876	.99999937	-.08628353	.01295777	-.05726387	-.02580354	-.03716337
31	-.02004440	.00781607	-.02425056	.99999937	.07751612	.00918563	-.03471378	.03032524	.05336169
32	-.02728305	-.00047624	-.05186546	.99999938	.15840611	-.01254808	.00559456	.05372289	-.10410899
33	.00742720	.02853663	.07726767	.99999936	.01231001	-.01196899	.06603814	.00536842	-.02067491
34	.02248006	.00499928	.03240412	.99999938	.10450463	-.00563131	.04009387	.02424284	-.09837470
35	.02759019	-.03619895	.00477388	.99999935	.15488365	.01243080	.02526360	.00323291	-.08568140
36	.00481778	.00425427	.05777808	.99999937	.03716464	.03084079	.03480711	-.00771685	-.05865909
37	-.01907676	-.00229034	.02900110	.99999936	.17067183	-.00614179	.08456544	-.01356226	-.09145650
38	-.00124161	.03784591	-.02160918	.99999936	.21591833	.00379802	.12010814	-.01888692	-.09832208
39	-.05060955	.04316664	-.04072666	.99999936	.02117680	-.06073176	.05541477	-.07435112	-.10010222
40	.02833521	-.05367609	.10415881	.99999937	-.09925430	.00978334	.09662792	-.05865797	-.02201539
41	.02345758	.01661230	-.01949951	.99999940	.11828136	.01867156	.16314228	-.02494228	.07631354
42	.06151456	.02353780	-.07675063	.99999937	.20968696	-.08496026	.04522864	-.10666464	.20155675
43	.00350716	-.00936242	-.01391938	.99999937	.25287880	.02492971	.21619616	-.00028458	.12674409
44	-.04428009	-.00568279	.08925383	.99999935	.33510110	-.03139800	.11230681	.02728690	.28807543
45	-.04708588	-.00835015	.00044644	.99999938	.14409443	-.01478370	-.03043536	-.00104728	.06164847
46	-.00692129	-.04903393	-.04144035	.99999939	.13443205	-.01059126	-.00452015	-.04870818	.08320337
47	.00098285	.02403071	-.01888670	.99999935	.07349809	-.04184462	-.02810420	-.01840259	.04321992
48	-.03292974	.02548752	-.01030388	.99999938	.08835999	-.01142180	-.03732850	.02948561	.03413900
49	-.02128211	.02490442	.02624880	.99999940	.06088148	.01523392	-.02001276	.04197037	.02644802
50	.06562750	.00320120	-.00924015	.99999937	.02546406	.03875932	.00122464	-.01722785	.22614392
51	-.01176894	-.02085787	.01269179	.99999940	.09838603	.01882065	.04342049	-.03332595	.09572067
52	-.05394648	-.02169568	.09557729	.99999939	.01574399	.03336888	.12678985	.00519907	.08510341
53	-.05544435	.08435539	-.01978063	.99999935	.20763331	.03249400	.06212822	.03854114	.25816723
54	-.07954005	.09138618	-.19304527	.99999938	.20011791	.06273524	.17308152	-.06267912	.42907491
55	-.31600590	.00092800	.00199873	.99999938	.31250678	.06616535	.00647413	.36655699	.53196479

COLUMN LOADINGS

VARIABLE	FACTOR 1	FACTOR 2	FACTOR 3	FACTOR 4	FACTOR 5	FACTOR 6	FACTOR 7	FACTOR 8	FACTOR 9
1	.40509492	-.03977143	-.17261725	.99999934	-.31584052	-.45200676	.27262220	.50541971	.03013511
2	.04260346	.08526091	.12414932	.99999933	-.16658890	.05051134	-.04304499	.10320140	.06625056
3	.00243497	-.02779215	.07105143	.99999940	-.14223161	-.00858258	.04158771	-.03114023	.02685651
4	-.01715967	-.00305588	-.05596912	.99999934	-.13482043	.01073684	.01443947	-.01670673	.01983504
5	-.00432347	.02508117	-.00347581	.99999928	.00655977	-.01828758	-.03050468	-.02607786	-.03152653
6	-.02872557	-.02436807	-.00469117	.99999939	.08153360	.01461472	-.03797163	.00619536	-.03774338
7	-.00412339	.01670788	.00224037	.99999936	.20475108	.00976912	.12473046	.00547291	-.02115051
8	-.06983376	-.02704225	.05230788	.99999937	.19815209	-.02639472	-.06230286	.07755389	.07133517
9	.06774794	.01398365	-.06745785	.99999940	.29333650	-.00305360	-.04135204	-.08484928	.58045103



FACTOR 1 CHARACTERISTIC VALUE : .0153315 PERCENTAGE OF INERTIA : 54.567

Table with columns: OBJECT, MASS, RHO, FACTOR, ABSOLUTE, RELATIVE, CUMULATIVE. Rows 1-9.

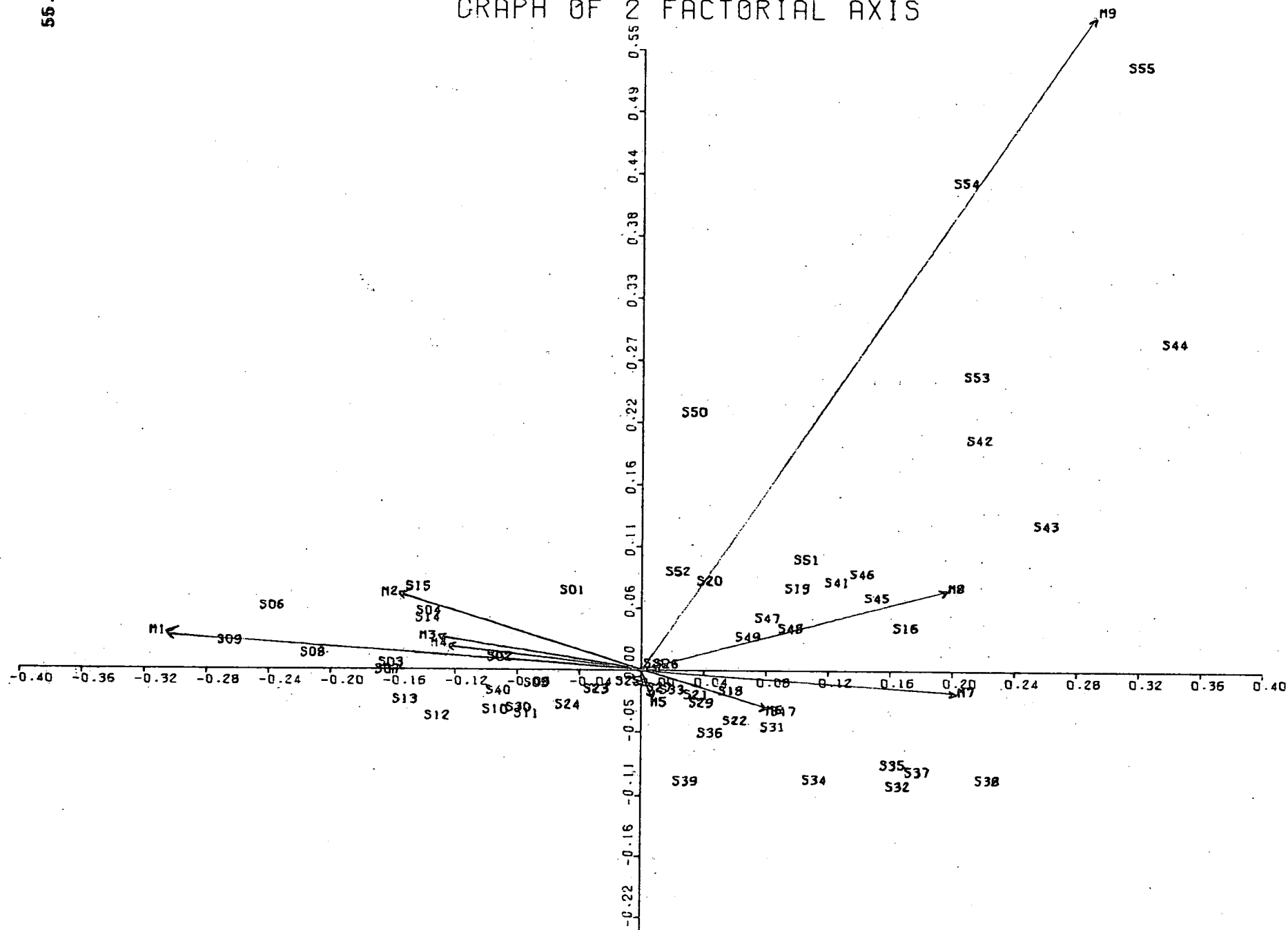
FACTOR 1 CHARACTERISTIC VALUE : .0153315 PERCENTAGE OF INERTIA : 54.567

Table with columns: SUBJECT, MASS, RHO, FACTOR, ABSOLUTE, RELATIVE, CUMULATIVE. Rows 1-55.

FACTOR		CHARACTERISTIC VALUE :		PERCENTAGE OF INERTIA :		
2		.0048687		17.328		
OBJECT	MASS	RHO	FACTOR	ABSOLUTE	RELATIVE	CUMULATIVE*
1	29.5000	.8302	.0301	.0225	.1094	.1094*
2	628.7999	.0717	.0663	2.3135	6.1221	6.1221*
3	3114.6996	.0296	.0269	1.8832	2.4408	2.4408*
4	5129.2993	.0226	.0198	1.6916	1.7401	1.7401*
5	6572.2991	.0036	-.0315	-5.4759	-27.2919	27.2919*
6	5357.8992	.0112	-.0377	-6.3983	-12.7113	12.7113*
7	2367.3997	.0584	-.0212	-8.8878	-7.7666	7.7666*
8	1029.5999	.0665	.0713	4.3920	7.6469	7.6469*
9	272.4000	.4412	.5805	76.9351	76.3610	76.3610*

FACTOR		CHARACTERISTIC VALUE :		PERCENTAGE OF INERTIA :		
2		.0048687		17.328		
SUBJECT	MASS	RHO	FACTOR	ABSOLUTE	RELATIVE	CUMULATIVE*
1	623.0000	.0191	.0681	2.4242	24.2782	24.2782*
2	577.0000	.0146	.0073	.0258	.3647	.3647*
3	590.0000	.0288	.0020	.0020	.0140	.0140*
4	661.0000	.0262	.0488	1.3182	9.0733	9.0733*
5	749.0000	.0113	-.0157	-1.549	-2.1769	2.1769*
6	492.0000	.0682	.0533	1.1703	4.1605	4.1605*
7	604.0000	.0306	-.0040	-.0080	-.0514	.0514*
8	580.0000	.0558	.0104	.0528	.1947	.1947*
9	519.0000	.0963	.0216	.2035	.4856	.4856*
10	496.0000	.0249	-.0390	-6.6340	-6.1219	6.1219*
11	477.0000	.0104	-.0425	-7.220	-17.3104	17.3104*
12	467.0000	.0274	-.0449	-7.895	-7.3548	7.3548*
13	379.0000	.0447	-.0303	-2.918	-2.0527	2.0527*
14	376.0000	.0305	.0422	5.617	5.8460	5.8460*
15	263.0000	.0540	.0710	1.1103	9.3263	9.3263*
16	787.0000	.0308	.0350	.8070	3.9745	3.9745*
17	593.0000	.0229	-.0395	-7.747	-6.8006	6.8006*
18	763.3000	.0121	-.0216	-2.977	-3.8576	3.8576*
19	728.0000	.0199	.0708	3.0580	25.2045	25.2045*
20	474.0000	.0128	.0770	2.3577	46.2640	46.2640*
21	639.0000	.0048	-.0251	-3.376	-13.2513	13.2513*
22	493.0000	.0093	-.0478	-9.451	-24.5149	24.5149*
23	494.0000	.0058	-.0200	-1.656	-6.8931	6.8931*
24	611.0000	.0088	-.0342	-5.999	-13.3680	13.3680*
25	506.0000	.0045	-.0133	-.0750	-3.9349	3.9349*
26	414.0000	.0016	.0018	.0011	.2050	.2050*
27	426.0000	.0009	-.0188	-1.256	-39.4243	39.4243*
28	320.0000	.0051	.0024	.0015	.1098	.1098*
29	478.0000	.0059	-.0320	-4.098	-17.3288	17.3288*
30	554.0000	.0158	-.0372	-6.414	-8.7596	8.7596*
31	638.0000	.0121	-.0534	-1.5229	-23.5013	23.5013*
32	702.0000	.0424	-.1041	-6.3782	-25.5384	25.5384*
33	484.0000	.0120	-.0207	-1.734	-3.5764	3.5764*
34	653.0000	.0244	-.0984	-5.2974	-39.6523	39.6523*
35	545.0000	.0342	-.0857	-3.3539	-21.4483	21.4483*
36	476.0000	.0104	-.0587	-1.3730	-33.0094	33.0094*
37	468.0000	.0461	-.0915	-3.2814	-18.1531	18.1531*
38	350.6000	.0730	-.0983	-2.8412	-13.2453	13.2453*
39	329.0000	.0288	-.1001	-2.7636	-34.7476	34.7476*
40	209.4000	.0377	-.0220	-.0851	-1.2842	1.2842*
41	200.0000	.0486	.0763	.9764	11.9775	11.9775*
42	120.0000	.1155	.2016	4.0866	35.1713	35.1713*
43	105.0000	.1288	.1267	1.4139	12.4742	12.4742*
44	90.0000	.2196	.2881	6.2610	37.7933	37.7933*
45	569.0000	.0280	.0616	1.8128	13.5749	13.5749*
46	489.0000	.0317	.0832	2.8378	21.8596	21.8596*
47	482.0000	.0111	.0832	2.547	16.8519	16.8519*
48	384.0000	.0132	.0341	.3752	8.8251	8.8251*
49	411.0000	.0086	.0264	.2410	8.1695	8.1695*
50	288.0000	.0580	.2261	12.3466	88.1454	88.1454*
51	143.0000	.0229	.0957	1.0983	39.9634	39.9634*
52	87.0000	.0372	.0851	.5282	19.4575	19.4575*
53	47.0000	.1267	.2582	2.6259	52.5866	52.5866*
54	71.0000	.1339	.4291	10.9575	58.6475	58.6475*
55	27.6000	.6193	.5320	6.5473	45.6949	45.6949*

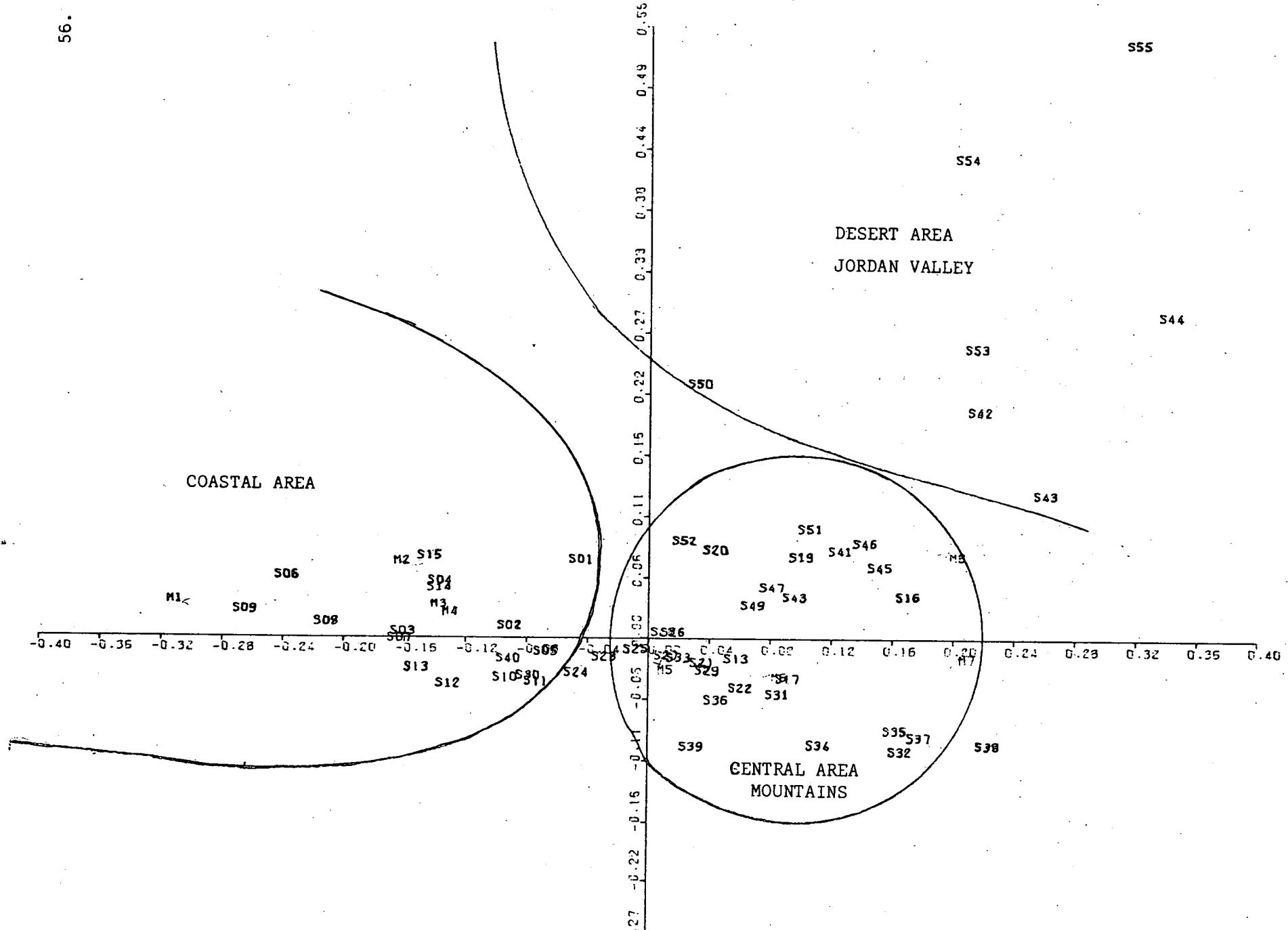
# GRAPH OF 2 FACTORIAL AXIS



# GRAPH OF 2 FACTORIAL AXIS

M9

56.



\*55

\*54

\*44

\*53

\*43

\*50

\*42

\*41

\*52

\*51

\*465

\*16 \*19 \*20

\*4\*49 \*1

\*15

\*40

\*1\*\*\*28

\*38 \*37\*35 \*1\*31\*29 \*253 \*2 \*\*14

\*34 \*3633 \*2411

\*32

\*30 \*7

\*12

\*6

\*39

\*10 \*13\*8

\*9

## C H A P T E R 5.

### GRAPHICAL TECHNIQUES FOR HIGH DIMENSIONAL DATA

(Andrew's method)

#### 5.1 INTRODUCTION.

The method of Andrew's and Multidimensional Scaling should be followed when the sum of the percentage of inertia of the first two factors are less than 60. One could consider, say the first five factors, until a sufficient percentage of inertia is obtained.

Pictures of data may be important functions in statistical analysis and they could be useful in the early stage of the analysis. Pictures could also be useful in the subjective art of model formulation, where they assist in the selection of variables or effects to be included in a model, and could help in checking the assumptions of a model.

For multivariate data the need is greater than for univariate data as the amounts of multivariate data are larger and the relationships, though frequently geometrical cannot be readily assimilated from a listing of the data.

First we would like to describe in section 1 a method for mapping  $k$  dimensional points into functions which may then be plotted and briefly describe some of its properties. In Section 3 we show how the first 5 factors of Correspondence analysis could be plotted as described in Section 2.

#### 5.2 FUNCTION PLOTS OF HIGH-DIMENSIONAL DATA.

The method is applicable to quantitative data in  $k$  dimensions, metric data. A data point may be represented as a vector  $\underline{x}_i = (x_1, \dots, x_m)$ . We could plot such a point by mapping it into a space of functions and plot the resulting functions. Many possible mappings could be done.



The following method has many useful geometrical and statistical properties and uses a family of functions which are widely understood.

For each  $k$  variate observation  $\underline{x}$ , define a function

$$f_{\underline{x}}(t) = \frac{1}{\sqrt{2}} x_1 + x_2 \sin(t) + x_3 \cos(t) + x_4 \sin(2t) + x_5 \cos(2t) + \dots$$

This function may be plotted over the range  $-\pi \leq t \leq \pi$ . Each data point will thus produce a curve drawn across the page.

Some interesting properties of such plots are discussed in Andrews(1972) and we would like to summarize these properties as given in Discriminant Analysis and Applications edited by T. Cacoullos, page 38-40.

- (1) The mapping is linear. If  $\underline{x}, \underline{y}$  and  $\underline{z}$  are points in  $k$ -dimensional space and if

$$\underline{x} = a\underline{y} + b\underline{z}$$

then the functions share the same linear relation

$$f_{\underline{x}}(t) = a f_{\underline{y}}(t) + b f_{\underline{z}}(t)$$

and so the functions of the average satisfies

$$f_{\underline{x}}(t) = m^{-1} \sum_{i=1}^m f_{\underline{x}_i}(t)$$

- (2) The mapping preserves distances. If the distance between two functions  $f$  and  $g$  is defined by

$$\|f - g\|_{L_2} = \int_{-\pi}^{\pi} |f(t) - g(t)|^2 dt,$$

(The distance used in the program (page 63) is defined by

$$\delta(\underline{x}, \underline{y}) = \sum_i |f_{\underline{x}}(t_i) - f_{\underline{y}}(t_i)|$$

then the distance between the functions corresponding to  $\underline{x}$  and  $\underline{y}$ ,

$$\|f_{\underline{x}}(t) - f_{\underline{y}}(t)\|_{L_2} = \pi \sum (x_i - y_i)^2$$

is proportional to the Euclidean distance between these points.

- (3) The mapping yields one-dimensional projections. For a particular value of  $t$  say  $t_0$ , the function value  $f_x(t_0)$  is proportional to the projection of  $\underline{x}$  on the vector  $\underline{f}_1$

$$\underline{f}_1(t_0) = (1/\sqrt{2}, \sin(t_0), \cos(t_0), \sin(2t_0), \dots).$$

As  $t_0$  changes the projections of the data on a continuum of directions are recorded on the plot.

- (4) The mapping preserves variances. If the original data have been transformed so that the components are approximately independent with equal variance  $\sigma^2$ , then the variance of  $f_x(t)$  is given by

$$\begin{aligned} \text{var}(f_x(t)) &= \sigma^2 \left( \frac{1}{2} + \sin^2(t_0) + \cos^2(t_0) + \sin^2(2t_0) + \dots \right) \\ &= \sigma^2 \begin{cases} k/2, & \text{if } k \text{ is odd,} \\ k/2 + \epsilon, |\epsilon| \leq 1/2, & \text{if } k \text{ is even} \end{cases} \end{aligned}$$

- (5) The mapping generates over all tests. Since the function value  $f_x(t)$  proportional to the projection of  $\underline{x}$  on any vector is less than the length of  $\underline{x}$ , tests may be constructed for any value of  $t$ . Thus a test of the hypothesis  $E(\underline{x}) = \underline{\mu}$  may be based on the inequality

$$\|f_x(t) - f_{\underline{\mu}}(t)\|^2 \leq \frac{1}{2}(k+1)\sigma^2 \chi_k^2(\alpha)$$

which is true with probability  $1 - \alpha$  for all values of  $t$ .

The properties discussed above also hold with obvious slight changes for functions of the form

$$f_x(t) = x_1 \sin(t) + x_2 \cos(t) + x_3 \sin(2t) + x_4 \cos(2t) + \dots$$

### 5.3 ANDREW'S METHOD IMPLIED ON THE FACTORS COMPUTED BY CORRESPONDENCE ANALYSIS.

A computer program (printed on page 63) takes the first  $n$  factors for its corresponding variable as computed by Correspondence analysis and plots the variable as described in section 2.

It is however necessary to decide how many factors present the vector  $\underline{x} = (x_1, \dots, x_n)$  (§5.2) as described in chapter 3 to help with the decision.

If we look at the Israeli rainfall data and use for example the first 5 factors for the specific stations as computed in chapter 4, it is possible to plot for each variable (i.e. each station) a graph by using the Andrew's method. The specific graphs can be see on page 66.

We are faced with another problem. If there are for example as in our Israeli rainfall analysis, say 55 variables, it is difficult to distinguish the difference or association between the variables on the 55 graphs. A program (page 64) was developed to solve this problem. During the plot of the different variables each x-axis is divided into  $n$  (say 1000) parts. For each value  $i$  on the x-axis the corresponding value on the y-axis is measured and subtracted from the value on the y-axis for the same  $i$  of every other graph. A total which specify the difference for all the  $y$  values is computed between each and every variable. Thus by just looking at the totals and then compare the graphs it may help us in finding the associations and oppositions between the different variables. This method will only save time because it could be very difficult to scan through all the graphs to find the associations. One could thus disregard this method especially in cases with not many variables.

During the construction of these totals of differences we found it applicable to multidimensional scaling which leads us to the next chapter.

REFERENCE TO PROGRAMS AND CORRESPONDING EXECUTION EXAMPLES.

	<u>Page.</u>
1. Program which plots the factors according to Andrew's Method.	63
2. Sample of how a subject or object would look like when plotted on the Calcomp.	65
3. Group 1 according to the stations as selected by the difference tables.	66
4. Group 2	70
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SUBROUTINE ANDREW(X,K,M,IBYS,NK,N1,AMIN,AMAKS,Y,INT,IND)
C *****
C X : MATRIX WITH FACTOR SCORES
C K : FACTORS
C M : GRAPHS
C *****
C X : MATRIKS VAN HOOFKOMPONENTWAARDES
C K : AANTAL HOOFKOMPONENTE WAT GEBRUIK WORD
C M : AANTAL GRAFIEKE
DIMENSION IBUF(1000),T(100),FT(100),IBYS(NK),X(K),Y(160,32)
IF(IND.EQ.1)CALL PLOTS(IBUF(1),1000,9)
CALL PLOT(0.0,-0.5,-3)
CALL PLOT(0.0,0.5,-3)
CALL FACTOR(0.400)
T(1)=-3.1415926535
INT=IFIX(6.2831853070/0.2)
INT1=INT+1
INT2=INT+2
DO 2 J=2,INT
2 T(J)=T(J-1)+0.2
IF(K.GT.5) GO TO 100
C -----
C COMPUTE VALUES BY USING ANDREWS METHOD.
C THE COMPUTATION IS DEPENDANT ON THESE FACTORS
C -----
GO TO (100,200,300,400,500),K
100 WRITE(6,900)
900 FORMAT(1H1,'ONGELDIGE AANTAL KOMPONENTE')
GO TO 10
200 DO 203J=1,INT
Y(IND,J)=X(1)*SIN(T(J))+X(2)*COS(T(J))
203 FT(J)=X(1)*SIN(T(J))+X(2)*COS(T(J))
GO TO 1000
300 DO 3 J=1,INT
Y(IND,J)=X(1)*SIN(T(J))+X(2)*COS(T(J))+X(3)*SIN(2*T(J))
3 FT(J)=X(1)*SIN(T(J))+X(2)*COS(T(J))+X(3)*SIN(2*T(J))
GO TO 1000
400 DO 403 J=1,INT
Y(IND,J)=X(1)*SIN(T(J))+X(2)*COS(T(J))+X(3)*SIN(2*T(J))
*+X(4)*COS(2*T(J))
403 FT(J)=X(1)*SIN(T(J))+X(2)*COS(T(J))+X(3)*SIN(2*T(J))
*+X(4)*COS(2*T(J))
GO TO 1000
500 DO 503J=1,INT
Y(IND,J)=X(1)*SIN(T(J))+X(2)*COS(T(J))+X(3)*SIN(2*T(J))
*+X(4)*COS(2*T(J))+X(5)*SIN(3*T(J))
503 FT(J)=X(1)*SIN(T(J))+X(2)*COS(T(J))+X(3)*SIN(2*T(J))
*+X(4)*COS(2*T(J))+X(5)*SIN(3*T(J))
1000 FT(INT1)=AMIN
FT(INT2)=AMAKS/5
T(INT1)=-3.1415926535
T(INT2)=0.8
C -----
C PLOT FACTORS
C -----
CALL SYMBOL(2.0,10.0,0.2,IBYS(1),0.0,N1)
CALL AXIS(0.0,0.0,2HPI,-2,8.0,0.0,T(INT1),T(INT2))
CALL AXIS(0.0,0.0,31HCORRESPONDENCE ANALYSIS FACTORS,31,
*10.0,90.0,FT(INT1),FT(INT2))

```

```

CALL SCALE(T(1),8.0,INT,1)
CALL SCALE(FT(1),10.0,INT,1)
CALL LINE(T(1),FT(1),INT,1,0,4)
CALL PLOT(10.0,0.0,-3)
IF(IND.EQ.M)GO TO 999
GO TO 10
999 CALL PLOT(10.0,0.0,999)
10 RETURN
END

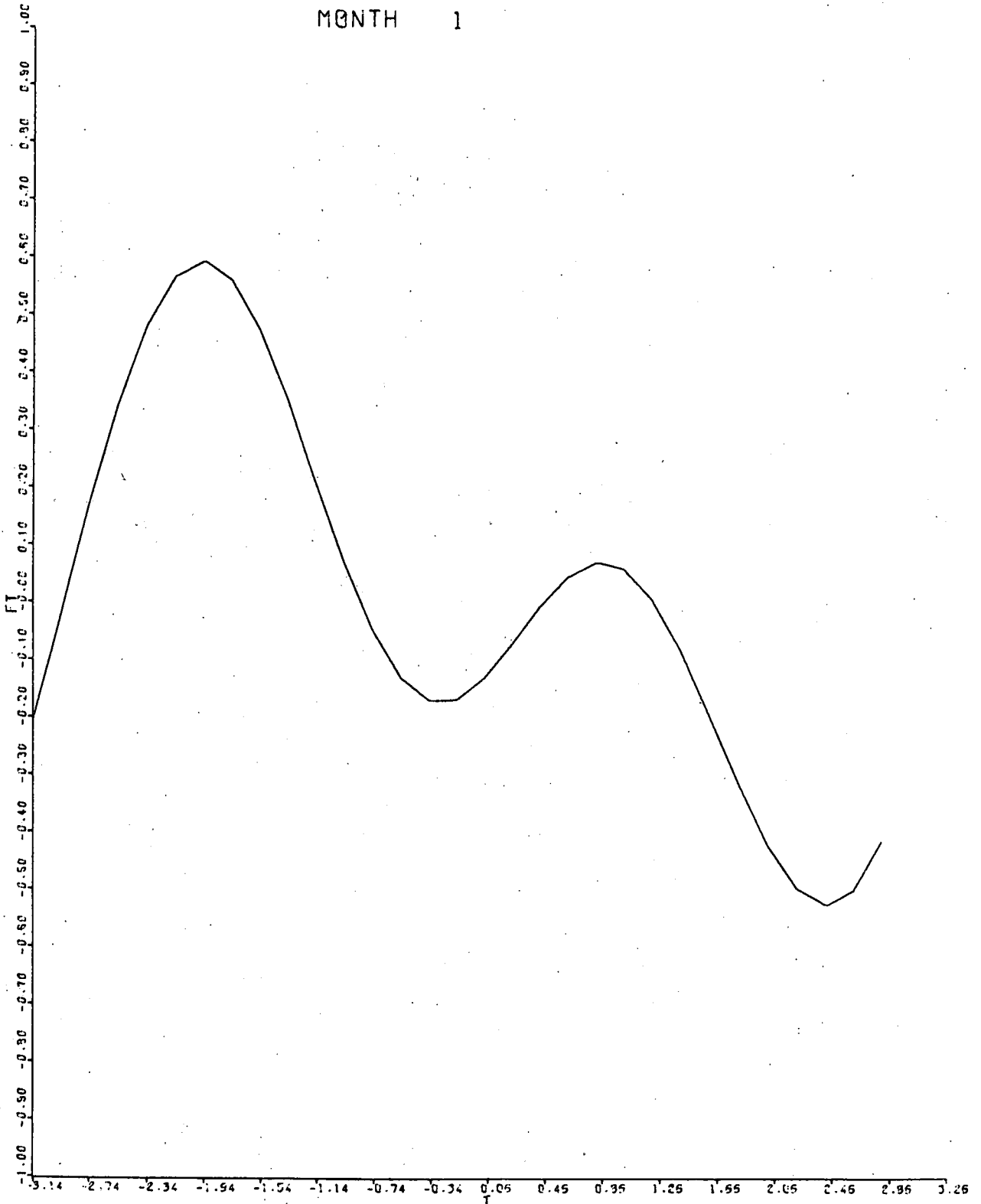
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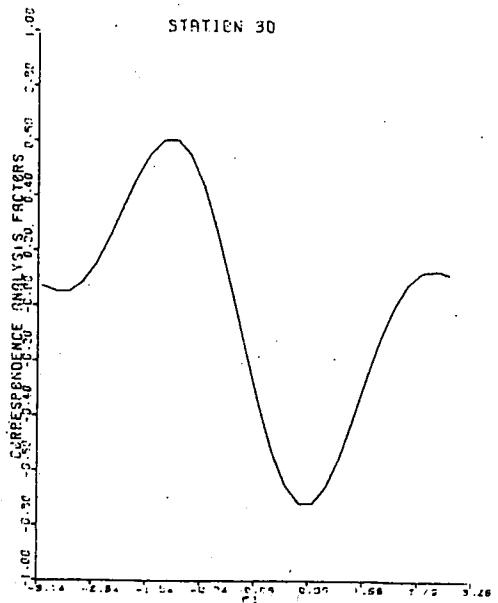
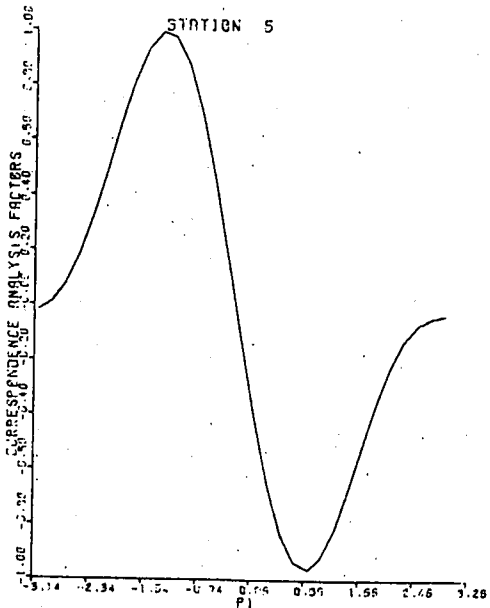
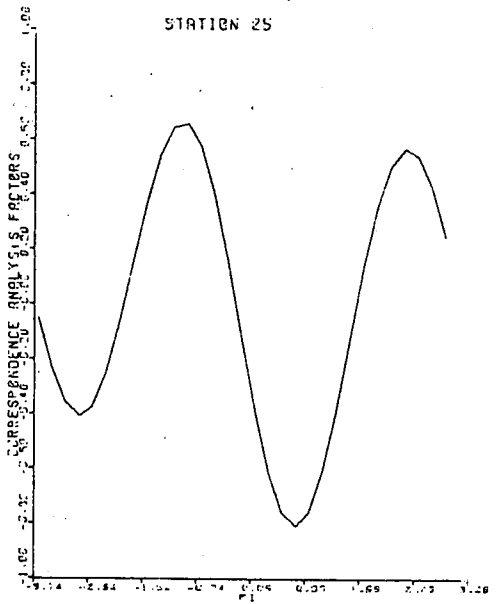
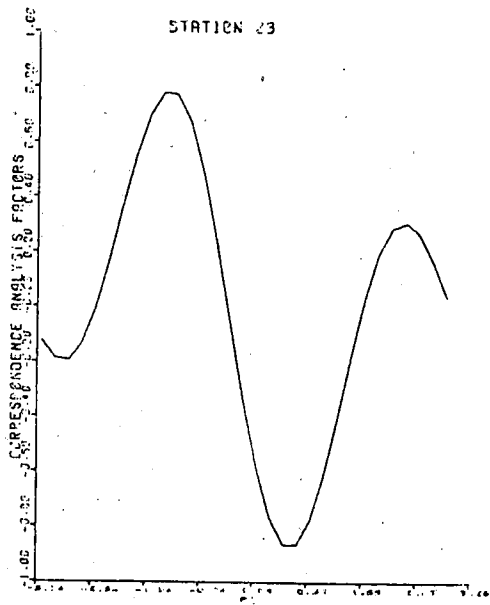
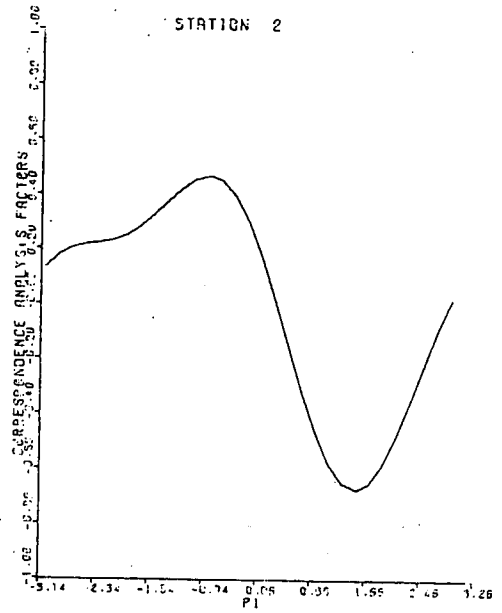
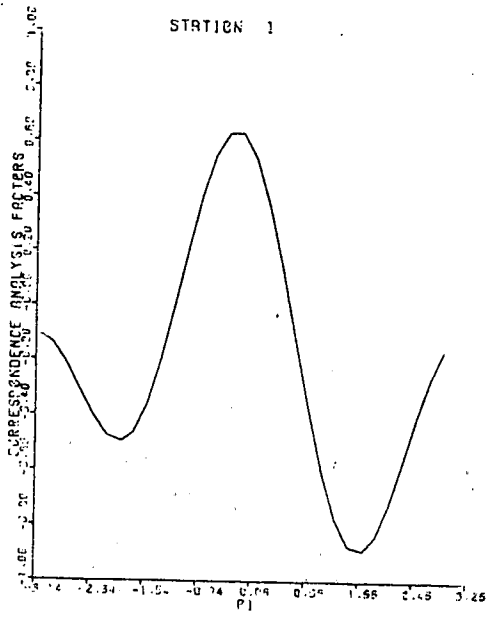
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C *****
C ANDREWS METHOD: D.BESTER.
C REFERENCE: CALCOULLOS,T. (1973) PAGE 37-59
C PARAMETER CARDS NEEDED:
C COLUMN 1-12 HEADING OF GRAPH (12 CHARACTERS ALFANUMERIC)
C COLUMN 13-24 FACTOR1 (CORRESPONDENCE ANALYSIS)
C COLUMN 25-37 FACTOR2
C      ::      ::      ::
C      ::      ::      ::
C      ::      ::      ::
C *****
C DIMENSION X(4),IBYS(2),Y(160,32)
C INT=0
C -----
C REQUEST FOR 500 MINUTE MAXIMUM PLOTTER TIME
C -----
CALL PLTIME(500)
DO 10I=1,55
READ(5,1)IBYS,X
1 FORMAT(2A6,4F13.8)
10 CALL ANDREW(X,4,55,IBYS,2,12,1.0,-1.0,Y,INT,I)
DO 11K=1,54
KK=K+1
DO 11I=KK,55
SOMVER =0.0
DO 12J=1,INT
VERSK =Y(K,J)-Y(I,J)
12 SOMVER=SOMVER+ABS(VERSK)
11 WRITE(3,13)K,I,SOMVER
13 FORMAT(5X,2I3,F7.4)
STOP
END

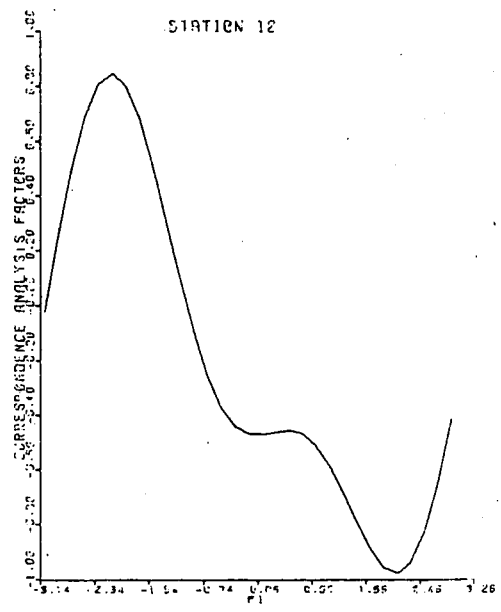
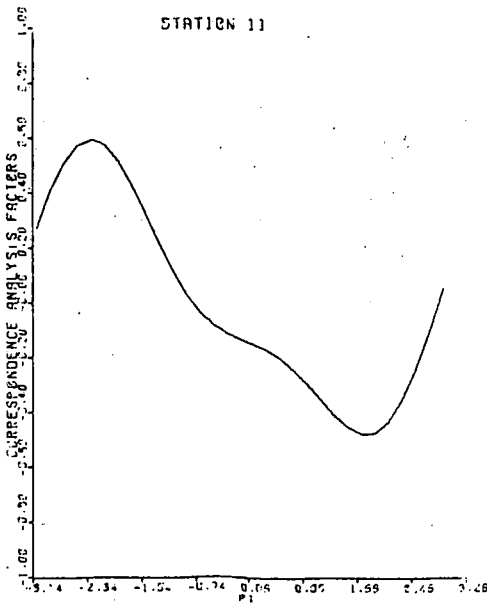
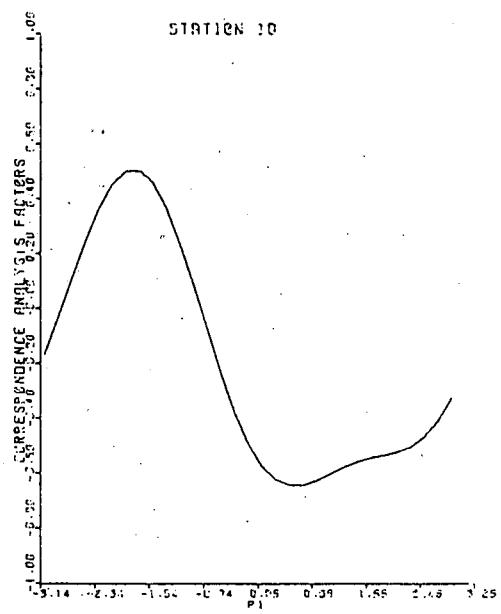
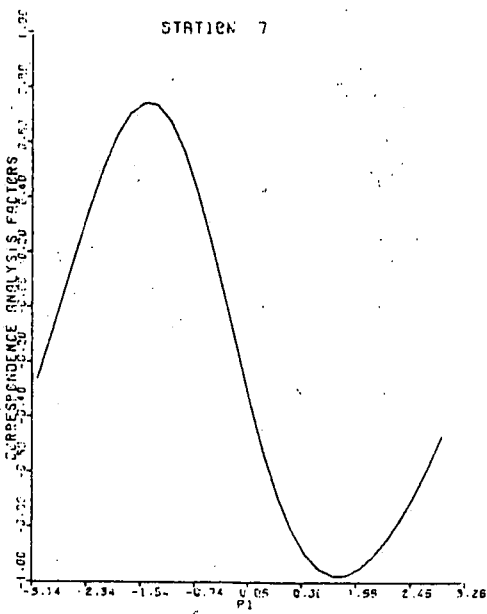
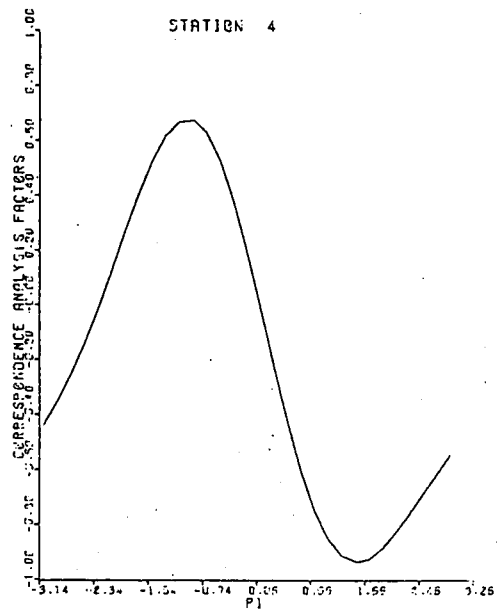
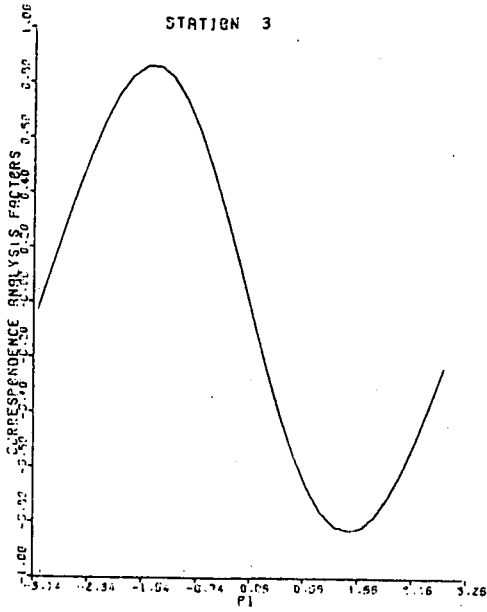
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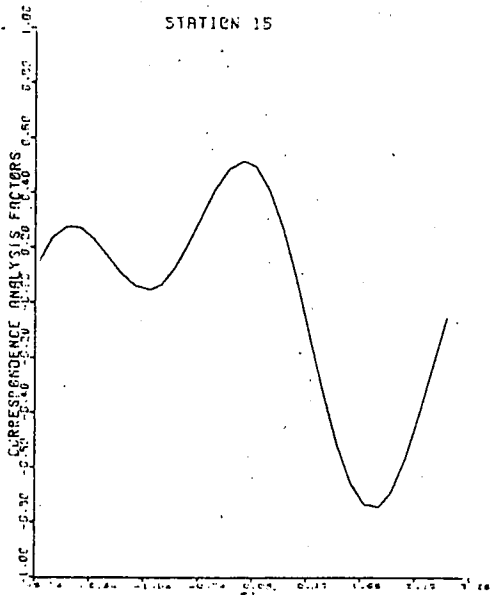
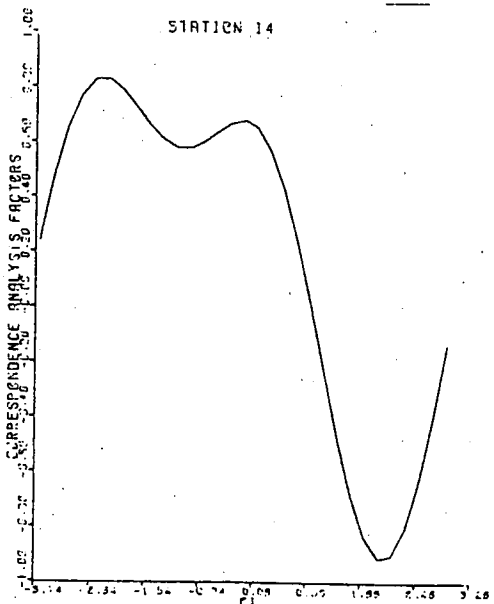
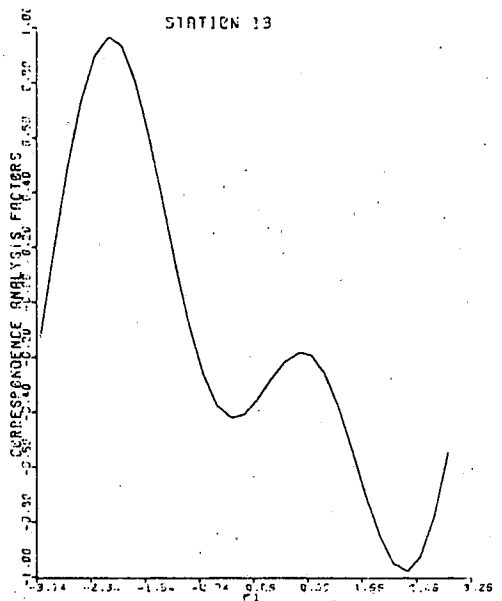
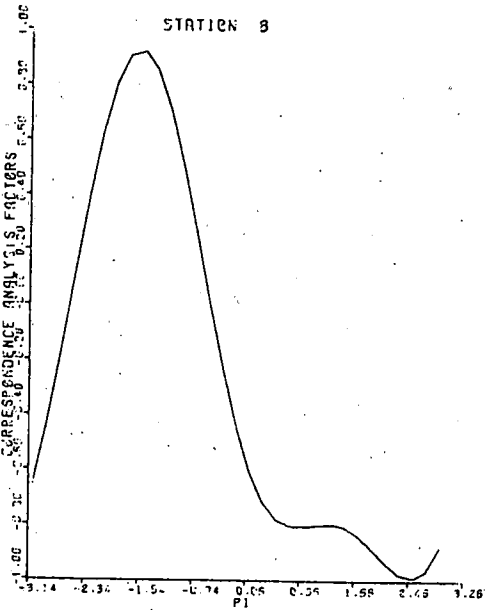
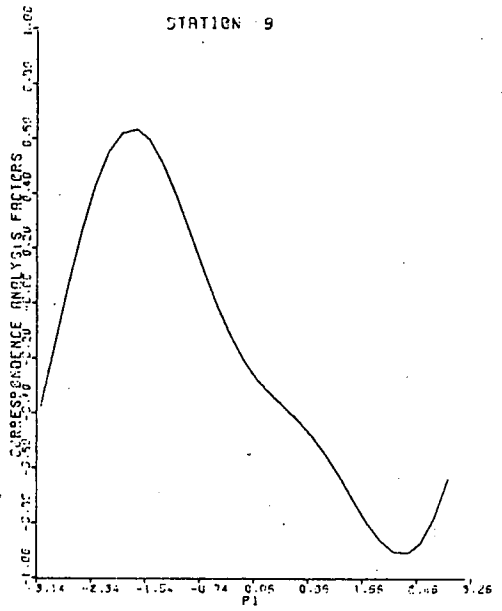
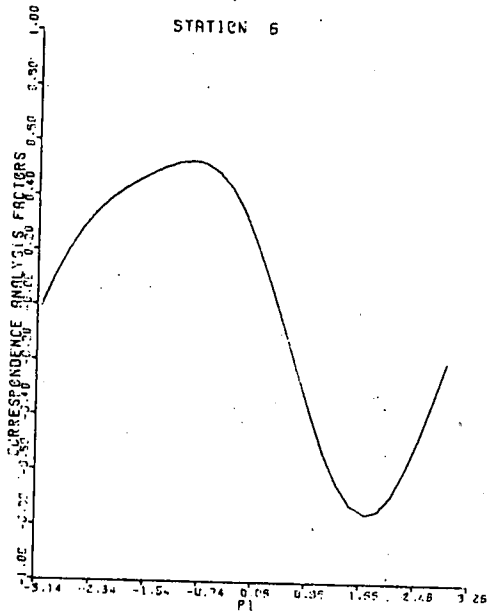
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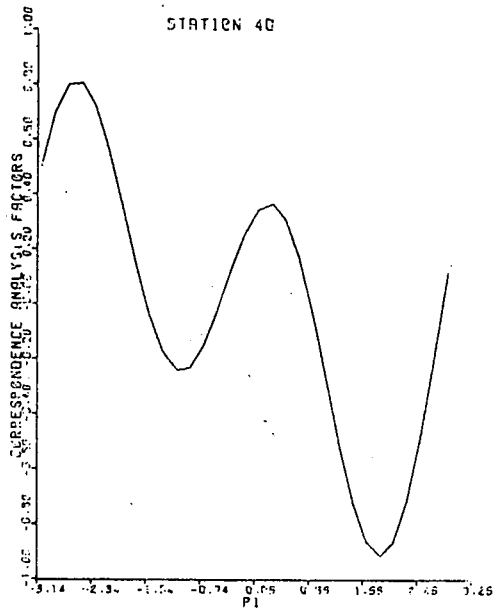
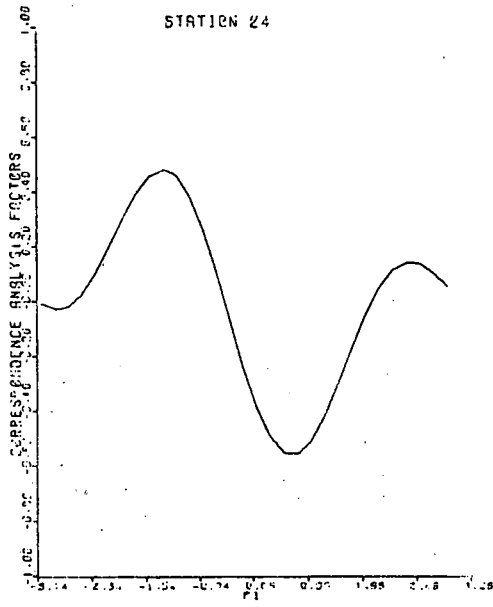


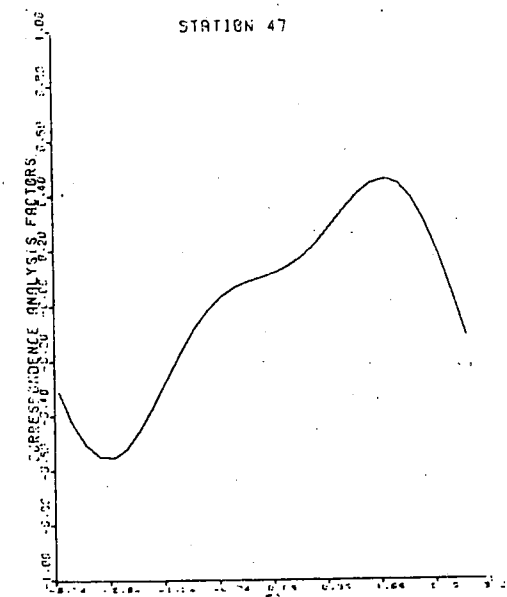
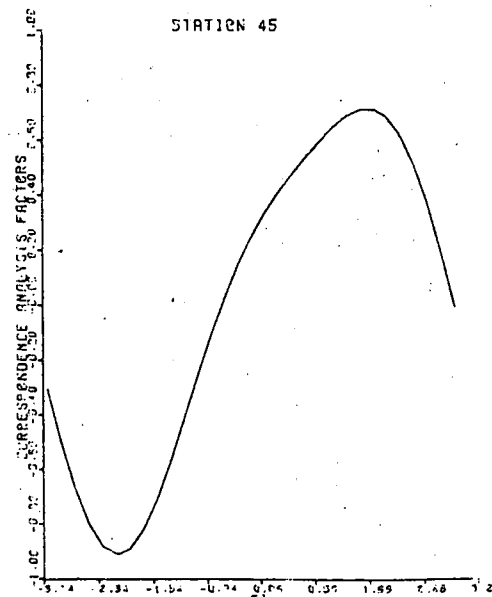
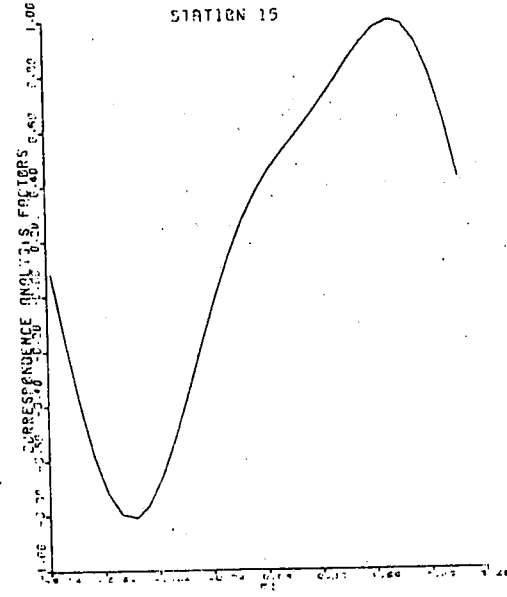
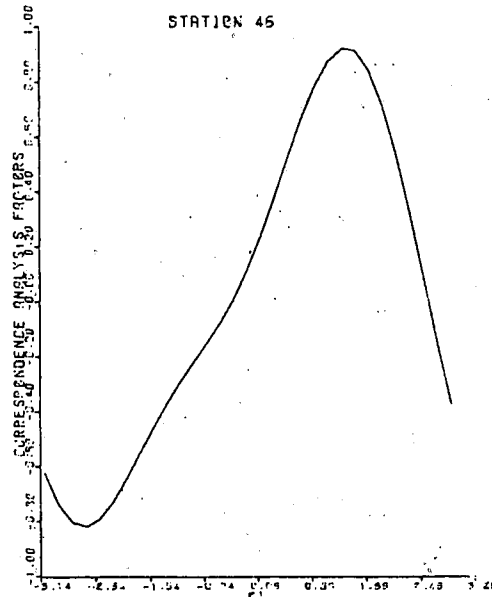
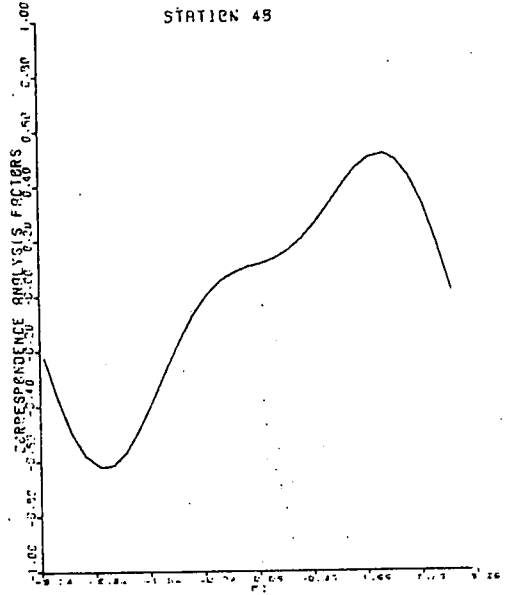
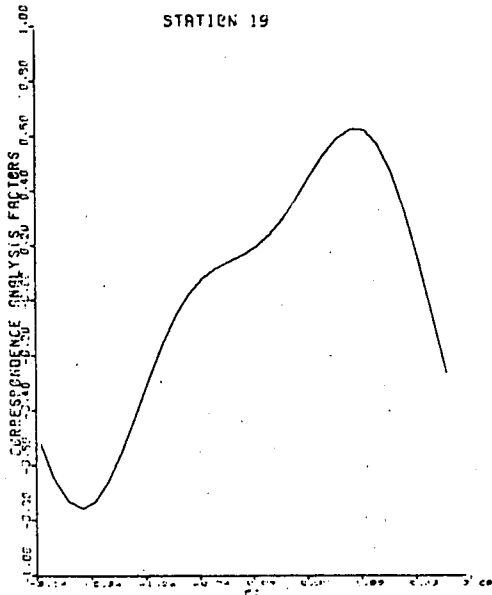


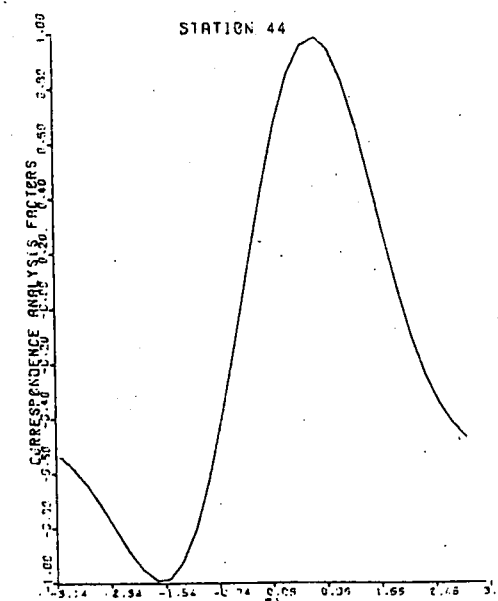
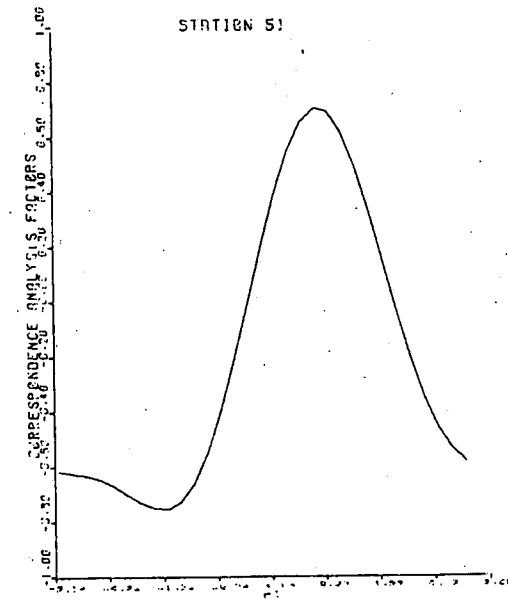
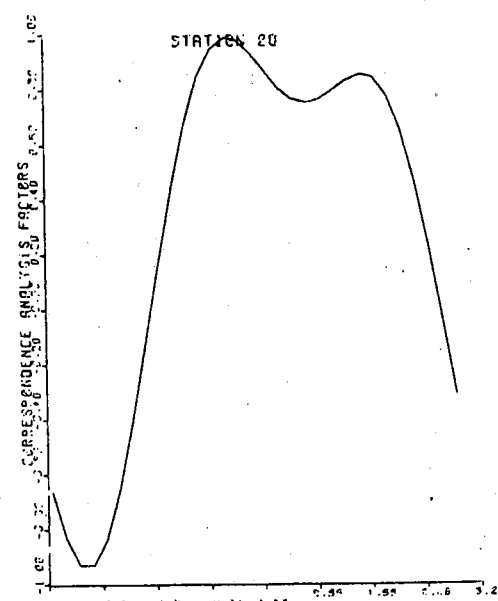
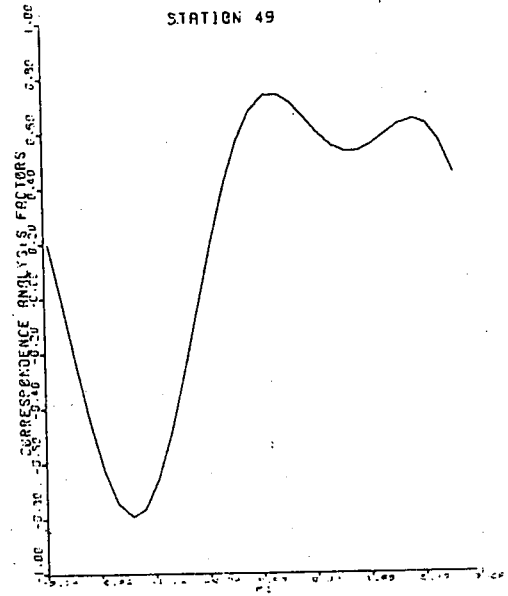
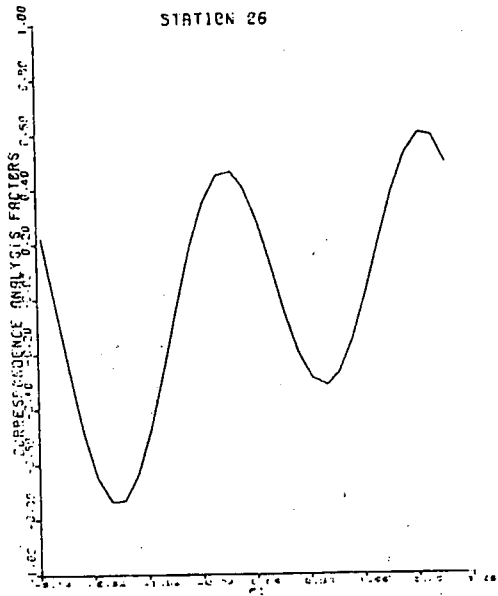


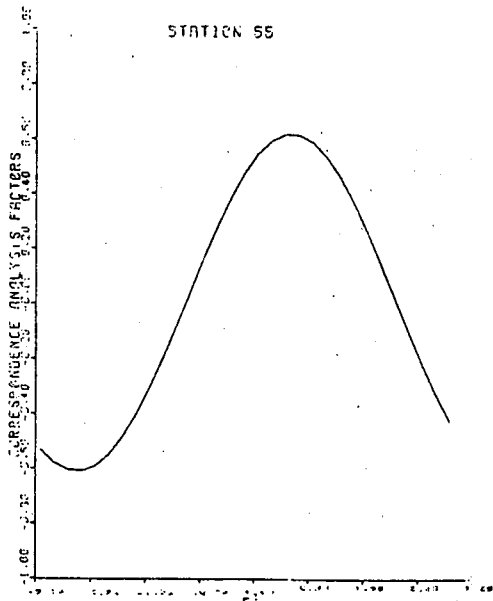
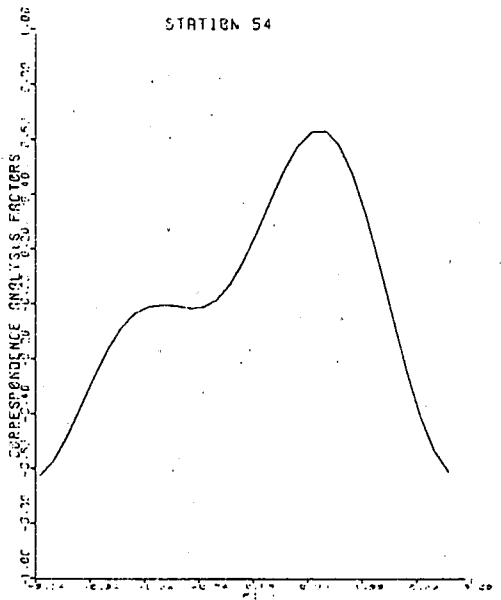
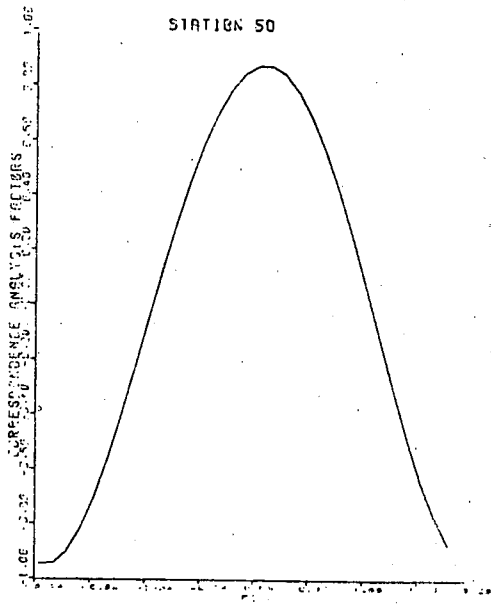
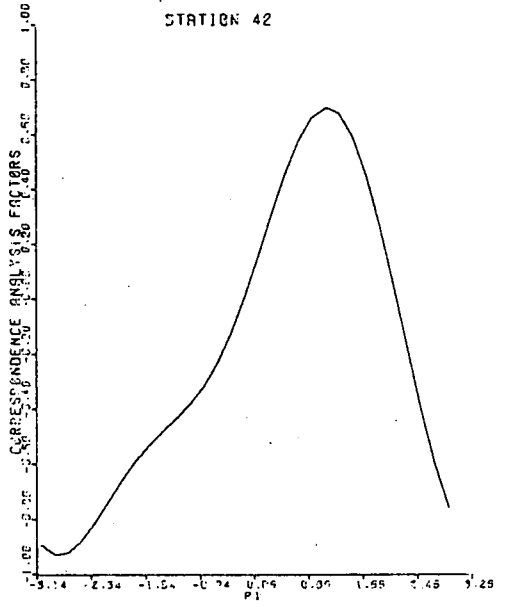
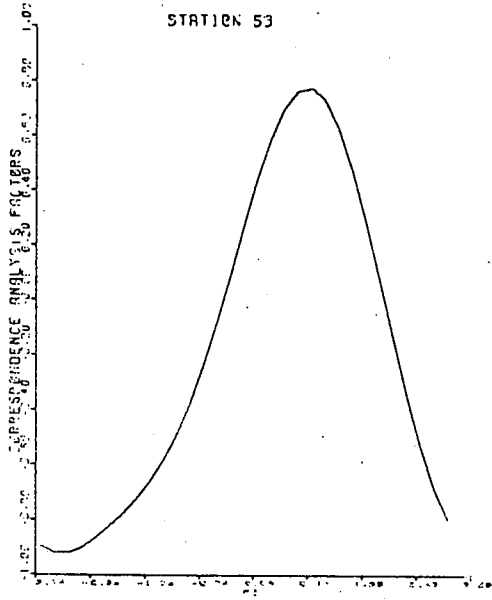


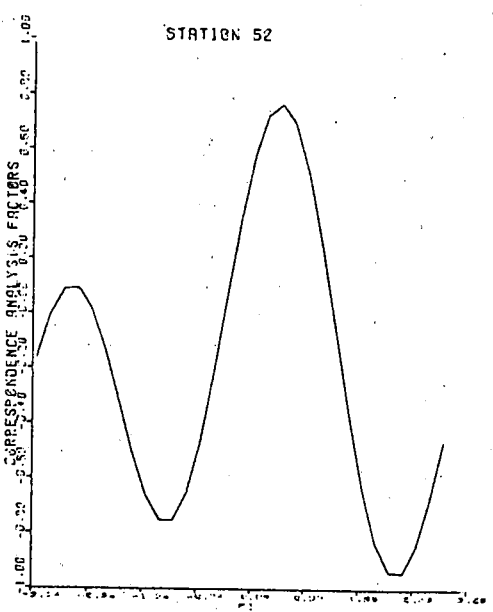
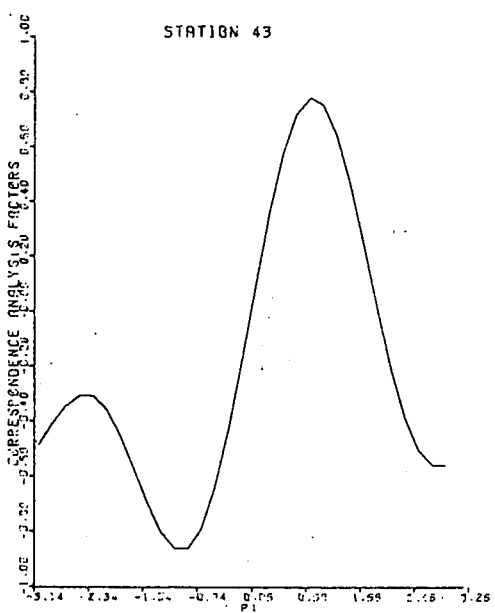
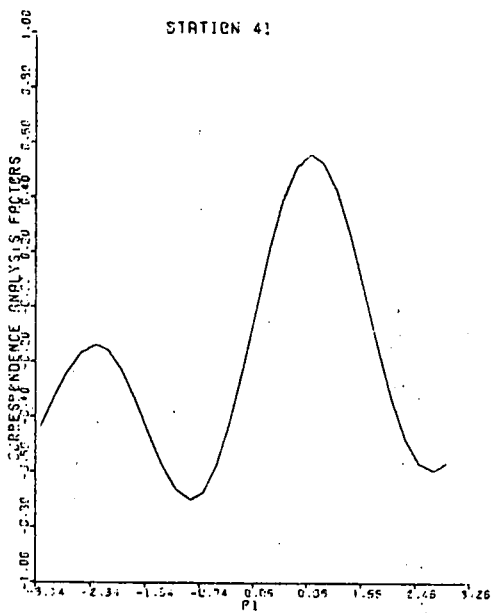


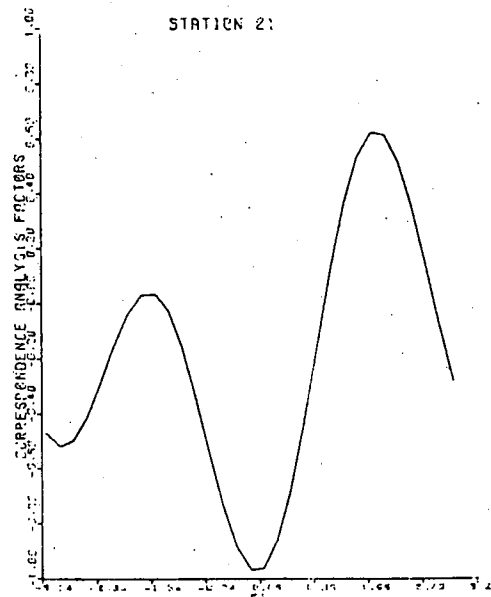
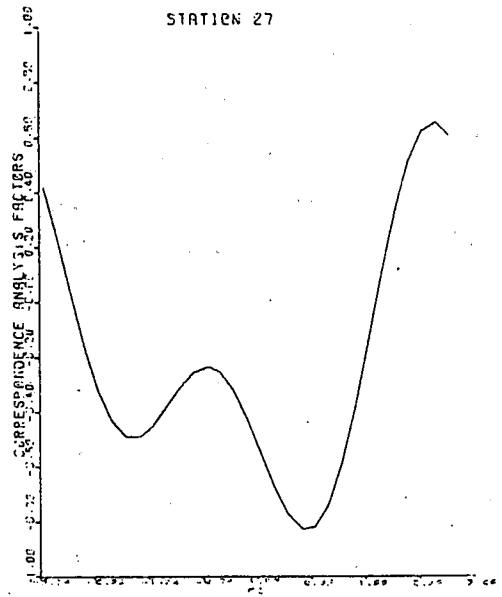
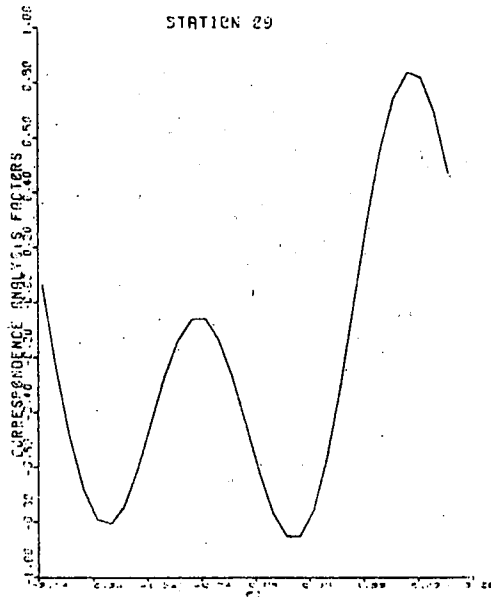
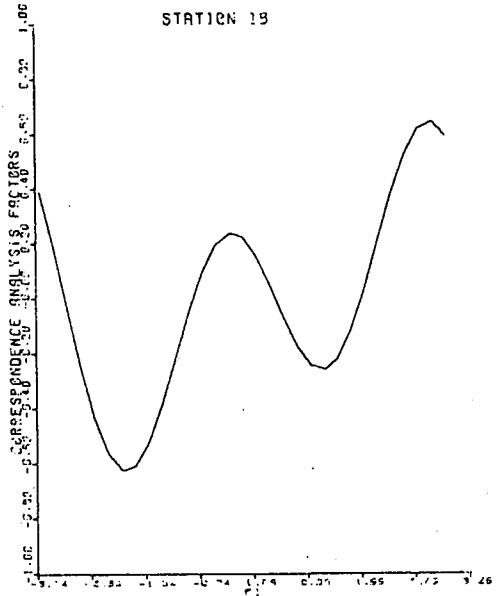
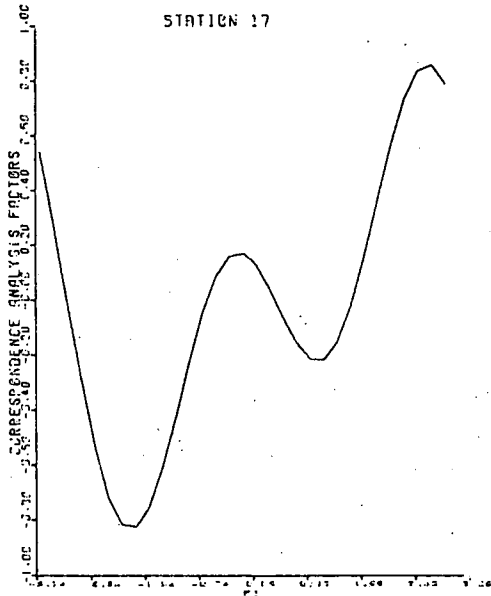




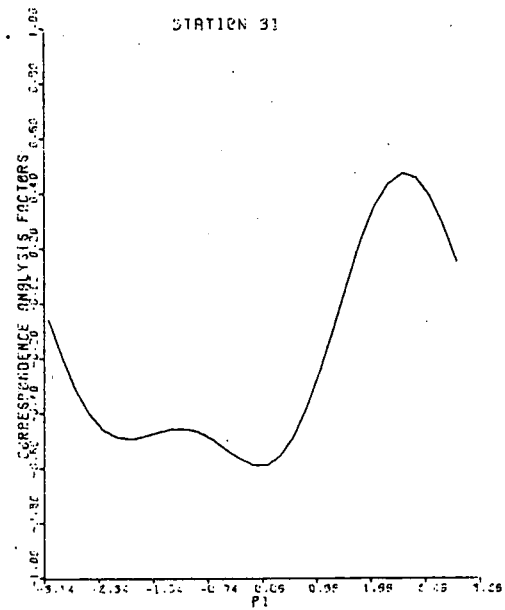
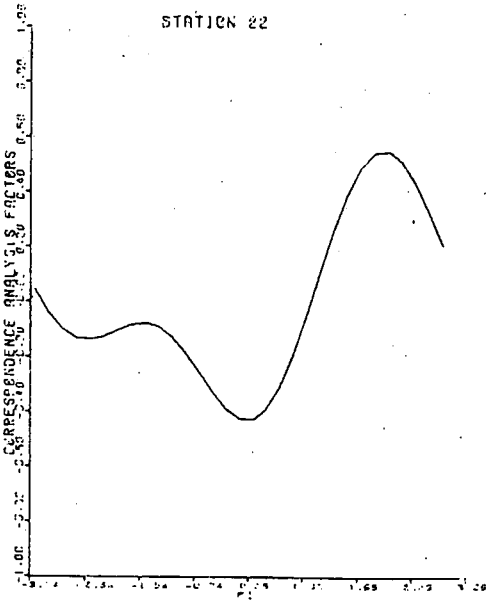
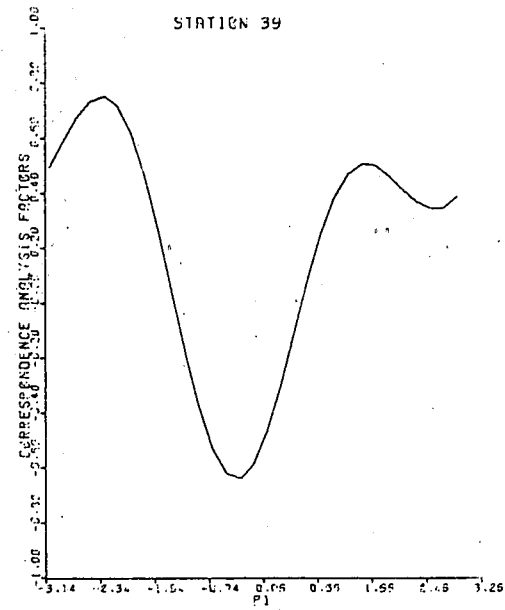
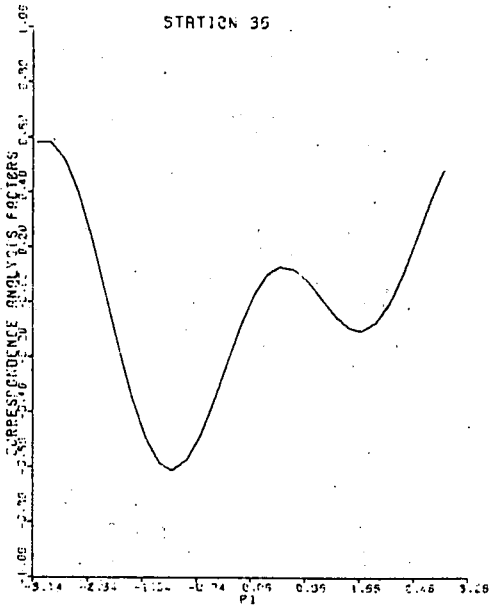
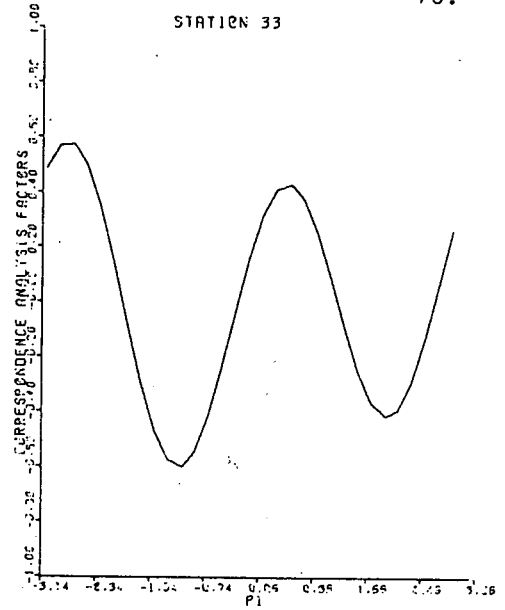
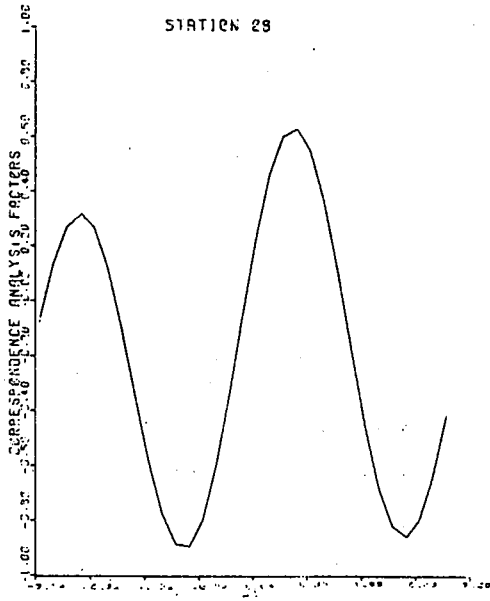


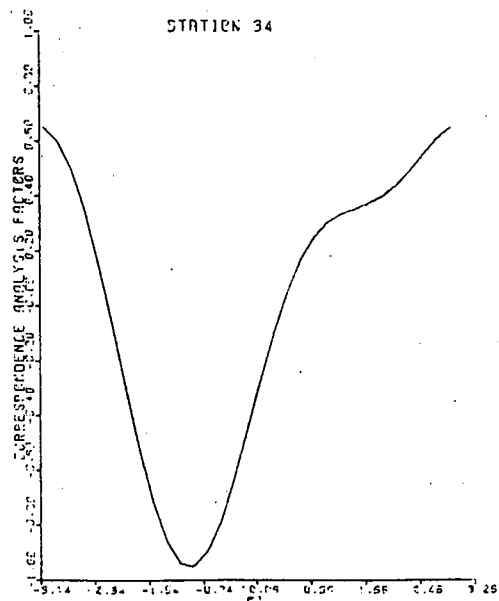
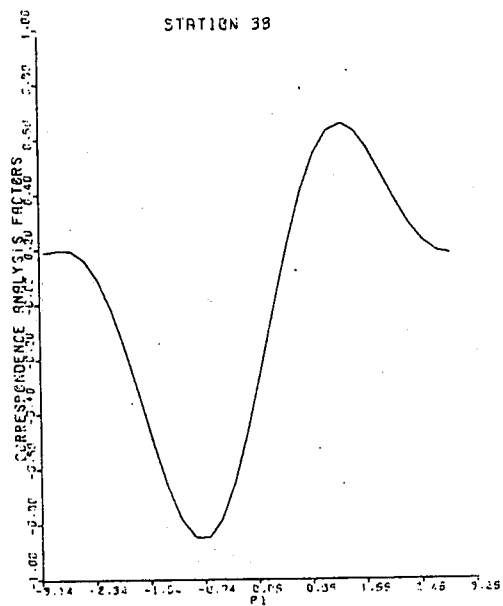
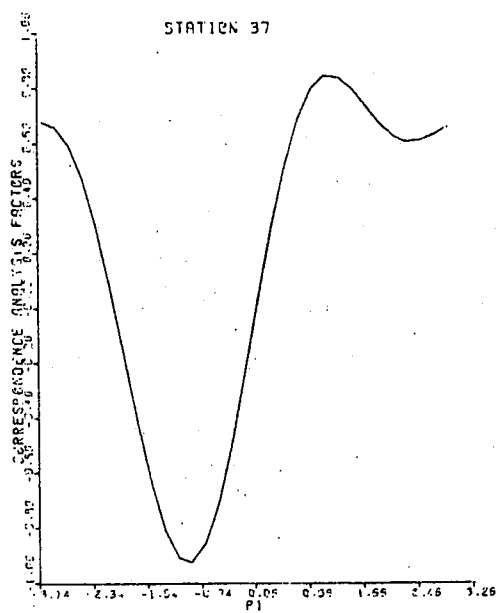
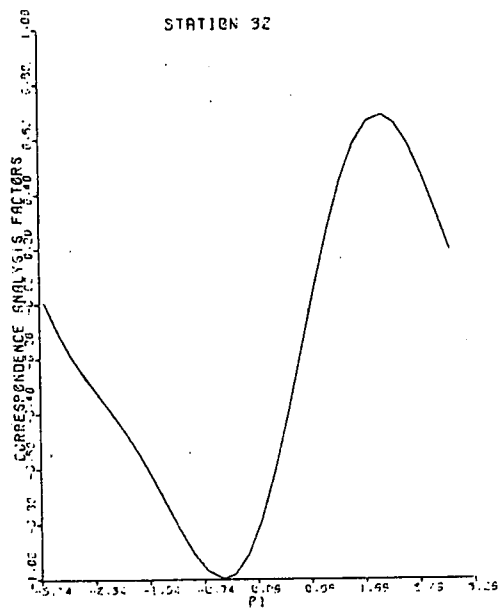
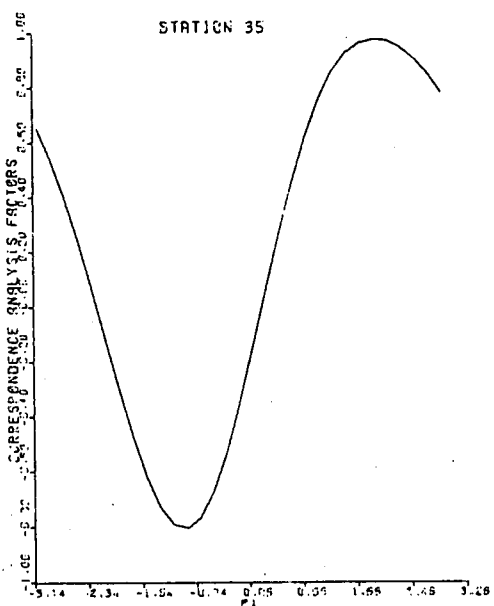


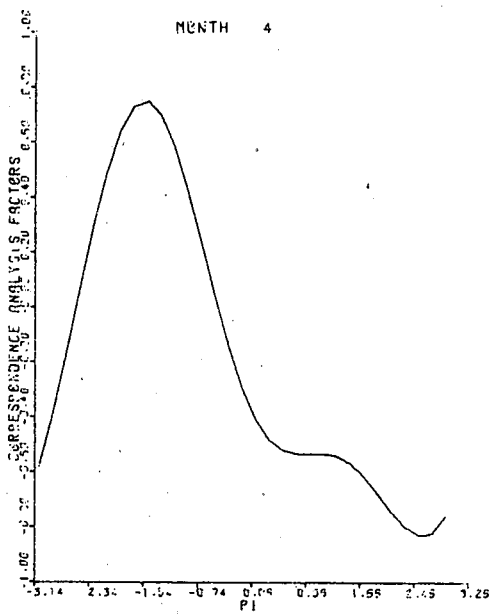
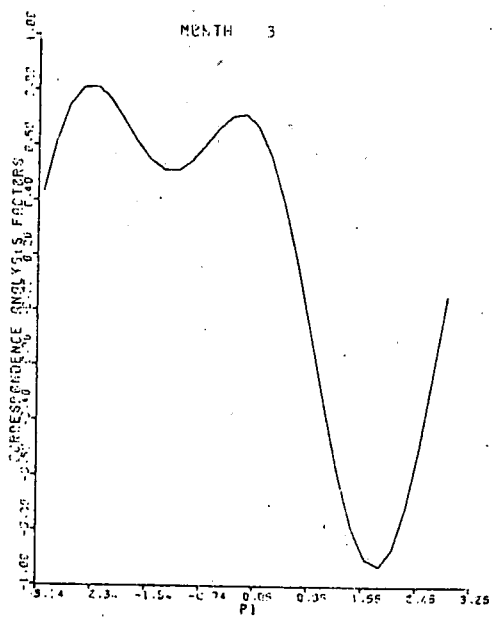
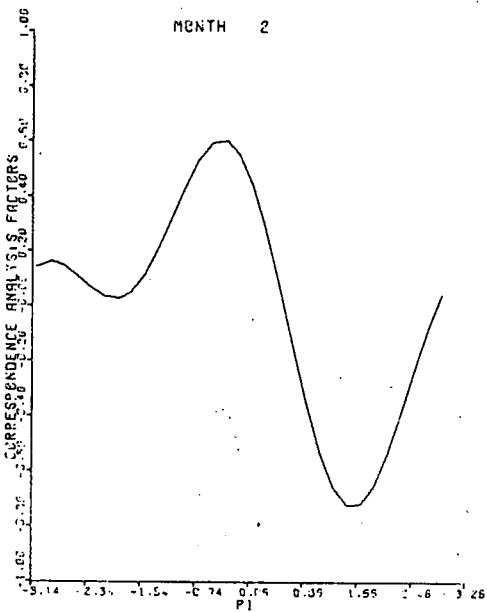
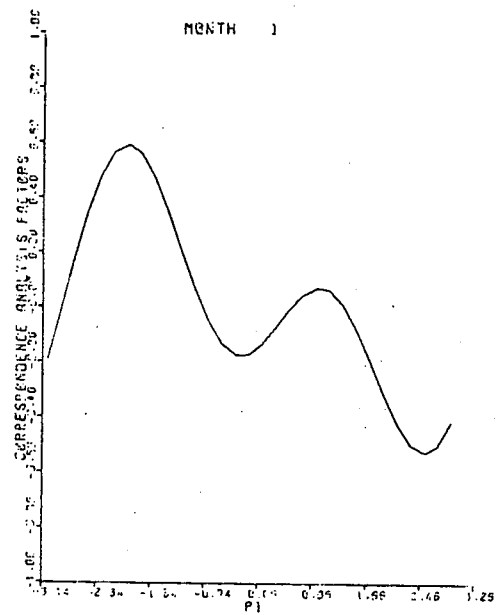


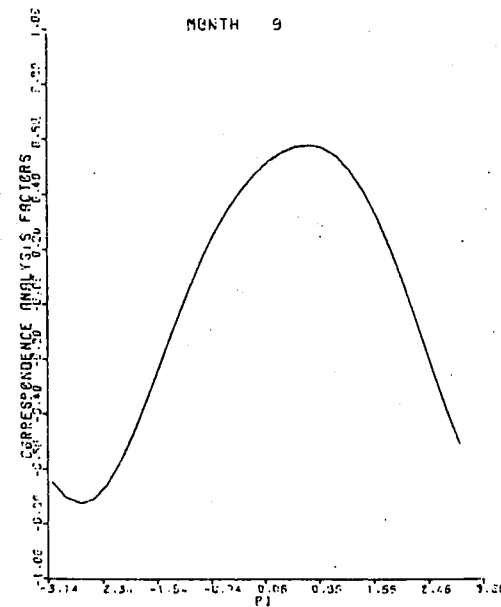
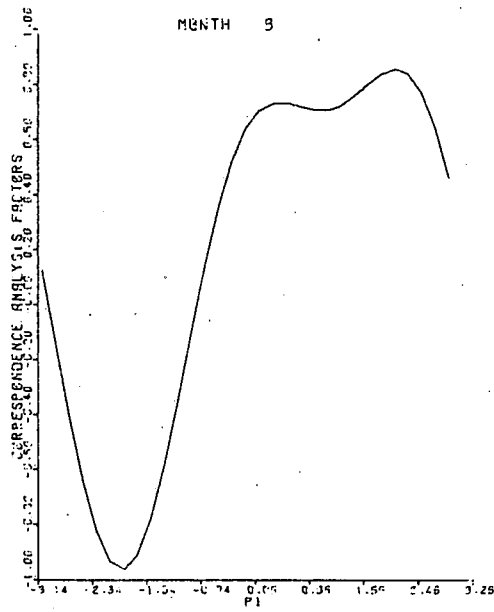
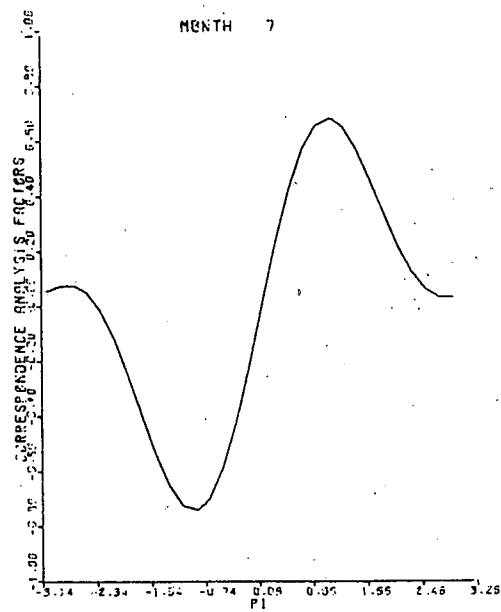
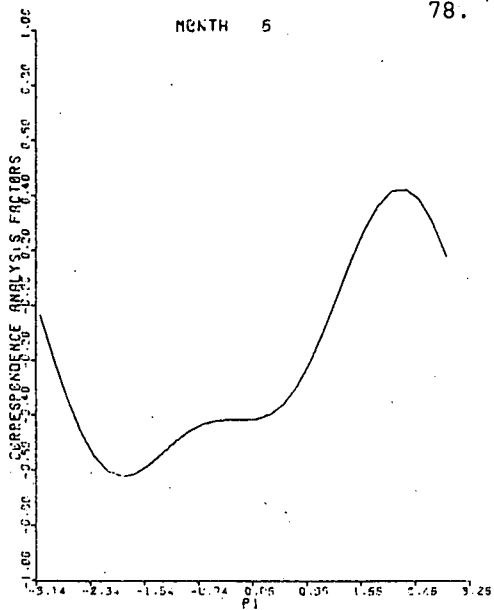
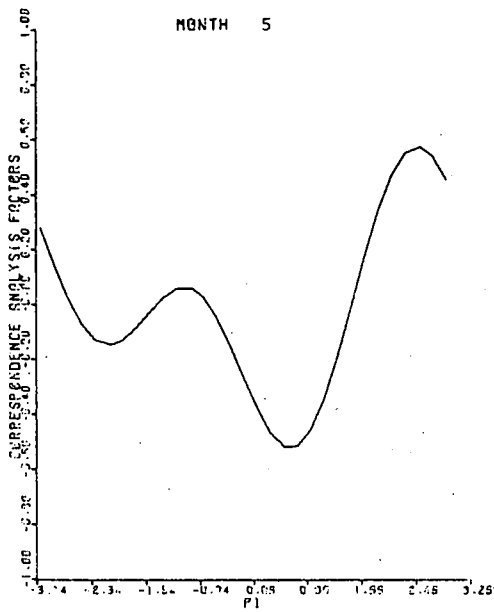














AN EXAMPLE OF THE DIFFERENCE TABLES

STATION DIFFERENCE STATION DIFFERENCE STATION DIFFERENCE STATION DIFFERENCE STATION DIFFERENCE STATION DIFFERENCE STATION DIFFERENCE

80.

9 1	5.2689	10 1	3.0681	11 1	2.6152	12 1	3.5239	13 1	4.3451	14 1	2.3686	15 1	2.3138	16 1	4.5805
9 2	3.8284	10 2	1.6099	11 2	1.3802	12 2	2.2249	13 2	3.2064	14 2	1.7054	15 2	2.5661	16 2	5.2764
9 3	2.4083	10 3	1.5901	11 3	2.1114	12 3	1.8208	13 3	2.6676	14 3	1.8004	15 3	3.0345	16 3	6.6577
9 4	3.1419	10 4	2.1901	11 4	2.4420	12 4	2.4782	13 4	3.3101	14 4	1.9518	15 4	2.9240	16 4	6.1301
9 5	4.0095	10 5	1.0949	11 5	1.4634	12 5	2.3281	13 5	3.2599	14 5	2.5784	15 5	3.7009	16 5	4.8894
9 6	2.4696	10 6	3.4943	11 6	3.7773	12 6	3.2234	13 6	3.3981	14 6	2.0460	15 6	2.3178	16 6	8.2039
9 7	2.3441	10 7	1.5737	11 7	2.1547	12 7	1.8446	13 7	2.6567	14 7	2.0528	15 7	3.3412	16 7	6.7348
9 8	1.5602	10 8	2.6081	11 8	3.3040	12 8	2.4004	13 8	2.5223	14 8	2.9746	15 8	4.4260	16 8	7.8457
9 10	3.6330	10 9	3.6330	11 9	4.0113	12 9	2.9807	13 9	2.6225	14 9	3.0709	15 9	4.0739	16 9	8.7865
9 11	4.0113	10 11	1.0112	11 10	1.0112	12 10	1.3739	13 10	2.2688	14 10	2.2959	15 10	3.7720	16 10	5.6281
9 12	2.9807	10 12	1.3739	11 12	1.3065	12 11	1.3065	13 11	2.2282	14 11	2.1191	15 11	3.1615	16 11	5.1932
9 13	2.6225	10 13	2.2688	11 13	2.2282	12 13	1.0949	13 12	1.0949	14 12	2.0562	15 12	3.3966	16 12	6.4527
9 14	3.0709	10 14	2.2959	11 14	2.1191	12 14	2.0562	13 14	2.3694	14 13	2.3694	15 13	3.9172	16 13	6.9570
9 15	4.0739	10 15	3.7720	11 15	3.1615	12 15	3.3966	13 15	3.9172	14 15	1.6939	15 14	1.6939	16 14	6.2329
9 16	8.7865	10 16	5.6281	11 16	5.1932	12 16	6.4527	13 16	6.9570	14 16	6.2329	15 16	6.8434	16 15	6.8434
9 17	7.3758	10 17	4.2055	11 17	3.6330	12 17	4.9373	13 17	5.6626	14 17	5.0516	15 17	5.6493	16 17	2.2666
9 18	6.6906	10 18	3.5635	11 18	3.0860	12 18	4.3925	13 18	5.1558	14 18	4.3650	15 18	4.9558	16 18	2.6341
9 19	7.4079	10 19	4.4942	11 19	4.1893	12 19	5.3496	13 19	5.8792	14 19	5.0043	15 19	5.7177	16 19	1.6196
9 20	6.4102	10 20	3.6838	11 20	3.5485	12 20	4.6212	13 20	5.1604	14 20	3.8388	15 20	4.5957	16 20	2.6630
9 21	6.0749	10 21	2.6128	11 21	2.4619	12 21	3.4502	13 21	3.9311	14 21	4.2727	15 21	5.0020	16 21	3.2113
9 22	6.6365	10 22	3.0836	11 22	2.9377	12 22	3.9609	13 22	4.4621	14 22	4.8189	15 22	5.5371	16 22	2.8366
9 23	4.8186	10 23	1.5549	11 23	1.8539	12 23	2.7953	13 23	3.6576	14 23	3.2470	15 23	4.2514	16 23	4.2046
9 24	4.6220	10 24	1.3099	11 24	1.8180	12 24	2.6496	13 24	3.5455	14 24	3.1496	15 24	4.2870	16 24	4.6379
9 25	5.1480	10 25	2.0947	11 25	2.1762	12 25	3.2344	13 25	4.1036	14 25	3.5465	15 25	4.3520	16 25	3.7151
9 26	5.6892	10 26	2.5310	11 26	2.1464	12 26	3.4098	13 26	3.9839	14 26	3.4415	15 26	4.1602	16 26	3.1617
9 27	5.5555	10 27	2.3005	11 27	1.8491	12 27	3.1165	13 27	3.7573	14 27	3.5243	15 27	4.2119	16 27	3.3739
9 28	5.5320	10 28	2.2883	11 28	1.8920	12 28	3.1190	13 28	3.6783	14 28	3.2392	15 28	3.9428	16 28	3.3398
9 29	6.0940	10 29	2.8031	11 29	2.5454	12 29	3.7103	13 29	4.5680	14 29	4.3755	15 29	5.0322	16 29	2.9423
9 30	4.1639	10 30	1.4212	11 30	1.9185	12 30	2.6976	13 30	3.6455	14 30	3.0077	15 30	4.0629	16 30	5.1966
9 31	7.1017	10 31	3.5639	11 31	3.3526	12 31	4.3759	13 31	4.9128	14 31	5.2669	15 31	5.9458	16 31	2.4470
9 32	8.9206	10 32	5.3356	11 32	5.0974	12 32	6.1532	13 32	6.6607	14 32	6.9751	15 32	7.6076	16 32	3.0287
9 33	6.1032	10 33	2.9859	11 33	2.1720	12 33	3.3925	13 33	3.9711	14 33	3.3929	15 33	3.7345	16 33	3.5268
9 34	7.8559	10 34	4.4311	11 34	3.8507	12 34	4.9484	13 34	5.4012	14 34	5.6785	15 34	6.1397	16 34	3.2061
9 35	8.7458	10 35	5.2158	11 35	4.7701	12 35	5.8855	13 35	6.3112	14 35	6.5499	15 35	7.0907	16 35	2.3968
9 36	6.4830	10 36	3.1889	11 36	2.4927	12 36	3.6911	13 36	4.2351	14 36	4.1179	15 36	4.5883	16 36	3.3780
9 37	9.1413	10 37	5.7364	11 37	5.1361	12 37	6.2554	13 37	6.7118	14 37	6.7995	15 37	7.2025	16 37	3.1474
9 38	10.0298	10 38	6.5177	11 38	6.0283	12 38	7.1438	13 38	7.5722	14 38	7.7155	15 38	8.1446	16 38	3.9683
9 39	6.2814	10 39	2.7807	11 39	2.3674	12 39	3.4297	13 39	3.9544	14 39	4.3663	15 39	5.1783	16 39	4.3487
9 40	4.3090	10 40	3.1526	11 40	2.2492	12 40	2.3778	13 40	2.8138	14 40	1.8007	15 40	2.4145	16 40	5.5120
9 41	7.8727	10 41	5.4782	11 41	5.1668	12 41	5.8540	13 41	5.9310	14 41	5.6470	15 41	6.1769	16 41	4.2008
9 42	10.2344	10 42	7.8043	11 42	7.4982	12 42	8.4381	13 42	8.6671	14 42	7.8790	15 42	8.3047	16 42	3.6215
9 43	10.7011	10 43	8.3848	11 43	8.0735	12 43	8.7982	13 43	8.8561	14 43	8.5217	15 43	8.9270	16 43	5.4566
9 44	13.3120	10 44	10.9142	11 44	10.6155	12 44	11.5156	13 44	11.7861	14 44	10.7491	15 44	10.7141	16 44	6.8066
9 45	8.4286	10 45	5.4030	11 45	5.0032	12 45	6.2343	13 45	6.7673	14 45	5.8723	15 45	6.4312	16 45	.6964
9 46	8.2560	10 46	5.2700	11 46	4.9278	12 46	6.0563	13 46	6.5083	14 46	5.8179	15 46	6.4625	16 46	1.5254
9 47	6.9516	10 47	3.9264	11 47	3.5980	12 47	4.7978	13 47	5.3509	14 47	4.6409	15 47	5.3187	16 47	1.8612
9 48	7.2555	10 48	4.1863	11 48	3.7942	12 48	5.0441	13 48	5.5972	14 48	4.9229	15 48	5.5944	16 48	1.5368
9 49	6.8186	10 49	3.7031	11 49	3.2912	12 49	4.5566	13 49	5.1132	14 49	4.1938	15 49	4.8569	16 49	2.0607
9 50	7.3562	10 50	5.7879	11 50	5.7089	12 50	6.3672	13 50	6.5855	14 50	5.0514	15 50	4.7216	16 50	4.7044
9 51	7.6491	10 51	4.7846	11 51	4.4848	12 51	5.5299	13 51	5.9630	14 51	5.0012	15 51	5.4387	16 51	2.2381
9 52	6.3211	10 52	4.3366	11 52	3.8022	12 52	4.2261	13 52	4.4266	14 52	3.3374	15 52	3.5652	16 52	4.4437
9 53	10.6639	10 53	8.5162	11 53	8.2160	12 53	9.0749	13 53	9.3273	14 53	8.2224	15 53	8.3011	16 53	4.4730
9 54	12.5377	10 54	11.0521	11 54	10.7339	12 54	11.4449	13 54	11.4341	14 54	10.5054	15 54	10.6515	16 54	8.6857
9 55	15.4557	10 55	13.8908	11 55	13.7312	12 55	14.5023	13 55	14.6527	14 55	13.2592	15 55	12.9003	16 55	10.1822









AN EXAMPLE OF THE DIFFERENCE TABLES

'84.

STATION DIFFERENCE    STATION DIFFERENCE    STATION DIFFERENCE    STATION DIFFERENCE    STATION DIFFERENCE    STATION DIFFERENCE    STATION DIFFERENCE    STATION DIFFERENCE

41 1	5.0190	42 1	6.4944	43 1	7.3097	44 1	9.1291	45 1	4.2257	46 1	4.3484	47 1	3.0918	48 1	3.3238
41 2	5.4172	42 2	7.4963	43 2	8.2801	44 2	10.4638	45 2	4.9788	46 2	5.0452	47 2	3.6137	48 2	3.8342
41 3	6.3632	42 3	8.6288	43 3	9.2638	44 3	11.5992	45 3	6.3761	46 3	6.2777	47 3	4.9073	48 3	5.1764
41 4	5.7579	42 4	7.9024	43 4	8.6488	44 4	10.7680	45 4	5.7713	46 4	5.6777	47 4	4.3771	48 4	4.6526
41 5	5.2100	42 5	7.2694	43 5	8.0506	44 5	10.4082	45 5	4.6319	46 5	4.6494	47 5	3.1740	48 5	3.4028
41 6	7.5894	42 6	9.8213	43 6	10.4640	44 6	12.4846	45 6	7.8618	46 6	7.7904	47 6	6.5328	48 6	6.8075
41 7	6.3889	42 7	8.6884	43 7	9.3096	44 7	11.6940	45 7	6.4532	46 7	6.3412	47 7	4.9780	48 7	5.2465
41 8	6.8738	42 8	9.3289	43 8	9.7741	44 8	12.3919	45 8	7.5178	46 8	7.2572	47 8	6.0204	48 8	6.3222
41 9	7.8727	42 9	10.2344	43 9	10.7011	44 9	13.3120	45 9	8.4286	46 9	8.2560	47 9	6.9516	48 9	7.2555
41 10	5.4782	42 10	7.8043	43 10	8.3848	44 10	10.9142	45 10	5.4030	46 10	5.2700	47 10	3.9264	48 10	4.1863
41 11	5.1668	42 11	7.4982	43 11	8.0735	44 11	10.6155	45 11	5.0032	46 11	4.9278	47 11	3.5980	48 11	3.7942
41 12	5.8540	42 12	8.4381	43 12	8.7982	44 12	11.5156	45 12	6.2343	46 12	6.0563	47 12	4.7978	48 12	5.0441
41 13	5.9310	42 13	8.6671	43 13	8.8561	44 13	11.7861	45 13	6.7673	46 13	6.5083	47 13	5.3509	48 13	5.5972
41 14	5.6470	42 14	7.8790	43 14	8.5217	44 14	10.7491	45 14	5.8723	46 14	5.8179	47 14	4.6409	48 14	4.9229
41 15	6.1769	42 15	8.3047	43 15	8.9270	44 15	10.7141	45 15	6.4312	46 15	6.4625	47 15	5.3187	48 15	5.5944
41 16	4.2008	42 16	3.6215	43 16	5.4566	44 16	6.8066	45 16	.6964	46 16	1.5254	47 16	1.8612	48 16	1.5368
41 17	5.2216	42 17	5.5441	43 17	6.8709	44 17	8.7839	45 17	2.3909	46 17	3.1574	47 17	2.2739	48 17	2.0071
41 18	5.0165	42 18	5.6978	43 18	6.9056	44 18	8.9560	45 18	2.6256	46 18	3.0363	47 18	1.9063	48 18	1.7197
41 19	3.8945	42 19	3.7080	43 19	5.5046	44 19	7.0494	45 19	1.1716	46 19	.9676	47 19	.6797	48 19	.8139
41 20	4.1004	42 20	4.5571	43 20	6.0037	44 20	7.6925	45 20	2.1988	46 20	2.0376	47 20	1.0002	48 20	1.3283
41 21	4.0158	42 21	5.7917	43 21	6.5087	44 21	9.1285	45 21	3.0109	46 21	3.0061	47 21	1.6544	48 21	1.8438
41 22	4.2228	42 22	5.8467	43 22	6.5755	44 22	9.2318	45 22	2.8228	46 22	3.0437	47 22	1.8677	48 22	1.7806
41 23	4.9202	42 23	6.7657	43 23	7.6092	44 23	9.9618	45 23	3.9656	46 23	4.0197	47 23	2.5258	48 23	2.7256
41 24	5.2430	42 24	7.2136	43 24	8.0267	44 24	10.3976	45 24	4.4116	46 24	4.4731	47 24	2.9785	48 24	3.1716
41 25	4.9818	42 25	6.4699	43 25	7.3972	44 25	9.7083	45 25	3.5228	46 25	3.6957	47 25	2.1591	48 25	2.2867
41 26	4.1265	42 26	5.7342	43 26	6.5988	44 26	8.9076	45 26	2.9452	46 26	3.0377	47 26	1.5195	48 26	1.7063
41 27	4.1905	42 27	6.0338	43 27	6.8620	44 27	9.2519	45 27	3.2070	46 27	3.2934	47 27	1.8426	48 27	1.9855
41 28	3.7016	42 28	5.7035	43 28	6.4437	44 28	8.8904	45 28	3.1154	46 28	3.0673	47 28	1.7395	48 28	1.9284
41 29	4.8549	42 29	6.0192	43 29	7.0022	44 29	9.3661	45 29	2.9426	46 29	3.2088	47 29	1.7501	48 29	1.7691
41 30	5.8006	42 30	7.7882	43 30	8.6112	44 30	10.9616	45 30	4.9961	46 30	5.0870	47 30	3.5774	48 30	3.7560
41 31	4.3424	42 31	5.6875	43 31	6.4466	44 31	9.0949	45 31	2.6418	46 31	2.9364	47 31	1.8942	48 31	1.7520
41 32	4.2061	42 32	6.0752	43 32	5.9301	44 32	9.1079	45 32	3.4756	46 32	3.7182	47 32	3.4680	48 32	3.2582
41 33	3.5129	42 33	5.9733	43 33	6.3629	44 33	8.8682	45 33	3.4657	46 33	3.6561	47 33	2.9363	48 33	3.0042
41 34	3.7455	42 34	6.4137	43 34	6.0122	44 34	9.0539	45 34	3.4511	46 34	3.9066	47 34	2.9353	48 34	2.7666
41 35	3.8020	42 35	5.8695	43 35	5.4246	44 35	8.5148	45 35	2.9047	46 35	3.4168	47 35	3.0999	48 35	2.8627
41 36	3.7807	42 36	6.2037	43 36	6.5102	44 36	9.1593	45 36	3.4703	46 36	3.7202	47 36	2.6620	48 36	2.6424
41 37	3.7689	42 37	6.1109	43 37	4.8273	44 37	8.2440	45 37	3.3273	46 37	3.6682	47 37	3.7590	48 37	3.5483
41 38	3.9864	42 38	5.9661	43 38	4.5649	44 38	8.1723	45 38	4.2313	46 38	4.3273	47 38	4.7363	48 38	4.5276
41 39	4.4039	42 39	7.0117	43 39	7.0644	44 39	10.0519	45 39	4.2956	46 39	4.3832	47 39	3.1831	48 39	3.2821
41 40	5.2857	42 40	7.5029	43 40	8.1771	44 40	10.5649	45 40	5.2594	46 40	5.3333	47 40	4.4352	48 40	4.5685
41 42	3.7591	42 41	3.7591	43 41	2.9443	44 41	6.1893	45 41	3.8966	46 41	3.3814	47 41	3.8785	48 41	4.0376
41 43	2.9443	42 43	3.8162	43 42	3.8162	44 42	4.2088	45 42	3.1795	46 42	2.8354	47 42	4.3185	48 42	4.2653
41 44	6.1893	42 44	4.2088	43 44	4.0376	44 43	4.0376	45 43	5.2241	46 43	4.7740	47 43	5.6664	48 43	5.7287
41 45	3.8966	42 45	3.1795	43 45	5.2241	44 45	6.5492	45 44	6.5492	46 44	6.2993	47 44	7.6160	48 44	7.6059
41 46	3.3814	42 46	2.8354	43 46	4.7740	44 46	6.2993	45 46	1.0159	46 45	1.0159	47 45	1.4974	48 45	1.2401
41 47	3.8785	42 47	4.3185	43 47	5.6664	44 47	7.6160	45 47	1.4974	46 47	1.5442	47 46	1.5442	48 46	1.4784
41 48	4.0376	42 48	4.2653	43 48	5.7287	44 48	7.6059	45 48	1.2401	46 48	1.4784	47 48	.3713	48 47	.3713
41 49	3.8911	42 49	4.6955	43 49	5.8250	44 49	7.9074	45 49	1.8009	46 49	2.0336	47 49	.9443	48 49	.8919
41 50	4.3683	42 50	3.8889	43 50	5.9530	44 50	6.4642	45 50	4.0213	46 50	3.5439	47 50	3.7120	48 50	3.9862
41 51	2.4974	42 51	3.0500	43 51	4.2029	44 51	6.1740	45 51	1.7124	46 51	1.5399	47 51	1.7827	48 51	1.8985
41 52	2.8489	42 52	5.0731	43 52	5.3635	44 52	7.5103	45 52	4.1651	46 52	4.1464	47 52	3.9905	48 52	4.1267
41 53	4.3075	42 53	1.4905	43 53	3.7082	44 53	3.1542	45 53	4.1657	46 53	3.9299	47 53	5.2266	48 53	5.2157
41 54	7.6074	42 54	5.1470	43 54	6.6806	44 54	6.2581	45 54	8.0330	46 54	7.2974	47 54	8.1911	48 54	8.3935
41 55	9.9820	42 55	6.8845	43 55	8.2390	44 55	5.0805	45 55	9.7999	46 55	9.5081	47 55	10.7458	48 55	10.7710

AN EXAMPLE OF THE DIFFERENCE TABLES

STATION DIFFERENCE STATION DIFFERENCE STATION DIFFERENCE STATION DIFFERENCE STATION DIFFERENCE STATION DIFFERENCE STATION DIFFERENCE

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49	1	2.5761	50	1	3.5916	51	1	3.4968	52	1	3.2644	53	1	6.7397	54	1	9.4914	55	1	11.5990
49	2	3.2204	50	2	4.9315	51	2	4.4463	52	2	3.7882	53	2	7.9976	54	2	10.5749	55	2	13.1358
49	3	4.6391	50	3	5.8435	51	3	5.6545	52	3	4.5899	53	3	9.1330	54	3	11.6058	55	3	14.1290
49	4	4.1364	50	4	4.8874	51	4	4.9463	52	4	4.4197	53	4	8.3019	54	4	10.8694	55	4	13.1175
49	5	2.9036	50	5	5.1709	51	5	4.2699	52	5	4.4071	53	5	7.9691	54	5	10.6282	55	5	13.2524
49	6	6.1457	50	6	6.3748	51	6	6.9703	52	6	5.2786	53	6	10.0347	54	6	12.2567	55	6	14.5212
49	7	4.7342	50	7	5.9753	51	7	5.7189	52	7	4.7947	53	7	9.2278	54	7	11.7151	55	7	14.2463
49	8	5.9394	50	8	6.4931	51	8	6.7120	52	8	5.6797	53	8	9.8062	54	8	12.0833	55	8	14.7519
49	9	6.8186	50	9	7.3562	51	9	7.6491	52	9	6.3211	53	9	10.6639	54	9	12.5377	55	9	15.4557
49	10	3.7031	50	10	5.7879	51	10	4.7846	52	10	4.3366	53	10	8.5162	54	10	11.0521	55	10	13.8908
49	11	3.2912	50	11	5.7089	51	11	4.4848	52	11	3.8022	53	11	8.2160	54	11	10.7339	55	11	13.7312
49	12	4.5586	50	12	6.3672	51	12	5.5299	52	12	4.2261	53	12	9.0749	54	12	11.4449	55	12	14.5023
49	13	5.1132	50	13	6.5855	51	13	5.9630	52	13	4.4266	53	13	9.3273	54	13	11.4341	55	13	14.6527
49	14	4.1938	50	14	5.0514	51	14	5.0012	52	14	3.3374	53	14	8.2224	54	14	10.5054	55	14	13.2592
49	15	4.8569	50	15	4.7216	51	15	5.4387	52	15	3.5652	53	15	8.3011	54	15	10.6515	55	15	12.9003
49	16	2.0607	50	16	4.7044	51	16	2.2381	52	16	4.4437	53	16	4.4730	54	16	8.6857	55	16	10.1822
49	17	1.7342	50	17	5.6218	51	17	3.2098	52	17	4.4687	53	17	6.3913	54	17	10.2634	55	17	12.0603
49	18	1.2762	50	18	5.0811	51	18	2.9755	52	18	4.1918	53	18	6.5201	54	18	9.9361	55	18	12.0298
49	19	1.4232	50	19	3.3318	51	19	1.7805	52	19	4.1797	53	19	4.6340	54	19	7.6550	55	19	10.1120
49	20	1.2520	50	20	2.9260	51	20	1.9386	52	20	3.9260	53	20	5.2364	54	20	8.0333	55	20	10.4948
49	21	1.8111	50	21	5.0116	51	21	3.1157	52	21	4.3099	53	21	6.7809	54	21	9.4904	55	21	12.3697
49	22	1.8529	50	22	5.4223	51	22	3.3227	52	22	4.4641	53	22	6.9077	54	22	9.7486	55	22	12.5405
49	23	2.2457	50	23	5.0387	51	23	3.8615	52	23	4.5542	53	23	7.5593	54	23	10.2621	55	23	12.8888
49	24	2.6603	50	24	5.4374	51	24	4.2974	52	24	4.7497	53	24	8.0013	54	24	10.7000	55	24	13.3246
49	25	1.8142	50	25	4.7900	51	25	3.6131	52	25	4.5957	53	25	7.2730	54	25	10.0086	55	25	12.5848
49	26	1.1765	50	26	4.4124	51	26	2.8027	52	26	3.5443	53	26	6.5234	54	26	9.2546	55	26	12.0087
49	27	1.4575	50	27	4.8080	51	27	3.1160	52	27	3.6629	53	27	6.8639	54	27	9.5836	55	27	12.4029
49	28	1.4404	50	28	4.4134	51	28	2.7165	52	28	3.1540	53	28	6.5092	54	28	9.1843	55	28	12.0906
49	29	1.5666	50	29	5.0590	51	29	3.3312	52	29	4.5429	53	29	6.9766	54	29	9.7438	55	29	12.4535
49	30	3.2139	50	30	5.7016	51	30	4.8277	52	30	4.9896	53	30	8.5137	54	30	11.2282	55	30	13.7592
49	31	1.8204	50	31	5.5694	51	31	3.2274	52	31	4.5618	53	31	6.7868	54	31	9.8656	55	31	12.4144
49	32	3.4286	50	32	7.0327	51	32	4.1847	52	32	5.3176	53	32	7.2378	54	32	10.7544	55	32	12.9111
49	33	2.2215	50	33	5.1332	51	33	2.9872	52	33	2.1942	53	33	6.7027	54	33	10.0373	55	33	12.4905
49	34	2.7099	50	34	6.5488	51	34	3.8115	52	34	4.1338	53	34	7.2958	54	34	11.0537	55	34	13.0519
49	35	3.0277	50	35	6.6082	51	35	3.7215	52	35	4.7551	53	35	6.8200	54	35	10.6579	55	35	12.4767
49	36	2.0189	50	36	5.7050	51	36	3.2867	52	36	3.0035	53	36	7.0537	54	36	10.5376	55	36	12.8415
49	37	3.6783	50	37	6.8839	51	37	3.9439	52	37	4.7091	53	37	6.9492	54	37	10.8811	55	37	12.6032
49	38	4.6575	50	38	7.7111	51	38	4.7500	52	38	5.4276	53	38	6.9955	54	38	10.7804	55	38	12.5446
49	39	2.8834	50	39	6.4373	51	39	4.2111	52	39	4.4346	53	39	7.9659	54	39	10.9809	55	39	13.6788
49	40	3.7649	50	40	6.0297	51	40	4.5375	52	40	3.1522	53	40	8.1804	54	40	10.7801	55	40	13.7660
49	41	3.8911	50	41	4.3683	51	41	2.4974	52	41	2.8489	53	41	4.3075	54	41	7.6074	55	41	9.9820
49	42	4.6955	50	42	3.8889	51	42	3.0500	52	42	5.0731	53	42	1.4905	54	42	5.1470	55	42	6.8845
49	43	5.8250	50	43	5.9530	51	43	4.2029	52	43	5.3635	53	43	3.7082	54	43	6.6806	55	43	8.2390
49	44	7.9074	50	44	6.4642	51	44	6.1740	52	44	7.5103	53	44	3.1542	54	44	6.2581	55	44	5.0805
49	45	1.8009	50	45	4.0213	51	45	1.7124	52	45	4.1651	53	45	4.1657	54	45	8.0330	55	45	9.7999
49	46	2.0336	50	46	3.5439	51	46	1.5399	52	46	4.1464	53	46	3.9299	54	46	7.2974	55	46	9.5081
49	47	.9443	50	47	3.7120	51	47	1.7827	52	47	3.9905	53	47	5.2266	54	47	8.1911	55	47	10.7458
49	48	.8919	50	48	3.9862	51	48	1.8985	52	48	4.1267	53	48	5.2157	54	48	8.3935	55	48	10.7710
49	50	4.0309	50	49	4.0309	51	49	1.8207	52	49	3.3990	53	49	5.5088	54	49	8.7589	55	49	11.0864
49	51	1.8207	50	51	2.9779	51	50	2.9779	52	50	3.8335	53	50	3.7520	54	50	6.3875	55	50	8.2901
49	52	3.3990	50	52	3.8335	51	52	2.6165	52	51	2.6165	53	51	3.8417	54	51	7.4050	55	51	9.5791
49	53	5.5088	50	53	3.7520	51	53	3.8417	52	53	5.2860	53	52	5.2860	54	52	8.4446	55	52	10.9355
49	54	8.7589	50	54	6.3875	51	54	7.4050	52	54	8.4446	53	54	4.7208	54	53	4.7208	55	53	5.7914
49	55	11.0864	50	55	6.2901	51	55	9.5791	52	55	10.9355	53	55	5.7914	54	55	5.5317	55	54	5.5317

C H A P T E R 6.

6. MULTIDIMENSIONAL SCALING.

6.1 Introduction.

Multidimensional scaling refers to a collection of techniques which have been developed for inferring multidimensional metric structure from nonmetric ordinal data.

Suppose there are  $m$  objects (difference totals, stations) to be scaled. Define the symmetric input data matrix

$$\Delta_{(m \times m)} = \begin{pmatrix} \delta_{11} & \cdots & \delta_{1m} \\ \vdots & & \vdots \\ \vdots & & \vdots \\ \delta_{m1} & \cdots & \delta_{mm} \end{pmatrix},$$

where for  $i \neq j$ ,  $\delta_{ij}$  denotes the observed dissimilarity between objects  $i$  and  $j$  ( $\delta_{ii}$  will never be used and therefore is not defined). Moreover, suppose  $\delta_{ij}$  is not subject to error or stochastic variation but is specified exactly.

There are three ways of how the  $\delta_{ij}$  may be obtained. First we could ask a subject to rank order all pairs of the  $m$  objects according to his perception of their degree of dissimilarity (there are  $M \equiv m(m-1)/2$  such pairs). The  $\delta_{ij}$ 's could taken as the  $M$  ranks of the ordered pairs.

Secondly the subject could be asked to place each of the  $M$  pairs on a scale (ranging from 0 to 10) according to his perception of their degree of dissimilarity. The 10 will for instance denote most dissimilar, which a 0 will denote least dissimilar. The  $\delta_{ij}$ 's would correspond to the values on the scale. Furthermore

the  $N$  subjects might each be used to rank the  $M$  pairs of objects, and the average rank could be used for the  $\delta_{ij}$ 's.

Third we could take the  $\Delta$  as the rank correlation matrix of the  $m$  objects. The off-diagonal elements are the measures of degree of closeness of the objects.

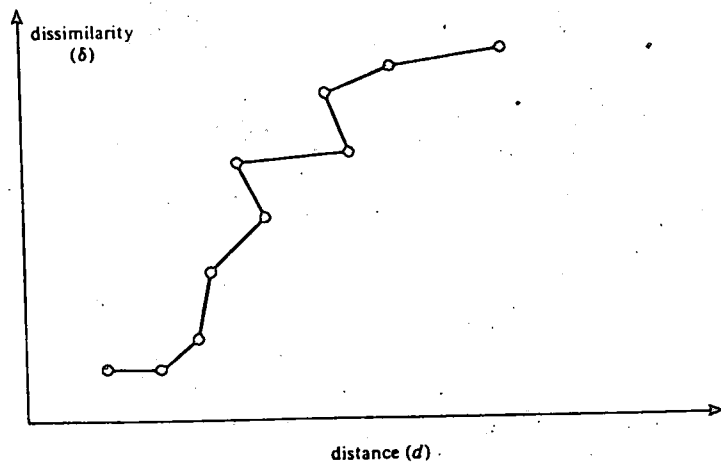
Let  $x_j : p \times 1$  denote the location vector of the  $j$ -th object in a space of dimension  $p$ ,  $j = 1, \dots, m$ . At the start of any scaling problem the  $x_j$ 's are unknown. Assume a particular set of  $p$ -vectors  $(x_1, \dots, x_m)$  is selected arbitrarily, just see how well this set fits the observed data, i.e. the dissimilarities  $\delta_{ij}$ . Furthermore the dimension  $p$  is generally unknown at the start, but let's assume it has been selected at some fixed value.

Define the distance between the  $i$ -th and  $j$ -th objects as

$$d_{ij} = |(x_i - x_j)'(x_i - x_j)|^{\frac{1}{2}} \quad \dots\dots\dots(1)$$

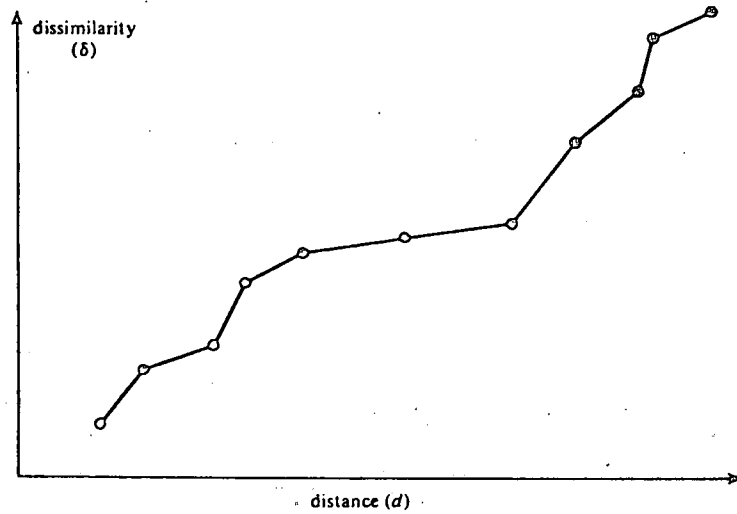
A scatterdiagram of the points  $(d_{ij}, \delta_{ij})$  may now be plotted to compare how well the trial distances match the dissimilarities.

The figure 15.2.1 below



Scattergram without Monotonicity

illustrates a hypothetical case in which monotonicity is not preserved. As the dissimilarities between objects increase, their distances do not necessarily increase, i.e. they sometimes decrease. A case in which there is a perfect match is shown in figure 15.2.2 below.



Scattergram Exhibiting Monotonicity

Lets discuss the goodness of Fit. Let  $x_1, \dots, x_m$  denote an arbitrary and known configuration of  $m$  points in  $p$ -space. The associated distances are defined in (1). Define the  $n \times 1$  vector of distances between pairs of points

$$D = (d_{i_1 j_1}, \dots, d_{i_n j_n})'. \quad (n \times 1)$$

Let  $\hat{d}_{ij}$  denote a "fitted" value of  $d_{ij}$ . Kruskal(1964) defined the goodness-of-fit measure

$$\text{stress} = S = \left| \frac{(D - \hat{D})'(D - \hat{D})}{D'D} \right|^{\frac{1}{2}}$$

where  $\hat{D} \equiv (\hat{d}_{ij})$ . Thus the stress of the configuration of points  $(x_1, \dots, x_m)$  is defined as

$$S(x_1, \dots, x_m) = \min_{\hat{D}} \left| \frac{(D - \hat{D})'(D - \hat{D})}{D'D} \right|^{\frac{1}{2}}$$

subject to the monotonicity constraint

$$\hat{d}_{i_1 j_1} \leq \hat{d}_{i_2 j_2} \leq \dots \leq \hat{d}_{i_n j_n}$$

That is,  $S(x_1, \dots, x_m)$  is a measure of how good a fit  $(x_1, \dots, x_m)$  is to the given  $\Delta$ .

Another problem arises, the choice of Dimension. Some problems dictate on appropriate value of  $p$ . For example there may be five fundamental factors which seems to characterize the essence of an object, and one could sought a solution in a space of dimension  $p = 5$ . as this is not always the case, the scaling problem should be solved for each of several values of  $p$ . If the  $p$ -stress drops below some tolerably low value such as 5 percent for some value of  $p$ , there is no need to go to a higher space of dimension since the fit is already quite good.

## 6.2 The use of multidimensional Scaling.

As already defined Correspondence analysis is one of a class of descriptive statistical methods, a class which also includes techniques such as multidimensional scaling and principal components analysis. The aim common to all these methods is to represent a data set by a number of points in multidimensional space, thus enabling a visual interpretation of the patterns existing in the data. The data observations can be imagined to occupy a space of high dimension.

Using the theory of multi-dimensional scaling, a program was developed by Dr. Underhill of the University of Cape Town to perform such a scaling. These programs have been changed to work at the University of the Orange Free State and is now available and working under

UNIVAC 1106 EXEC. These programs are listed on page 91.

The difference tables as described in Chapter 5 were being used as input for the Multidimensional Scaling program.

### 6.3 Interpretation of Andrew's and Multidimensional method on Correspondence analysis factors.

The main objective by using the method of Andrew's and Multidimensional scaling was to obtain the same graph as the two dimensional graph on page 55 when only the first two factors were considered. From the Multidimensional Scaling programs we obtained two printouts which reproduced firstly a diagram of the 55 Israeli stations and secondly a diagram of the 9 rainfall months.

These two diagrams were superimposed by using the centre points which were defined in the Multidimensional Scaling program. One must also note the scaling factor which is printed by this program and accordingly align the two graphs. The resultant graph can be seen on page 98. There is a definite similarity to the two dimensional graph on page 55.

One could also make the same interpretation as described on page 36. We again have the objects and subjects on the same graph. Note the variation in rainfall between month 1 and month 9. Station 6 and Station 9 are positively correlated to month 1, while Station 44 is negative.

We could in the same manner group the stations to form specific areas relating to page 99. On comparison to the actual map of Israel on page 100 there is again a definite resemblance.



```

REAL DISSIM(2000),CONF(5,400),DIST(2000)
INTEGER T,IJ(2000),II(2000),JJ(2000),TIES(2000)
READ (5,100) M,T,L
100 FORMAT(5X,I4,2I3)
READ(5,101) (II(MM),JJ(MM),DISSIM(MM),MM=1,M)
101 FORMAT(6X,2I3,F6.0)
DO 1 MM=1,M
  1 IJ(MM)=1000*II(MM)+JJ(MM)
  CALL SORT(DISSIM,IJ,M,TIES)
  WRITE(6,102) (DISSIM(I),I=1,M)
  WRITE(6,103) M,(IJ(I),I=1,M)
102 FORMAT('1 DISSIMILARITIES MATRIX',/(12F10.3))
103 FORMAT(' #DISSIM ',I10,/(12I10))
WRITE(11) M,T,L,IJ,DISSIM,DIST , TIES
DO 2 I = 1,12
  CALL CONFIG (M,T,L,IJ,TIES ,CONF,DIST)
2 CONTINUE
END

```

```

SUBROUTINE SORT (DISSIM,IJ,M,TIES)
REAL DISSIM(1)
INTEGER IJ(1) , TIES(1)
DO 1 J=2,M
  J1=J-1
  AMIN = DISSIM(J1)
  LEAST =J1
  DO 4 K=J,M
    IF (DISSIM(K)-AMIN) 3,3,4
  3 AMIN = DISSIM(K)
  LEAST = K
  4 CONTINUE
  SAVE = DISSIM(J1)
  ISAVE = IJ(J1)
  DISSIM(J1) = AMIN
  IJ(J1) = IJ(LEAST)
  DISSIM(LEAST) = SAVE
  1 IJ(LEAST) = ISAVE
  DISSIM(M+1) = DISSIM(M) + 1
  NOTIE = 1
  I = 0
  K = 1
  2 I = I + 1
  5 K = K + 1
  IF(K.EQ.M+2) GOTO 6
  IF (DISSIM(I).EQ. DISSIM(K)) GOTO 5
  IF(K-I.EQ.1) GOTO 2
  NOTIE = NOTIE + 1
  TIES(NOTIE) = 1000 * I + K-1
  I = K
  GOTO 5
  6 IF (NOTIE .NE.1) TIES(1) = NOTIE
  RETURN
END

```

```

SUBROUTINE CONFIG(M,T,L,IJ,TIES ,CONF,DIST)
REAL CONF(5,1),DIST(1),DHAT(2000),GRAD(5,400),OLGRAD(5,400),
* STRES(5)
INTEGER T,IJ(1),TIES(2000)
DATA          ONE/1./
IE = 0
SMALL = .01
K = K+1
DO 8 LL=1,L
DO 8 IT = 1,T
8 CONF(IT,LL) = 0.
CALL CREATE(CONF,T,L)
CALL NORMAL(CONF,T,L)
GMAG = 1.
ITER = 0
GOTO 10
ENTRY FINCON( M,T,L,IJ,TIES ,CONF,DIST)
100 FORMAT(2I2)
READ(5,100,END=40)  NUM , IX
DO 21 J = 1,NUM
21 READ(11)  ITER,GMAG,STRES,ALPHA,GRAD,CONF
IF(IX.EQ.0) GOTO 22
READ(5,103)  ( I ,(CONF(J,I), J=1,3), IT=1,IX)
103 FORMAT (I2, 3F6.2)
22 CONTINUE
WRITE(5,104)  NUM , ((CONF (I,J),I=1,T),J = 1,L)
104 FORMAT ('OCONTINUATION OF ITERATION NO. ',I3/' STARTING FROM CONF
*IGURATION'/ (12F10.3))
IE = 1
SMALL = .000001
10 CONTINUE
ITER = ITER +1
CALL NORMAL(CONF,T,L)
CALL DISTAT(IJ,DIST,T,M,CONF,DHAT, TIES)
CALL FITTER(DHAT,M)
DO 2 LL=1,L
DO 2 IT=1,T
OLGRAD(IT,LL) = GRAD(IT,LL)
2 GRAD(IT,LL) = 0.
OLGMAG=GMAG
OLNEW = 0.
CALL GRADIT(DIST,DHAT,T,L,IJ,STRESS,GRAD,GMAG,CONF,M)
CHANGE=ABS(STRESS - STRES(5) )
IF(STRESS.LT.SMALL.OR. CHANGE.LT. 0.001) GOTO 11
DO 5 LL =1,L
DO 5 IT = 1,T
5 OLNEW = OLNEW + OLGRAD(IT,LL) *GRAD(IT,LL)
COSTH = OLNEW/(L*OLGMAG*GMAG)
DO 6 J=1,4
6 STRES(J) = STRES(J+1)
STRES(5) = STRESS
IF(ITER.NE.1) GO TO 3
OLGMAG = GMAG
DO 4 J=1,5
4 STRES (J) = STRESS
COSTH = 1.
ALPHA = 0.2
3 ALPHA = ALPHA*4.** (COSTH**3.)*(1.3/(1.+AMIN1(ONE,
* STRESS/STRES(1))))* AMIN1(ONE,STRESS/STRES (4))

```

```

DO 7 LL=1,L
DO 7 IT=1,T
7 CONF(IT,LL) = CONF(IT,LL) + ALPHA*GRAD(IT,LL)/GMAG
GOTO 10
11 WRITE(6,105)K,ITER,CHANGE,STRESS,((CONF ( I,J),I=1,T),J=1,L)
105 FORMAT(' ITERATION ',I3,' NO OF ITERS ',I3,' CHANGE ',F7.4,
*' STRESS ',F7.4/(12F10.3) ) )
WRITE(6,101) (IJ(I),I=1,M)
101 FORMAT(' IJ MATRIX'/(12I10) ) )
WRITE(6,102)(DIST(I),I=1,M)
WRITE(6,120)(DHAT(I),I=1,M)
102 FORMAT(' DIST MATRIX'/( 12F10.3 ))
120 FORMAT(' DHAT MATRIX'/( 12F10.3 ))
CALL TODPLT(CONF,L)
IF(IE.NE.1) WRITE(11) ITER,GMAG,STRES,ALPHA,GRAD , CONF
RETURN
40 CALL EXIT
END

```

```

SUBROUTINE CREATE (CONF,T,L)
INTEGER T
REAL CONF(5,1)
READ 100, N
100 FORMAT (I5)
PRINT 101, N
101 FORMAT ('1SEED: ',I6)
DO 1 LL=1,L
DO 1 IT=1,T
1 CONF(IT,LL) = RANDOM(N)
RETURN
END

```

```

SUBROUTINE NORMAL (CCNF,T,L)
INTEGER T
REAL CONF(5,1), AMEAN(100)
SQUARE=0.
DO 4 J=1,T
AMEAN(J)=0.
DO 3 K=1,L
3 AMEAN(J)=AMEAN(J)+CONF(J,K)
4 AMEAN(J)=AMEAN(J)/L
DO 5 K=1,L
DO 5 J=1,T
CONF(J,K)=CONF(J,K)-AMEAN(J)
5 SQUARE = SQUARE+ CONF(J,K)**2
SQUARE = SQRT(L/SQUARE)
DO 6 K=1,L
DO 6 J=1,T
6 CONF(J,K)=CONF(J,K)*SQUARE
RETURN
END

```

```

SUBROUTINE DISTAT(IJ,DIST,T,M,CONF,DHAT,TIES)
REAL DIST(1),DHAT(1),CONF(5,1)
INTEGER IJ(1),T,TT , TIES(1)
DO 1 K=1,M
I = IJ(K)/1000
J = IJ(K)-1000*I
SQUARE = 0.
DO 2 TT=1,T
2 SQUARE = SQUARE+(CONF(TT,I)-CONF(TT,J))**2
1 DIST(K) = SQR(T(SQUARE)
IF(TIES(1) .NE.0) CALL TIE(TIES,DIST,IJ)
DO 11 K = 1,M
11 DHAT(K) = DIST(K)
RETURN
END

```

```

SUBROUTINE FITTER(DHAT,M)
REAL DHAT(1)
INTEGER DOTHER(2000),SATIS
DO 1 J=1,M
1 DOTHER(J) = 0
IACTIV = 1
4 NUPDOW = 1
5 CALL SATSFY(DHAT,DOTHER,M,NUPDOW,IACTIV,SATIS,NEXT,NEXT1,
* IACTV1,NOBLOC)
IF (SATIS.EQ.-1) GO TO 2
NUPDOW = -NUPDOW
CALL SATSFY(DHAT,DOTHER,M,NUPDOW,IACTIV,SATIS,NEXT,NEXT1,
* IACTV1,NOBLOC)
IF(SATIS.EQ.-1) GO TO 2
IF(DOTHER(IACTIV).NE.0) IACTIV = IACTIV + DOTHER(IACTIV)-1
IACTIV = IACTIV+1
IF(IACTIV.NE.M+1) GO TO 4
J = 1
3 J = J+1
IF (J.EQ.M+2) RETURN
IF (DOTHER(J-1).EQ.0) GO TO 3
K = J+DOTHER(J-1)-2
DO 6 KJ=J,K
6 DHAT(KJ) = DHAT(J-1)
J=K+1
GO TO 3.
2 CALL JOIN(DHAT,DOTHER,NEXT,IACTIV,NEXT1,IACTV1,NOBLOC,M)
NUPDOW = -NUPDOW
GO TO 5
END

```

```

FUNCTION RANDOM(N)
N = N * 3125
RANDOM = FLOAT(N)/ 34359738337.00
IF (RANDOM .LT.0.0) RANDOM = -RANDOM
RETURN
END

```

```

SUBROUTINE SATSFY(DHAT,DOTHER,M,NUPDOW,IACTIV,SATIS,NEXT,
5 NEXT1,IACTV1,NOBLOC)
INTEGERDOTHER(1),SATIS
REAL DHAT(1)
SATIS = 1
IF (NUPDOW.EQ.-1. AND. IACTIV.EQ.1) RETURN
IF (DOTHER(IACTIV).NE.0) GO TO 2
IACTV1 = IACTIV
NOACBL = 1
GO TO 1
2 IACTV1 = IACTIV + 1
NOACBL = DOTHER(IACTIV)
1 IF (NUPDOW .EQ. -1) GO TO 4
NEXT = IACTIV + NOACBL
IF (NEXT.EQ.M+1) RETURN
IF (DOTHER(NEXT) .NE.0) GO TO 3
5 NEXT1 = NEXT
NOBLOC = NOACBL+1
GO TO 6
4 NEXT = IACTIV-1
IF(DOTHER(IACTIV-1).EQ.0) GO TO 5
NEXT = DOTHER(IACTIV-1)
3 NOBLOC = NOACBL + DOTHER(NEXT)
NEXT1 = NEXT+1
6 IF ((NUPDOW*DHAT(IACTIV)).GT.(NUPDOW*DHAT(NEXT))) SATIS=-1
RETURN
END

```

```

SUBROUTINE GRADIT(DIST,DHAT,T,L,IJ,STRESS,GRAD,GMAG,CONF,M)
REAL DIST(1),DHAT(1),GRAD(5,100),CONF(5,1)
INTEGER IJ(1),T,TT
SSTAR = 0.
TSTAR = 0.
GMAG = 0.
DO 1 K=1,M
SSTAR = SSTAR+(DIST(K)-DHAT(K))**2
1 TSTAR = TSTAR + DIST(K) **2
STRESS = SQRT(SSTAR/TSTAR)
DO 4 K=1,M
I = IJ(K)/1000
J = IJ(K) -1000*I
IF (I.EQ.J) GO TO 4
TERM = STRESS*((DIST(K)-DHAT(K))/SSTAR-DIST(K)/TSTAR)
* /DIST(K)
DO 2 TT=1,T
ATERM = -TERM*(CONF(TT,I)-CONF(TT,J))
GRAD(TT,I) = GRAD(TT,I) + ATERM
GRAD(TT,J) = GRAD(TT,J) - ATERM
2 CONTINUE
4 CONTINUE
DO 3 LL=1,L
DO 3 TT=1,T
3 GMAG = GMAG+(GRAD(TT,LL)**2)
GMAG = SQRT(GMAG/L)
RETURN
END

```

```

SUBROUTINE JOIN (DHAT,DOTHER,I,J,I1,J1,NOBLOC,M)
INTEGER DOTHER(1)
REAL DHAT(1)
I = MIN0 (I,J)
J = I
IEND = I+NOBLOC-1
DHAT(I+1) = DHAT(J1)+DHAT(I1)
DOTHER(I) = NOBLOC
DHAT(I) = DHAT(I+1)/NOBLOC
DOTHER(IEND) = I
RETURN
END

```

```

SUBROUTINE TIE(TIES,DIST,IJ)
REAL DIST(1)
INTEGER TIES(1), IJ(1)
ITIE = TIES(1)
DO 1 KK = 2,ITIE
I = TIES(KK)/1000
J = TIES(KK) - 1000 * I
I = I+1
3 MARK = 0
DO 2 K = I,J
IF (DIST(K-1) .LE. DIST(K)) GO TO 2
SAVE = DIST (K)
DIST(K) = DIST(K-1)
DIST(K-1) = SAVE
ISAVE = IJ(K)
IJ(K) = IJ(K-1)
IJ(K-1) = ISAVE
MARK = 1
2 CONTINUE
IF (MARK .NE. 0) GOTO 3
1 CONTINUE
RETURN
END

```

```

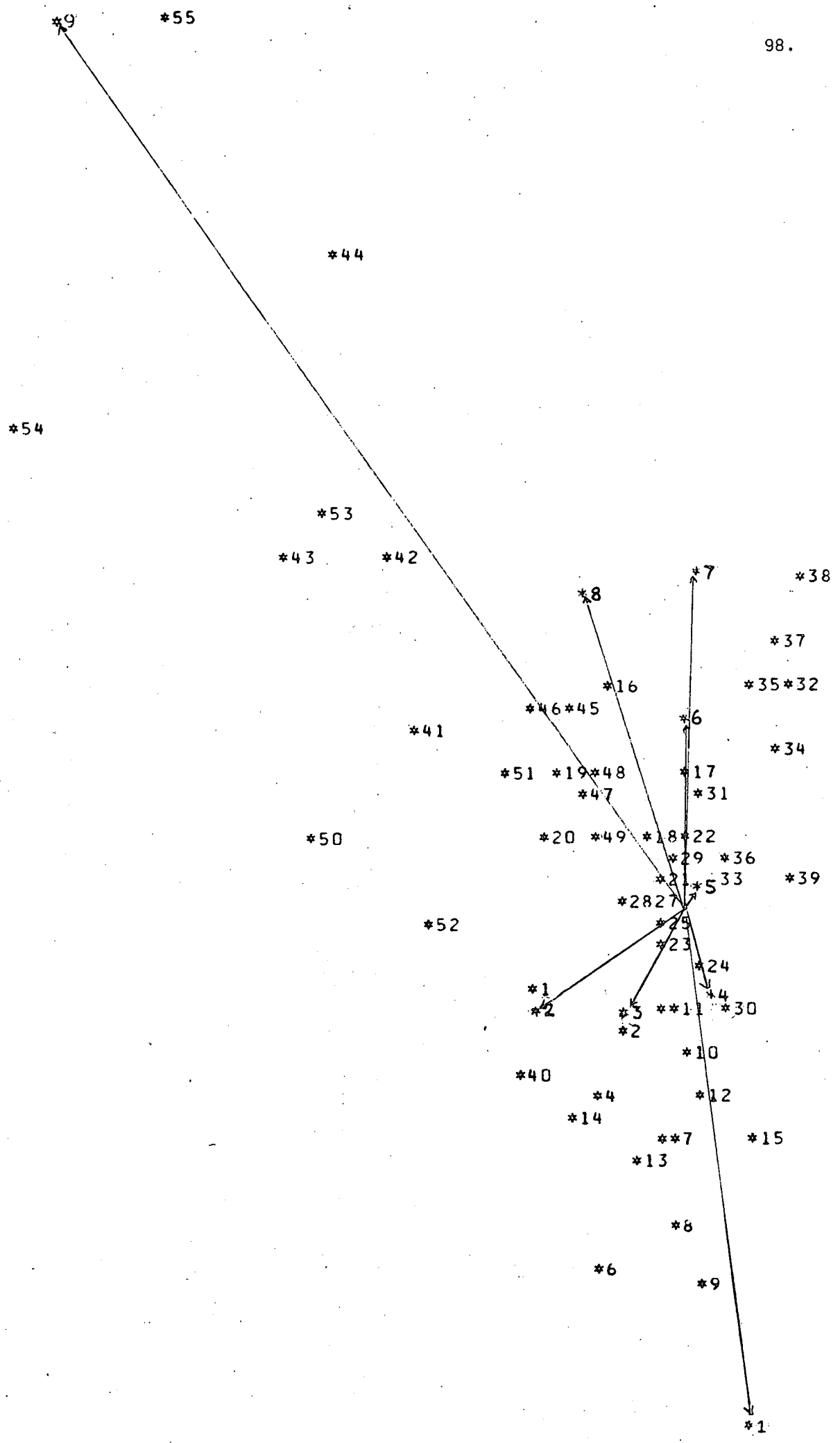
FUNCTION GAUSS (AM,P,N)
1 V1 = 2. * RANDOM(N) - 1
V2 = 2. * RANDOM(N) - 1
S = V1 *V1 + V2 *V2
IF (S.GE.1.) GOTO 1
VAR = V1 * SQRT(ALOG(S) *(-2.) / S)
GAUSS = ( P * VAR + 1. ) * AM
RETURN
END

```

```

SUBROUTINE TODPLT(CONFIG,M)
C   TO GENERATE MAP FROM CONFIGURATION
REAL  CONFIG(5,1),MXC1,MXC2,MNC1,MNC2,MIDC,MIDR,SCALE
C   MAP SCALED TO 104*60 AS WIDTH:BREATH::2.25:4.0
CHARACTER*107 SPACE(61)
CHARACTER*2 NUMBER(60)
INTEGER R,C,BLANK
DATA NUMBER/'1','2','3','4','5','6','7','8','9','10',
*'11','12','13','14','15','16','17','18','19','20',
$'21','22','23','24','25','26','27','28','29','30',
%'31','32','33','34','35','36','37','38','39','40',
&'41','42','43','44','45','46','47','48','49','50',
#,'51','52','53','54','55','56','57','58','59','60'/
C   INITIALIAZE SPACE TO BLANKS
SPACE(1)='START'
DO 1 R=2,61
    SPACE(R)=' '
1   CONTINUE
SUBSTR(SPACE(61),105,3)='END'
C
C   FIND MAX AND MIN VALUES OF CONFIG1, CONFIG2
MXC1,MXC2,MNC1,MNC2=0
DO 3 L = 1,M
    MXC1=AMAX1 (MXC1,CONFIG(1,L))
    MXC2=AMAX1 (MXC2,CONFIG(2,L))
    MNC2=AMIN1 (MNC2,CONFIG(2,L))
    MNC1=AMIN1 (MNC1,CONFIG(1,L))
3   CONTINUE
C   DETR MIDPT CONFIGURATIONS (VERTICAL,HORIZONTAL)
C   AND SCALING FACTOR
MIDC=(MXC1+MNC1)/2.
MIDR=(MXC2+MNC2)/2.
SCALE=AMAX1(MXC1-MNC1,MXC2-MNC2)/2.
WRITE(6,100)MIDC,MIDR,SCALE
100 FORMAT(T2,'CENTRE POINTS ARE ',2F10.3,' SCALING FACTOR',
*'F8.4/T2,' COL FRAC ROW FRAC TOWN ROW COL')
C   DETERMINE MAP FOR OUTPUT
DO 4 L=1,M
    R=31+30./SCALE*(CONFIG(2,L)-MIDR)
    C=53+52./SCALE*(CONFIG(1,L)-MIDC)
    SUBSTR(SPACE(R),C,3)='*'*&NUMBER(L)
    WRITE(6,101)CONFIG(1,L),CONFIG(2,L),L,R,C
101  FORMAT(T2,2F10.2,3I5)
4   CONTINUE
    I=I+1
    WRITE(6,102)I,SPACE
102  FORMAT('1',I3,104(' #')/( ' [',A107, ' ]' ) )
RETURN
END

```





\*9

\*55

DESERT AREA  
JORDAN VALLEY

\*54

\*44

\*53

\*43

\*42

\*8

\*7

\*38

\*37

\*35\*32

\*16

\*34

\*41

\*46\*45

\*6

\*51 \*19\*48

\*17

\*31

\*47

\*20 \*49 \*18\*22

\*29 \*36

\*21 \*533 \*39

\*50

\*28\*27

\*52

CENTRAL AREA  
MOUNTAINS

\*25

\*23

\*24

\*1

\*2

\*3

\*\*11

\*4

\*30

\*2

\*10

\*40

\*4

\*12

\*14

\*\*7

\*15

\*13

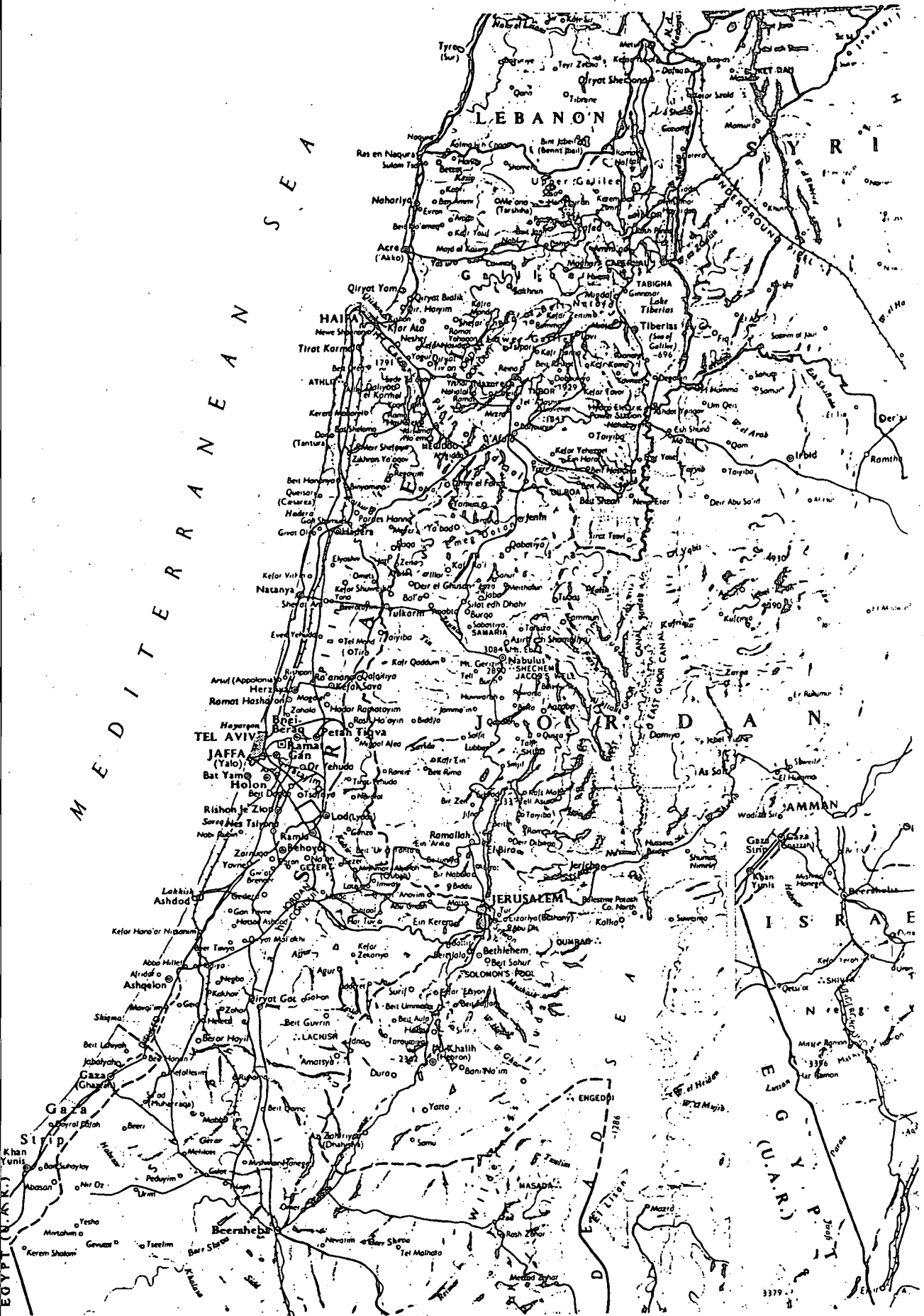
COASTAL AREA

\*8

\*6

\*9

\*1



S U M M A R Y

After the first trial run the Correspondence Analysis program prints all the factors as column and row loadings. Select two factors with the highest characteristic value (Ignore the characteristic value 1). If these factors contribute 60 or more to the percentage of inertia, the two dimensional graph will be obtained by plotting the subjects and objects on the same axis. If this is not the case the method of Andrew's and Multidimensional Scaling should be followed. The association between the subjects and objects is obtained by grouping the graphs as plotted by the Andrew's program with the aid of the difference tables. The representations of the objects and subjects on the same axis is obtained by the Multidimensional Scaling program.

Sometimes, when struggling with a particularly difficult interpretation and situation, we ask ourselves whether our efforts are worthwhile. If it is certain that Correspondence analysis reveal structural relationships between elements, can we trust in the individual axes which generate the planes in which we observe the projections of the clouds? Other statisticians do not use Correspondence analysis but other ways of constructing and analyzing clouds (e.g. classical factor analysis). Here it is common practise to rotate the axes, i.e. in the subspace spanned by the first principal axes of inertia of the cloud other axes (orthogonal or not) are chosen the interpretation of which appear easier. For these analysis the more a factor coincides with one of the variables of the table or a group of strongly correlated variables, the more it is interpretable. We are completely opposed to this practise for many reasons. Firstly, if the data is fairly homogenous and the sampling not too sparse the interpretation is often rather easy, thanks to the principle of distributional equivalence. Secondly, it has appeared in numerous applications that a modification of the original data usually does not modify the nature of the computed factors, causing perhaps only a permutation of their order. This kind of stability leads us to believe that one has to pay some respect to the individuality of the factors as computed in

## Correspondence analysis.

Some practitioners often ask: among the set of characteristics (subjects) used to describe the objects, which are the least useful concerning the interpretation of the first computed factors. Another question may be measuring only what determines the important factors of a first study (the experimental basis of which is perhaps chosen to confirm some simple concepts) are we not running the risk of restricting ourselves. This is the sort of questions representative of an attitude which we are trying to avoid.

However, having established the conclusions of a study performed on a rather exhaustive table ( $k(I,J)$ ) it is conceivable that one might wish to locate a set, say  $S$ , of supplementary elements on the factorial axes not by taking into account the whole table, but only a reduced table. One can compute the factors without repeating the analysis, with the usual formula:

$$G_{\alpha}^r(s) = (\lambda_{\alpha}^r)^{-\frac{1}{2}} \sum \{F_{\alpha}(i)k(i,s)/k(s) | i \in I_r\}.$$

Here we are starting to tackle difficulties that can really only be evaluated by someone who has already practised Correspondence analysis.

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