

STATISTICAL PREDICTION OF LATE MIOCENE CLIMATE

BY

A. A. FERNANDES AND SHYAM M. GUPTA

TECHNICAL REPORT No. NIO/TR-5/94

NATIONAL INSTITUTE OF OCEANOGRAPHY

DONA PAULA, GOA

INDIA 403-004

MAY 1994

## PREFACE

Ever since Imbrie and Kipp(1971) applied factor analysis and multiple regression analysis for predicting late Pleistocene climate using planktonic foraminifera, this technique of statistical prediction is being used world wide. However this is the first time this technique has been used by Indian scientists. The technique has been used to predict late Miocene climate in the Bay of Bengal using radiolaria. The software used for this purpose has been indigenously developed. Listed below are the milestones of this undertaking:

- 1] Development of software for factor analysis      1982-83  
Publication: Fernandes A A and R Mahadevan,  
1982. Factor analysis of multivariate data.  
NIO Tech. Rept. No. 2/82, October 1982
- 2] Development of software for multiple regression analysis. The impetus for taking up this work came from association with Dr Andrzej Wroblewski, Institute of Oceanology, Poland.      1988-89
- 3] Successful repetition of the computations of Imbrie and Kipp(1971). This endeavour was aimed at displaying competence for performing statistical prediction of storm surges.      1988-89
- 4] Application of the Imbrie and Kipp(1971) method to radiolaria in the Bay of Bengal (Present work).      1993-94

CONTENTS		Page
Abstract		3
1. Introduction		4
2. Multiple regression analysis		7
3. Factor analysis		12
4. Prediction of Pleistocene climate in the Caribbean		17
5. Prediction of Miocene climate in the Bay of Bengal		25
Acknowledgements		32
References		33
Tables 5.1 - 5.15		36-52
Program Listings		
A] Main programs used for prediction of climate during late Miocene:		
(1) CUTOF5.FOR		53
(2) FACQ3.FOR		56
(3) GETTAB4.FOR		70
(4) MULRAS.FOR		71
(5) CABLESZ.FOR		79
B] Programs for preparing a Table DEP2-LEV.DAT of modern environmental conditions at the sites of the surface sediment samples from digital Levitus data:		
(1) READL:SYMB		81
(2) GETLEV.FOR		83
(3) OBJA4.FOR		84
(4) LEVT2.FOR		87

## ABSTRACT

The theory of statistical prediction, which includes multiple linear regression analysis and empirical orthogonal function analysis (also known as factor analysis) is reviewed. The work of Imbrie and Kipp, 1971 (IK) in predicting palaeotemperatures during late Pleistocene period in the Atlantic Ocean using planktonic foraminiferal data is reviewed. We have repeated the computations of IK using indigenously developed software. The results of our computations tallied identically with the results presented by IK. We have applied the method of IK for predicting palaeo oceanographic parameters in the Indian Ocean during late Miocene period using radiolarian data. The results indicated that the warmer periods coincided with periods of lesser salinity, i.e. greater precipitation and run-off; and that the monsoon started prior to 8.5 million years before present.

## § 1. INTRODUCTION

Statistical prediction has been widely used in meteorology, oceanography and the earth sciences. In his pioneering work on statistical weather forecasting, Lorenz(1956) studied the predictability of the daily sea level pressure field over the United States and Southern Canada. Imbrie and Kipp(1971) predicted Pleistocene temperatures in the Caribbean Sea, Atlantic Ocean using foraminiferal data. This work became a trend setter in that it has spawned various applications for predicting palaeoclimate using foraminifera as well as radiolaria. Some applications for the Indian Ocean are Dow(1978), Prell et al(1980), Cullen(1981) and Morely(1989). Davis(1976) studied the predictability of the monthly sea surface temperature and sea level pressure over the North Pacific Ocean. Aubrey et al(1980) studied the predictability of beach profile changes in Southern California due to changes in the wave field.

Statistical prediction also known as optimal linear prediction is different from dynamical prediction. In dynamical prediction, the parameter or process to be predicted is modelled in terms of a set of differential equations, which may include initial and boundary conditions, that it is known to satisfy. Usually the governing equations are so complicated as to be unsolvable by either analytical or numerical methods. The equations are made amenable to solution by making certain simplifying assumptions; for example in modelling ocean

currents, the geostrophic approximation is made.

In case of statistical prediction no such a priori assumption need be made. Statistical prediction comprises of using observed data for establishing a linear relationship between the parameter to be predicted known as the predictand (or estimand) and a set of variables known as predictors on which the predictand is thought to depend. The problem of determining the linear relationship is known as multiple regression analysis and is discussed in Section 2. Once the relationship or formula or regression equation is determined, it is then used for prediction purposes.

The simplest application of statistical prediction involves just multiple regression analysis. An application of relevance to the Indian subcontinent is the prediction of the date of onset and the quantum of rainfall over India. Walker(1924) used the following regressional formula with six predictors for operational forecasting of the seasonal (June to September) rainfall over Peninsular India from antecedent meteorological features in other parts of the world:

Peninsular rainfall departure in inches

$$= 1.61F_1 - 0.29F_2 - 0.02F_3 - 77.3F_4 - 0.21F_5 - 0.35F_6$$

where  $F_1$  = average of April and May departure from normal pressure averaged for Santiago, Buenos Aires, and Cordoba (mm of mercury)

$F_2$  = May Zanzibar percentage rainfall departure from normal

- $F_3$  = October through February Java percentage  
rainfall departure from normal
- $F_4$  = Average of September, October and November  
Capetown pressure departure (inches of mercury)
- $F_5$  = October through April South Rhodesian rainfall  
departure
- $F_6$  = Average of March and April Dutch Harbour  
temperature (degrees F)

Similar equations are still being used by the India Meteorological Department for forecasting the rainfall over India during the South West Monsoon. This problem is known as long-range prediction.

The use of regressional formulae is all pervasive. Often we do not consciously realize that we are using regressional formulae. We just think of them as formulae. For example given below is the formula used for determining the water temperature with an Aanderaa recording current meter from the N value (which ranges from 0 to 1023 depending on the temperature):

$$\begin{aligned} &\text{Temperature in degrees Centigrade} \\ &= -2.455 + 0.02299 N \\ &\quad - 0.1344 \times 10^{-5} N^2 + 0.1937 \times 10^{-8} N^3 \end{aligned}$$

When the number of predictors is large compared to the total number of observations (the sample size) used for determining the regression formula, multiple regression analysis is vitiated by a phenomenon known as artificial predictability (see Davis, 1976). When this happens the predictand will appear to be correlated with a

linear combination of predictors eventhough in reality no such correlation exists, so that the regression formula will be good for the original sample, but will be bad when applied to new data.

To avoid artificial predictability, two avenues are open. One, increase the sample size. This is often not possible. The other alternative is to reduce the number of predictors. Predictors which are poorly correlated with the predictand may be excluded by a process of "screening". An objective method for reducing the number of predictors to a few new independent predictors is known as empirical orthogonal function (EOF) analysis and is discussed in Section 3. The newly derived predictors are known as EOFs. EOF analysis is also known as principal component analysis or factor analysis.

In Section 4 we review the work of Imbrie and Kipp(1971) which deals with the prediction of palaeotemperatures at a location in the Atlantic Ocean during late Pleistocene using foraminiferal data. This application of statistical prediction involves the use of both multiple regression analysis and factor analysis. In Section 5, we have applied the method of Imbrie and Kipp(1971) for predicting palaeo-oceanographic parameters at a location in the Bay of Bengal (presently an island) during late Miocene period using radiolarian data.

## § 2. MULTIPLE REGRESSION ANALYSIS

For detailed information on multiple regression analysis, an excellent text-book is Snedecor(1961). We



shall now give the theory of multiple regression analysis.

Let  $x_i$ , ( $i=1,2,\dots,n$ ) and  $y$  be observed variables, where the dependent variable  $y$ , known as the predictand, and the  $n$  independent variables known as predictors be defined for a sample of size  $N$ . We shall denote the arithmetic mean of a variable over the sample by an overbar, and other summations over the sample

by  $\sum_s$ .

The object of the analysis is to express  $y$  as a linear combination of  $x_i$ , viz.

$$y = c_0 + \sum_{i=1}^n c_i x_i$$

where  $c_i$  are constants to be determined. It is more convenient to express the above equation in the deviate form

$$y = \bar{y} + \sum_{i=1}^n c_i (x_i - \bar{x}_i)$$

as it will require the determination of  $n$  instead of  $(n+1)$  unknowns,  $c_i$ . The above equation in deviate form, leads to  $N$  equations in  $n$  unknowns,  $c_i$ . Three cases arise, the third case being of interest to us.

Case (i):  $n > N$ , i.e. the number of predictors is larger than the sample size, so that the number of unknowns is larger than the number of equations. In this case the equations are undetermined so that there exists no unique solution.

Case (ii):  $n = N$ , i.e. the number of predictors equals the sample size, so that there are as many unknowns as the number of equations. In this case the equations are

exactly determined and an unique solution exists.

Case (iii) :  $n < N$ , i.e. the number of predictors is less than the sample size so that the number of unknowns is less than the number of equations. In this case the equations are overdetermined, and therefore one has to look for a solution that best fits the sample data in a least squares sense. To this end we express the sample data as follows:

$$y = \bar{y} + \sum_{i=1}^n c_i (x_i - \bar{x}_i) + r \quad \dots (2.1)$$

where  $r$  is the residual error. The constants  $c_i$  have to be determined so that  $\sum_s r^2$  is minimum, for which it is

necessary that

$$\frac{\partial}{\partial c_j} \sum r^2 = 0, \quad \forall j = 1, 2, \dots, n$$

This gives rise to the following  $n$  normal equations:

$$\sum_{i=1}^n c_i \sum_s (x_i - \bar{x}_i)(x_j - \bar{x}_j) = \sum_s (y - \bar{y})(x_j - \bar{x}_j) \quad \forall j = 1, 2, \dots, n$$

The above  $n$  normal equations have  $n$  unknowns  $c_i$  and can therefore be solved by standard methods.

We thus obtain an estimate  $\hat{y}$  of the predictand which best fits the data sample in a least squares sense:

$$\hat{y} = \bar{y} + \sum_{i=1}^n c_i (x_i - \bar{x}_i) \quad \dots (2.2)$$

Eq(2.2) is known as the regression equation/ formula. It is also known as the transfer function. Eq(2.2) is sometimes expressed as

$$\hat{y} = c_0 + \sum_{i=1}^n c_i x_i$$

where,  $c_0 = \bar{y} - \sum_{i=1}^n c_i \bar{x}_i$        $\dots (2.3)$

A measure generally used to determine the closeness with which the regression equation fits the data sample, is known as the hindcasting skill. The hindcasting skill is defined with the help of total and explained variance. The total variance or the sum of squares of deviations of  $y$  from its mean may be expressed as

$$\sum_S (y - \bar{y})^2 = \sum_S (y - \hat{y})^2 + \sum_S (\hat{y} - \bar{y})^2 + 2 \sum_S (y - \hat{y})(\hat{y} - \bar{y})$$

The first term on the right is the variance of error or the unexplained variance. The second term on the right is the variance of the predicted value or the explained variance, i.e. the variance explained by the regression equation. The last term on the right can be easily shown to be identically equal to zero.

We define:

1. Hindcasting skill

$$\begin{aligned} &= \text{Explained variance} / \text{Total variance} \\ &= \sum_S (\hat{y} - \bar{y})^2 / \sum_S (y - \bar{y})^2 \quad \dots (2.4) \end{aligned}$$

The hindcasting skill (HCS) is also known as the proportion of variance explained, and from its definition, its value lies between 0 and 1. If the HCS is close to 1, then the regression equation fits the data well. And if the HCS is close to 0, the regression equation fits the data poorly. For using the regression equation for prediction purposes, it is not only necessary that the HCS be close to 1 for the data sample used in determining the regression equation, but it should be close to one for the population also, i.e. for any new data sample. For a finite sample size, when the number of predictors is large

compared to the sample size, i.e. the ratio  $n/N$  is large (note that the ratio is always  $\leq 1$ ), the phenomenon of artificial predictability becomes significant. Davis(1976) shows that the HCS computed by Eq(2.4) is always in excess of the true HCS by an amount of the order of  $n/N$ . As pointed out by Lorenz(1956), "...the greater the number of predictors, the greater is the probability that some linear combination of these predictors, will be highly correlated with the predictand within the sample, even though it may be uncorrelated with the predictand within the population". Under these circumstances the regression formula will be good for the original sample, but bad when applied to new data. To avoid artificial predictability the number of predictors  $n$ , as a thumb rule may be chosen such that  $n/N < 0.1$

Besides the hindcasting skill, some other parameters are generally used to assess the results of multiple regression analysis, see for example Snedecor(1961). They are defined below:

2. Standard error of estimate,  $S_{Y,X}$  adjusted for degrees of freedom

$$S_{Y,X} = \sqrt{\left[ \sum_s (Y - \hat{Y})^2 \right] / (N - n - 1)}$$

3. Coefficient of multiple correlation,  $R_{Y,X}$  adjusted for degrees of freedom

$$R_{Y,X} = \sqrt{1 - S_{Y,X}^2 / S_Y^2}$$

$$\text{where } S_Y = \sqrt{\sum_s (Y - \bar{Y})^2 / (N - 1)}$$

4. Standard partial regression coefficients,  $P_i$  for each independent variable  $x_i$ :

$$P_i = c_i \sqrt{\frac{\sum (x_i - \bar{x}_i)^2}{\sum (y - \bar{y})^2}}$$

Of the above parameters  $S_{Y,X}$  and  $R_{Y,X}$  are adjusted for degrees of freedom. The standard partial regression coefficients are used to gauge the importance of various predictors in the regression equation.

Though Eq(2.2) and (2.3) represent a linear relationship, one can determine the regression equation for any nonlinear process by considering some of the predictors  $x_i$  as squares, cubes, products etc., of other predictors. For example let us imagine a quadratic process. If we start out with  $n$  predictors, then the total number of predictors including squares and products equals  $2n + {}^n C_2 = n(n + 3)/2$ , which for  $n=4$  original predictors, gives a total of 14 predictors if we are to retain all quadratic terms.

### § 3 FACTOR ANALYSIS

For detailed information on factor analysis, some excellent text-books are Joreskogg et al(1976), Kendall(1975) and Rummel(1970). The technique of factor analysis was first introduced by Spearman in 1904. Since then, factor analysis has been used extensively wherever large tables of multivariate data are encountered. Kendall(1975) cites fields as diverse as agriculture, anthropology, archaeology, biometrics, economics,

education, industry, medicine, meteorology, physics and sociology where techniques of multivariate analysis including factor analysis are currently applied. Joreskogg et al(1976) claim that the technique of factor analysis has greatly altered the methodology in various specialist fields such as palaeontology, sedimentology, petrology, mining geology, geochemistry, stratigraphy, environmental geology and chemical geology.

Factor analysis enables one to study (say) social phenomena in situ. There is no need to abstract phenomena to the laboratory setting or to select only certain variables and assume that others are constant. The inter relationships between behaviour and environment can be analysed as they exist in real life.

Essentially the aim of factor analysis is to quantitatively summarise and reveal information hidden in a large multivariate table. By taking advantage of inherent inter-dependencies in the set of a large number of variables, factor analysis yields a small number of underlying, generally unobservable factors. As a result, a small number of factors will account for approximately the same amount of information as is present in the much larger set of variables.

We shall now briefly describe the methodology for constructing factors. More elaborate descriptions are given by Joreskogg et al(1976) and Fernandes and Mahadevan(1982).

Let  $X$  be a real valued data matrix having  $N$  rows

representing  $N$  observations, and  $n$  columns representing  $n$  data variables, i.e. the matrix  $X$  is of size  $N \times n$ . The object is to replace the  $n$  data variables (i.e. the columns of  $X$ ) by a few new variables known as factors or empirical orthogonal functions. To this end we consider the singular value decomposition of the data matrix  $X$  (see Joreskog et al, 1975 or Fernandes and Mahadevan, 1982)

$$X = U \Gamma V^T \quad \dots\dots (3.1)$$

where the matrices  $U$  and  $V$  are of sizes  $N \times r$  and  $n \times r$  respectively and have their column vectors orthonormal,  $\Gamma$  is a diagonal matrix of size  $r \times r$ , and  $T$  denotes the transpose of the matrix  $V$ . Eq(3.1) is known as the singular value decomposition as any matrix  $X$  has a unique representation of the above form.

To determine the matrices  $U$ ,  $V$  and  $\Gamma$  we first pre-multiply both sides of Eq(3.1) and post-multiply by  $V$  to obtain

$$X^T X V = V \Gamma U^T U \Gamma V^T V \quad \dots\dots (3.2)$$

and since  $U^T U = V^T V = I$ , the identity matrix as by assumption the column vectors of the matrix  $U$  and  $V$  are orthonormal, we may write Eq(3.2) as follows:

$$R V = V \Lambda \quad \dots\dots (3.3)$$

where  $R = X^T X$  is a square symmetric matrix of order  $n \times n$ , and  $\Lambda = \Gamma^2$  is a diagonal matrix with diagonal elements  $\lambda_i$ . Eq(3.3) may be recognized as a matrix eigenvalue problem - the problem of determining the eigen values  $\lambda_i$  and corresponding eigen vectors  $V_i$  of the matrix  $R$ .

To solve the eigen value problem, we may write

Eq(3.3) in longhand as follows:

$$\begin{bmatrix} r_{11} & r_{12} & r_{1n} \\ r_{21} & r_{22} & r_{2n} \\ \dots & \dots & \dots \\ \dots & \dots & \dots \\ r_{n1} & r_{n2} & r_{nn} \end{bmatrix} \begin{bmatrix} v_{11} & v_{12} & v_{1r} \\ v_{21} & v_{22} & v_{2r} \\ \dots & \dots & \dots \\ \dots & \dots & \dots \\ v_{n1} & v_{n2} & v_{nr} \end{bmatrix} = \begin{bmatrix} v_{11} & v_{12} & v_{1r} \\ v_{21} & v_{22} & v_{2r} \\ \dots & \dots & \dots \\ \dots & \dots & \dots \\ v_{n1} & v_{n2} & v_{nr} \end{bmatrix} \begin{bmatrix} \lambda_1 & 0 & 0 \\ 0 & \lambda_2 & 0 \\ \dots & \dots & \dots \\ \dots & \dots & \dots \\ 0 & 0 & \lambda_r \end{bmatrix}$$

Equating the i'th column of the product matrix on either side of the above equation, we have,

$$\begin{aligned}
 (r_{11} - \lambda_i)v_{1i} + r_{12}v_{2i} + \dots + r_{1n}v_{ni} &= 0 \\
 r_{21}v_{1i} + (r_{22} - \lambda_i)v_{2i} + \dots + r_{2n}v_{ni} &= 0 \\
 \dots + \dots + \dots + \dots &= 0 \\
 \dots + \dots + \dots + \dots &= 0 \\
 r_{n1}v_{1i} + r_{n2}v_{2i} + \dots + (r_{nn} - \lambda_i)v_{ni} &= 0 \\
 \dots \dots \dots (3.4)
 \end{aligned}$$

If the determinant of the coefficients of v in the above equations is not equal to zero, the set of Eq(3.4) leads to the trivial solution



$$V_i = \begin{bmatrix} v_{1i} \\ v_{2i} \\ \dots \\ \dots \\ v_{ni} \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ \cdot \\ \cdot \\ 0 \end{bmatrix}, \quad i = 1, 2, \dots, n$$

And if the determinant of the coefficients of  $v$  is zero, we obtain an  $n'$  th degree polynomial in  $\lambda_i$ , which will have  $n$  roots  $\lambda_i$ . And since  $R$  is real, square and symmetric and of rank  $r$ , the roots  $\lambda_i$  are all non negative,  $r$  of them being positive. For each of these positive roots  $\lambda_i$ , which are known as eigen values, Eq(3.4) yields a solution vector

$$V_i = \begin{bmatrix} v_{1i} \\ v_{2i} \\ \dots \\ \dots \\ v_{ni} \end{bmatrix}, \quad i = 1, 2, \dots, r$$

which is known as eigen vector or empirical orthogonal function. As given in Fernandes and Mahadevan(1982), the square root,  $\sqrt{\lambda_i}$  of the eigen values arranged in descending order down the principal diagonal form the matrix  $\Gamma$  and the corresponding normalized eigen vectors  $V_i$  of the matrix  $R$  arranged from left toward right form the columns of  $V$ . Then the matrix  $U$  is obtained by post-multiplying Eq(3.1) by  $V \Gamma^{-1}$ . Thus is obtained the singular value decomposition of the matrix  $X$  as expressed by Eq(3.1). The columns of  $U$  and  $V$  are known as empirical orthogonal functions.

Generally the magnitude of the eigen values reduces rapidly from its highest value and instead of r terms, only few terms, say k, where  $k < r < n$  are needed for close representation of the data matrix, as follows:

$$X = U \Gamma V^T = \sum_{i=1}^r U_i V_i^T \cong \sum_{i=1}^k \lambda_i U_i V_i^T \quad \dots (3.5)$$

$$X = (U \Gamma) V^T = \xi V^T \cong \xi_{(k)} V_{(k)}^T \quad \dots (3.6)$$

where  $\xi = U \Gamma$ ; and  $\xi_{(k)}$  and  $V_{(k)}$  are matrices composed of the first k columns of the matrices  $\xi$  and  $V$  respectively.

Eqs(3.5) and (3.6) represent the singular value decomposition and the Q-mode factor model respectively. A measure of closeness defined by the ratio

$$\frac{\sum_{i=1}^k \lambda_i}{\sum_{i=1}^r \lambda_i}$$

is generally used to determine the cut-off value k.

Empirical orthogonal functions (EOF)  $U_i$  and  $V_i$  are often used (e.g. Aubrey et al, 1980) in applications of statistical analysis and prediction. In other cases the EOFs  $\xi_i$  and  $V_i$  are used; and optionally varimax rotation of the EOFs is performed for better interpretation of results.

#### §4. PREDICTION OF PLEISTOCENE CLIMATE IN THE CARRIBEAN

The emergence of man occurred during the Pleistocene which began about one and a half million years ago. It was during the Pleistocene that glaciations had occurred. From evidence left on land by four glaciations, attempts were being made to determine the time frame of the glaciations. The record of glaciations on the continents is badly

garbled because each successive ice sheet as it spread over land tended to destroy the evidence of earlier glaciations. The evidence pieced together from a study of glacial sediments at a number of sites however suggested that the intervals of mild climate separating the ice ages were long, probably longer than the ice ages themselves. But the estimates of the duration of the interglacial periods varied by many thousand years due to disagreement regarding rates of "weathering" of the sediments. The dating of sediments by the radio-isotope method is only a recent development.

The focus then turned to the ocean due to the development of devices which could take long cores of sediment from the depths of the ocean. A large part, often the major part of ocean sediments consist of microscopic shells or skeletons of planktonic foraminifera and radiolaria. The shells of foraminifera are made of calcium carbonate while shells of radiolaria are made of silica. Certain species of foraminifera are sensitive to temperature changes and can be used as an indicator of climate change.

In the words of Ericson and Wollin(1966) referring to foraminifera says "Certain species are sensitive to temperature, and accordingly are restricted geographically to certain climatic zones. The extremely slow but continuous rain of these shells upon the ocean floor provides an ideal recording mechanism. As the millenia roll by and climatic changes occur, the populations of

species sensitive to temperature shift from latitude to latitude. The complete record of these shifts is there, word for word, page by page; like a forgotten language it can be deciphered if one has the patience of a cryptographer and the inquisitiveness of a detective".

For as Ericson and Wollin(1966) narrate "In 1935 W. Schott concluded that the appearance of the planktonic foraminifer Globorotalia Menardii in abundance in uppermost layer of sediment in cores from the equatorial Atlantic recorded the commencement of post glacial time; and that the underlying layer without G. M. represented deposition during the last ice age. Radio-carbon dating has fully confirmed Schott's surmise".

Sometimes the direction of coiling of certain species of foraminifera is an indicator of climate change. For example the propensity of Globigerina Pachyderma in sediments coiling to the left indicates cold climate whereas the propensity of the same species coiling to the right indicates warmer climate.

Thus the climate change during the Pleistocene could be predicted (more appropriately hindcasted) qualitatively from the relative abundances of certain temperature sensitive species of foraminifera from sediment cores. This does not mean that all cores contain the undisturbed Pleistocene record. Sometimes on continental rises "slumping" occurs, i.e. a portion of unconsolidated sediment gets dislodged due to some disturbances like an earth tremor, and flows down the slope as a turbidity

current. The effect is that on the continental rise a core may have sections of sediment missing due to slumping; and cores in ocean basins may have "extra" sediments due to the turbidites which have a distinct signature.

We shall now briefly review the work of Imbrie and Kipp(1971) who reconstructed late Pleistocene environmental conditions. An excellent summary of this work is given by Joreskogg et al(1975), pg 160-165.

Imbrie and Kipp(1971) presented a quantitative method for predicting Pleistocene climate from foraminiferal assemblages obtained using Q-mode factor analysis. Relationships between modern foraminiferal assemblages and environmental variables (temperature and salinity in surface waters) were obtained in the form of regression equations, which were then applied to Pleistocene assemblages thus predicting the environmental conditions during late Pleistocene.

To obtain modern foraminiferal assemblages sixty one cores were chosen from widespread geographic locations in the Atlantic Ocean so as to be representative of different environmental conditions. Samples from the uppermost layers of these cores, known as core-tops were analysed for determining the percentage abundance of different species of foraminifera. To obtain the Pleistocene assemblages, a 10.9 metre long core taken from the Caribbean Sea in the Atlantic Ocean was chosen. 110 samples were taken from this core, one from every 10 centimetres of its length, and analysed for determining

the percentage abundance of different species of foraminifera. These 110 samples are referred as the core samples. 22 species were found to exceed 2 percent abundance in at least one core-top and core samples. Imbrie and Kipp(1971) thus obtained a 61 X 22 core-top matrix and a 110 X 22 core matrix of percentage abundance of species, each column of these matrices representing a species.

The following two transformations were carried out on the core-top and core matrices. The elements of each column were divided by the range for the species. The range was computed across both core-top and core samples with the lower limit always taken as zero percent. Range division was done in order to give equal weighting to each species. The data matrices thus transformed were then row-normalized, i.e. for every row, each element of the row was divided by the square root of the sum of the squares of elements along the row. The core-top data matrix  $W_{ct}$  and the core data matrix  $W_c$  were thus obtained.

A Q-mode factor analysis of the transformed core-top data matrix  $W_{ct}$  was then performed. Five factors were selected, i.e.  $k = 5$  in Eq(3.6). The factors were rotated by the varimax method to obtain

$$W_{ct} \cong B_{ct} F^T$$

where  $W_{ct}$  is the range and row normalized core-top data matrix,  $B_{ct}$  is the varimax factor loading matrix,  $F$  is the varimax factor score matrix, and the superscript  $T$  of  $F$  refers to the transpose of the matrix  $F$ .

The matrix F described the community structure of the foraminifera. Each column of this matrix represents an independent assemblage of foraminifera species. The computations of Imbrie and Kipp(1971) showed that the species *G. ruber*, *G. sacca*, *G. aequi*, *G. mentu*, *G. obliq* and *G. gluti* formed a distinct assemblage.

That the five assemblages were geographically and ecologically meaningful was shown by the columns of the matrix  $B_{ct}$ . For example, when the first column of  $B_{ct}$  was plotted onto a geographical projection of the region sampled, high loadings were found in the tropics (see Fig 4.1), whence the assemblage represented by the first column of F was given the name tropical assemblage. Similarly the second, third, fourth and fifth assemblage were named as subtropical, polar, subpolar and gyre margin assemblages respectively. The modern foraminiferal assemblages were thus obtained. These modern assemblages were found to be related to present day surface environmental parameters like average winter temperature. For example, in Fig 4.2 are plotted the varimax factor loadings of the subtropical assemblage against the sea surface winter temperature at each of the core-top sites. It was found that the curve peaked at around  $15^{\circ}$  C. Similarly for the tropical, subpolar and polar assemblages the curve peaked at around  $25^{\circ}$  C,  $5^{\circ}$  C and  $0^{\circ}$  C respectively.

To obtain a quantitative relationship between the surface environmental conditions and the factor loadings

of each assemblage, it is noted that the curve in Fig 4.2 is essentially parabolic, i.e. the process is quadratic. As a result of factor analysis, the 22 data variables (the species) have been reduced to just five factors or assemblages for which loadings (i.e. matrix  $B_{ct}$  having 61 rows and five columns) have been determined at each of the 61 locations, with which surface environmental parameters are related quadratically. To find this relationship is a problem in multiple regression analysis described in Section 2. Since in the Caribbean core data, the polar assemblage did not figure, only four of the five assemblages which gives rise to 14 quadratic terms (as shown in Section 2) were considered.

By multiple regression analysis, sets of coefficients  $k_0, k_1, \dots, k_{14}$  were determined such that an environmental parameter, say, average winter temperature was expressed in terms of the factor loadings of four assemblages as follows:

$$T_w = k_0 + k_1 b_1 + k_2 b_2 + \dots + k_4 b_4 + k_5 b_1^2 + k_6 b_2^2 + \dots + k_8 b_4^2 + k_9 b_1 b_2 + k_{10} b_1 b_3 + \dots + k_{14} b_3 b_4 \quad \dots (4.2)$$

where  $T_w$  is the estimated temperature, and the  $b$ 's are the columns of the varimax factor loading matrix  $B_{ct}$  save for the third column which represents the polar assemblage. Having computed the coefficients  $k_i$ , Eq(4.2) can be used for prediction of palaeotemperatures from Pleistocene assemblages.

A Q-mode factor analysis of the range and row



normalized core matrix  $W_C$  could give the Pleistocene assemblages, but this was not done by Imbrie and Kipp(1971). As pointed out by Joreskogg et al(1976), Imbrie and Kipp (1971) employed an innovative method that used the results of factor analysis of the core-top data matrix  $W_{ct}$ . Eq(4.1) can be rewritten as

$$B_{ct} = W_{ct} F \quad \dots\dots\dots (4.3)$$

since  $F^T F = I$ , the identity matrix as the columns of  $F$  are orthonormal. From Eq(4.3) we see that  $F$  is a transformational matrix mapping  $W_{ct}$  into the varimax factor loading matrix of modern foraminiferal assemblages  $B_{ct}$ . This suggests that Pleistocene assemblages may be obtained as follows:

$$B_C = W_C F$$

where  $B_C$  is a 110 X 5 matrix of loadings of the ,  $W_C$  is the core data matrix and  $F$  is the varimax factor score matrix obtained from the factor analysis of the core-top data.

Excluding the polar assemblage, the remaining four assemblages were used in the transfer function i.e. Eq(4.2) to determine surface environmental variables at each of the 110 levels which represent a span of approximately 450,000 years before present.

We have repeated the computations of Imbrie and Kipp(1971) using indigenously developed software. For the core-top data, the varimax factor loading and factor score matrices obtained by us were nearly identical to that of Imbrie and Kipp(1971). Our predicted values of winter

temperature, summer temperature and surface salinity at the 110 levels of the Caribbean core representing a time span of 450,000 years before present were within  $\pm 0.1^{\circ}$  C and  $\pm 0.1$  parts per mille respectively from those of Imbrie and Kipp(1971).

#### § 5 PREDICTION OF MIOCENE CLIMATE IN THE BAY OF BENGAL

We have predicted some surface environmental parameters during late Miocene in the Bay of Bengal using radiolarian data. We have strictly followed the method of Imbrie and Kipp(1971). Shells of foraminifera are subject to dissolution under certain circumstances. To avoid this problem radiolaria are used.

In the words of Briggs(1971) "Calcium has been widely used by nature as a building block but palaeontologists find this choice of material something of a drawback. Under certain conditions it dissolves. Calcium carbonate is found in marble, limestone, coral, chalk, and shells. It is the fifth element in world abundance and very important in plants and the human body. But as the shell of dead protozoa sink through water that is undersaturated with calcium carbonate, the shell loses the chemical gradually to the environment around it. If the bottom is shallow, the shell will reach the bottom safely and be buried before it has been dissolved. If it has to sink in deep water, however, below what is known as the depth of compensation, it will cease to exist. In such deep cases, palaeontologists often look to a protozoan fossil known as radiolaria whose shell is based on silica. Ocean water

dissolves silica very slowly. Seen through a fifty power microscope, radiolaria are some of the most beautiful constructions in all nature. They are either spherical or helmet-shaped, and very often they have long delicate spines that radiate from the centre. The variety of radiolaria ornamentation is so great that they are one of the most diverse groups of animals known. The first Challenger described 4,217 species".

While working with foraminifera it has been a practice to work at species level. But while working with radiolaria, because of the greater diversity it has been found more convenient to work with coarser taxonomy, i.e. at the group level.

In the Atlantic and Pacific Oceans large temperature gradients are observed due to the effect of polar icecaps, while the salinity gradients are small. In contrast in the Bay of Bengal, which has no access to the icecap at the north, salinity gradients predominate due to the huge fresh water discharge by the Brahmaputra, Ganges and the Irrawadi rivers.

The core-top data used in our work comes from 42 core or grab samples roughly in the region  $2^{\circ}\text{N}$  to  $17^{\circ}\text{S}$  and  $70^{\circ}\text{E}$  to  $90^{\circ}\text{E}$  (see Table 5.1). The samples were taken using three ships, viz. RV Gaveshani, MV Farnella and MV Skandy Surveyor as part of the NIO polymetallic nodules project. The core data came from the Sawai Bay Formation, Neill Island, Andamans (Fig 5.1). During Miocene times Neill island lay beneath the ocean. The Neill Island pseudo-core

comprising of 10 samples had been the subject of a study by Gupta and Srinivasan(1992), whose stratigraphy placed the samples at late Miocene, between 5.0 and 8.5 million years before present. At the 42 core-top locations surface environmental parameters, viz., temperature and salinity during spring (May, June, July) and fall (Nov, Dec, Jan) ; and primary productivity during the north east and south west monsoons are given in Table 5.2 .Temperature and salinity was interpolated from the  $1^{\circ} \times 1^{\circ}$  gridded seasonal Levitus digital data available on magnetic tape from NOAA. Primary productivity was interpolated from Wyrтки's Atlas for the Indian Ocean. In Fig 5.2, however, we have reproduced from the Atlas of Wyrтки(1971) the temperature, salinity and primary productivity in the region bounded by  $10^{\circ}$  N to  $20^{\circ}$  S; and,  $60$  to  $90^{\circ}$ E - during the north east and south west monsoon.

For both the core-top and core samples percentage abundance of 47 radiolarian groups were determined. After excluding Miocene radiolarian groups that have no modern analogue, as well as three deep dwellers, viz. siphocampe, Botryostobus and sethoperinids, we found that 25 groups (Table 5.3) exceeded 2 percent abundance in at least one core-top and one core sample. The table also gives the range of abundance of each group. The range has been computed across both the core-top and core samples. For computing the range the minimum abundance was taken as zero percent. The  $42 \times 25$  core-top and  $10 \times 25$  core data matrices of percentage abundance which are given in Tables

5.4 and 5.5 respectively were then range and row normalized.

A Q-mode factor analysis of the normalized core-top data gave rise to four factors or assemblages explaining 89.2 percent of the variance of the data. The varimax factor loading matrix and the varimax factor score matrix are given in Tables 5.6 and 5.7 respectively. Factor loadings at the 42 core-tops have also been shown in Fig(5.3).

The above four assemblages were found to be related to geographically distinct water masses. The first assemblage (South Western) accounting for 28.9 % of the variance of the data, has high loadings in the south western area (Fig 5.3), and is dominated by Artiscins (*Didymocyrtis Tetrathalmus*), Pyloniids (*Tetrapyle Octacantha*, *Octopyle Stenoona* and *Hexapyle Dodecantha*), *Acrosphaera* and *Hexacantium*. This assemblage is correlated with cooler ( $23-27^{\circ}$  C), hypersaline ( $> 34.5$  ppt) and highly productive ( $0.2-0.5$  mgC/m<sup>3</sup>/h) surface water mass during spring (south west monsoon).

The second assemblage (North Eastern) accounting for 23.4 % of the variance has high loadings in the north eastern area and is dominated by *Spongaster Sponcore*, *Spongodiscids*, *Stylodyctya* and *Elatomma Haliomma*. This assemblage is correlated with warmer ( $> 27^{\circ}$  C SST), hyposaline ( $< 34.5$  ppt) and low productivity ( $0.05-0.1$  mgC/m<sup>3</sup>/h) water mass during the south west monsoon.

The third important assemblage (Transitional)

accounting for 22 % of the variance of the data has high loadings along the 34.5 ppt isohaline during the SW monsoon which diagonally separates two contrasting assemblages, viz., the South Western Hypersaline and the North Eastern Hyposaline assemblages. This assemblage is dominated by *Disolenia Siphanosphaera*, *Collosphaera*, *Eucyrtidium* and *Euchiloniids* (*Euchitonia Elegans*, *Euchitonia Furcata*, *Euchitonia species*, *Dictyocoryne Truncata*, *Dictyocorine Profunda* and *Hymeniastrum Euclidis*).

The fourth assemblage (Southern) accounting for 14.9 % of the variance has high loadings in the southern part of the basin, south of 10-12<sup>0</sup> S hydrographic front of Wyrcki(1973) in the equatorial Indian Ocean. This assemblage is dominated by *Lamprocyclas Cyrtis*, *Anthocyrtidium* and *Lophospyris Phormospyris*.

To find the relationship between surface ecological parameters and modern radiolarian assemblages, a multiple regression analysis was performed. The four factors of the factor loading matrix (Table 5.6) gives rise to 14 quadratic terms just like that of Imbrie and Kipp(1971). These are the independent variables. The surface environmental parameters at the core-top locations (Table 5.2) are the dependent variables. The results of the multiple regression analysis are given in Tables 5.8 to 5.13.

From Tables 5.8 to 5.13 we see that in case of fall temperature, fall salinity and north east monsoon

potential primary productivity; the proportion of variance explained is low and the multiple correlation coefficient is zero or close to it, signifying that these surface environmental parameters are not related to modern radiolarian assemblages. Therefore prediction of these environmental parameters during Miocene will not be reliable, and therefore a figure is not provided. However Table 5.14 lists all the estimates including the unreliable ones.

In case of spring temperature, spring salinity and south west monsoon potential primary productivity; the proportion of variance explained and the multiple correlation coefficient are high. Therefore prediction of these environmental parameters during late Miocene are likely to be reliable. These predictions are presented in Fig 5.4. We see from this figure that there are two periods of greater warming denominated as W-8 and W-11, and two periods of lesser warming denominated by W-9 and W-10. We also note that the peaks in temperature are associated with troughs in salinity and vice versa, indicating a warm-humid, cold-arid scenario. Also note that spring salinity shows a decreasing trend from around 8.5 million years to around 5 million years (Ma) before present, indicating that the monsoon started prior to 8.5 Ma.

In obtaining predictions of environmental conditions (SST and salinity during spring and fall) during late Miocene, as mentioned earlier, we have used the Levitus digital data set for interpolating modern environmental

conditions at the sites of the 42 surface sediment samples. Initially instead of the Levitus data we had used the atlas of Wyrтки(1971) for interpolating modern environmental conditions (SST, salinity and potential primary productivity) at the sites of the sediment samples. We switched over to the Levitus digital data set in case of SST and salinity because of difficulties in precise interpolation from contoured charts associated with the Wyrтки data.

Still the predictions of environmental conditions during late Miocene obtained using Wyrтки's data (see Table 5.15) were found to be qualitatively identical to that obtained by using the Levitus data in that both the predictions indicate two periods of greater warming (W-8 and W-11) and two periods of lesser warming (W-9 and W-10). But there are two differences, one, there is a shift in time in the location of W-9 and W-10; and two, while the Levitus data set gives rise to a range of  $\approx 3.1^{\circ}\text{C}$  in temperature variation during late Miocene, in case of the Wyrтки data the range is hardly  $\approx 1.2^{\circ}\text{C}$ . We may account for the disparity in the ranges by noting that the Levitus data represents a mean over a three month interval of all historical data, whereas the Wyrтки temperature data represents the picture in a single month in the year 1963 during the International Indian Ocean Expedition.

The above numerical (quantitative) predictions are an extension of the work of Gupta and Srinivasan (1992), who



on qualitative grounds identified just two warmer periods, viz., W-9 and W-11.

Fig 5.5 shows the salinity during modern times in the Bay of Bengal. and at Neill Island, Andamans during late Miocene. We see that the hyper saline > 34.5 parts per mille water-mass, which during modern times lies to the south of Sri Lanka, was apparently located over the Andamans during late Miocene; indicating that as the monsoon strengthened the hypersaline water was pushed out of the Bay of Bengal.

#### CONCLUSIONS

The technique of statistical prediction has been indigenously developed and has been used to predict late Miocene climate in the Bay of Bengal. This opens the way for other likely applications in palaeontology, meteorology and oceanography in NIO.

#### ACKNOWLEDGEMENTS

The authors wish to thank the Director, NIO for the facilities provided. They wish to thank Shri L V G Rao and Shri R R Nair for encouraging this work. The radiolarian surface sediment samples were collected during surveys of polymetallic nodules, which were financed by the Department of Ocean Development, New Delhi. The authors are indebted to Shri G Narayanaswami and Dr P Vethamony for their help in publishing this report.

## REFERENCES

- Aubrey D G, D I Inman and C I Winant, 1980. The statistical prediction of beach changes in southern California. *J. Geophys. Res.*, Vol 85, No. C6, pp 3264-3276.
- Briggs P. 200,000,000 years beneath the sea. Holt, Rinehart and Winston, New York, 1971, pg 228.
- Cullen J L, 1981. Microfossil evidence for changing salinity patterns in the Bay of Bengal over the last 20,000 years. *Palaeogeogr. Palaeoclimatology, Palaeoecology*, Vol 35, pp 315-356.
- Davis R E, 1976. Predictability of sea surface temperature and sea level pressure anomalies over the north Pacific Ocean. *J Phys Oceanogr*, Vol 6, No 3, pp 249-266.
- Dow R L, 1978. Radiolarian distribution and late Pleistocene history of the of the south eastern Indian Ocean. *Mar. Micropalaeontology*, Vol 3, pp 203-227.
- Ericson D B and G Wollin. The deep and the past. Jonathan Cape, London, 1966, pg 292.
- Fernandes A A and R Mahadevan, 1982. Factor analysis of multivariate data. NIO Technical Report No. 2/82, NIO, Dona Paula, Goa, October 1982.
- Gupta S M and M S Srinivasan, 1992. Late Miocene radiolarian biostratigraphy and paleoceanography of Sawai Bay Formation, Neill Island, Andamans, India. *Micropaleontology*, Vol 38, No. 3, pp 209-235.
- Imbrie J and N G Kipp, 1971. A new

micropaleontological method for quantitative micropaleontology: Application to a late Pleistocene Caribbean core. In: K Turekian (Editor), The late Cenozoic glacial ages. Yale University Press, New Haven.

Joreskog K G, J E Klován and R A Reyment. Methods in geomathematics 1: Geological factor analysis. Elsevier Scientific Pub. Co., Amsterdam, 1976, pg 178.

Kendall M. Multivariate analysis. Charles Griffin & Co. Ltd. London, 1975.

Levitus S, 1982. Climatological Atlas of the world oceans. NOAA Prof Paper 13, Rockville, Md., U S Govt. Printing Office, Washington D C

Lorenz E N, 1956. Empirical orthogonal functions and statistical weather prediction. MIT, Massachusetts, Scientific Report No 1, Statistical forecasting project, pg 49.

Morely J J, 1989. Radiolarian-based transfer functions for estimating palaeoceanographic conditions in the south Indian Ocean. Marine Micropalaeontology, Vol 3, pp 203-227.

Prell W L, W H Huston, D F William, A W H Be, K Geitzenauer and B Molina, 1980. Surface circulation in the Indian Ocean during the LGM. Quat. Res., Vol 14, pp 309-336.

Rummel R J. Applied factor analysis. North Western University Press, Evanston, 1970, pg 617.

Snedecor G W. Statistical methods applied to experiments in agriculture and biology. Allied Pacific,

Bombay, 1961, pg 534.

Wyrтки K, (Editor) 1971. Oceanographic Atlas of the  
International Indian Ocean Expedition. National Sci.  
Foundation, Washington D C, pg 531.

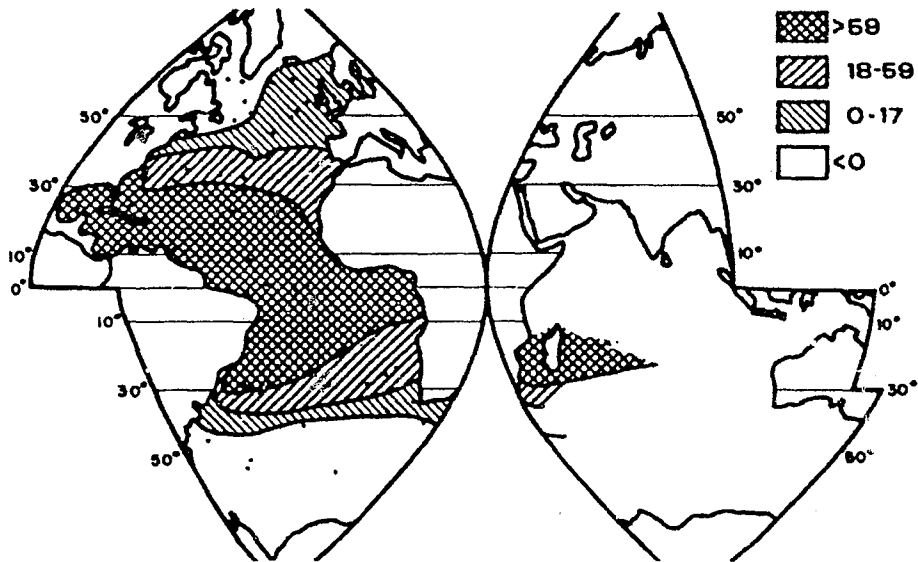


Fig.4.1 Geographic variation of the contribution of the tropical assemblage

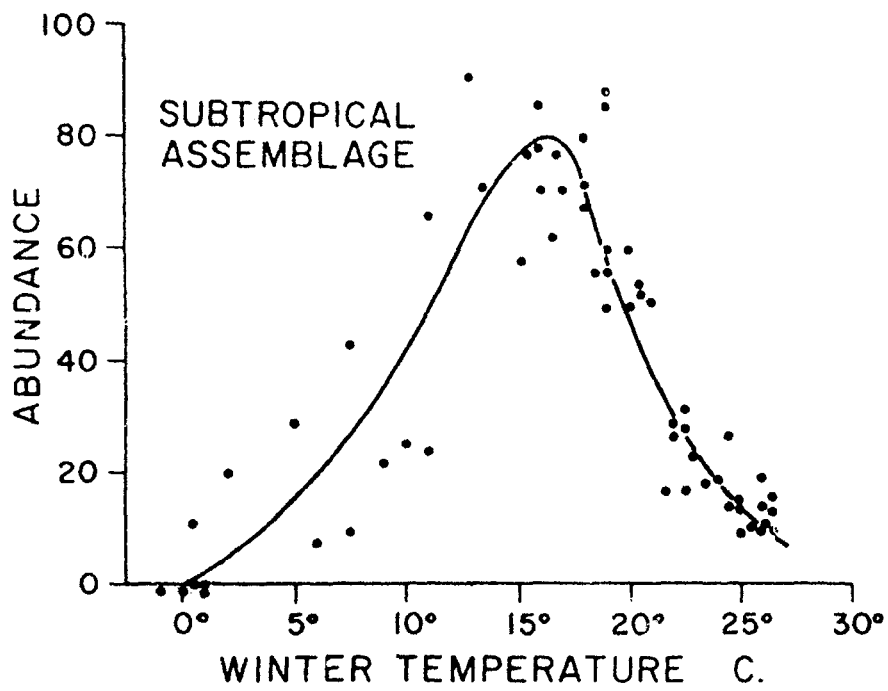


Fig.4.2. Abundance of the subtropical assemblage versus winter surface temperature for 61 core top samples

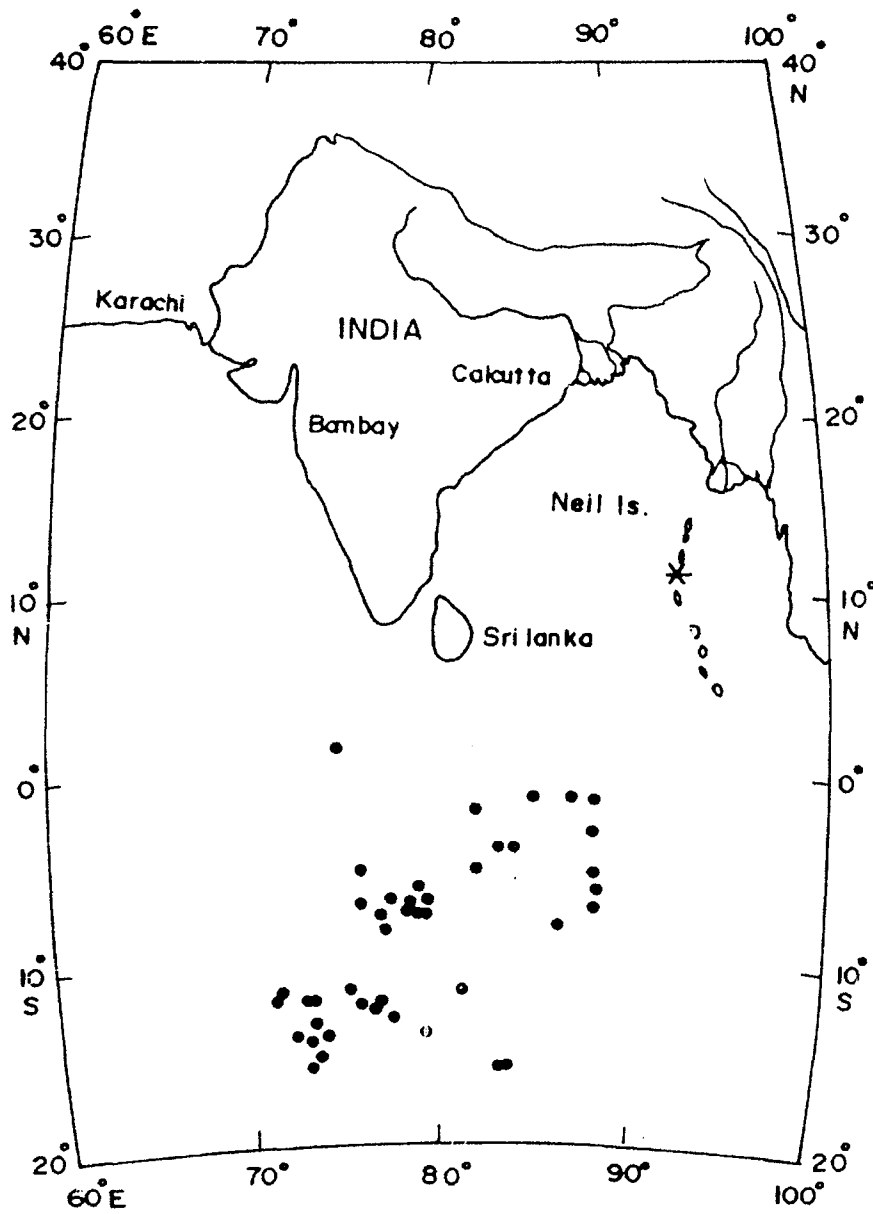


FIG. 5.1 LOCATION OF NEILL ISLAND, SAWAI BAY FORMATION \* AND SURFACE SEDIMENT RADIOLARIAN SAMPLES •

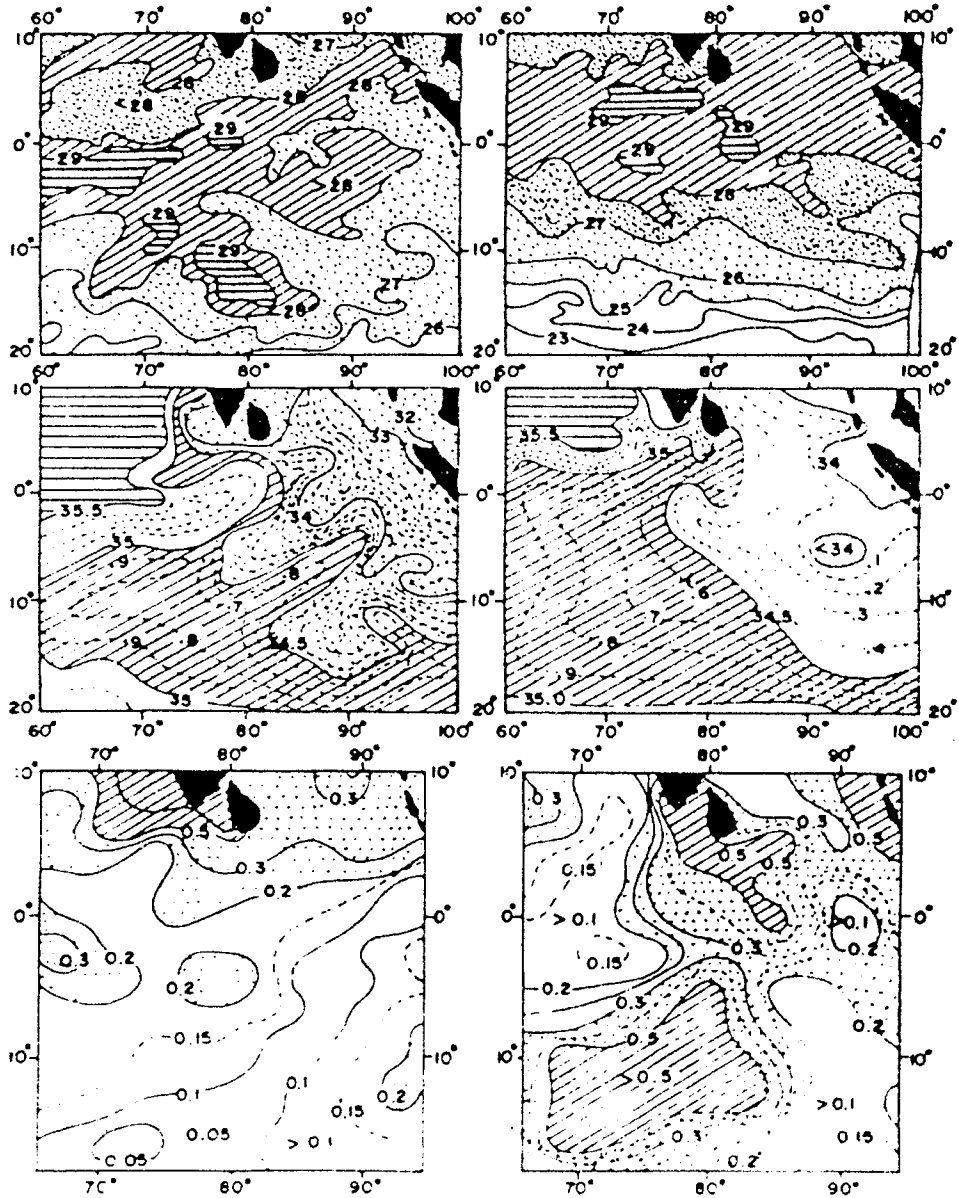


FIG.52 MODERN OCEANOGRAPHIC CONDITIONS (TOP) SST; (MIDDLE) SALINITY; (BOTTOM) PPP; LEFT: NE MONSOON RIGHT: SW MONSOON.



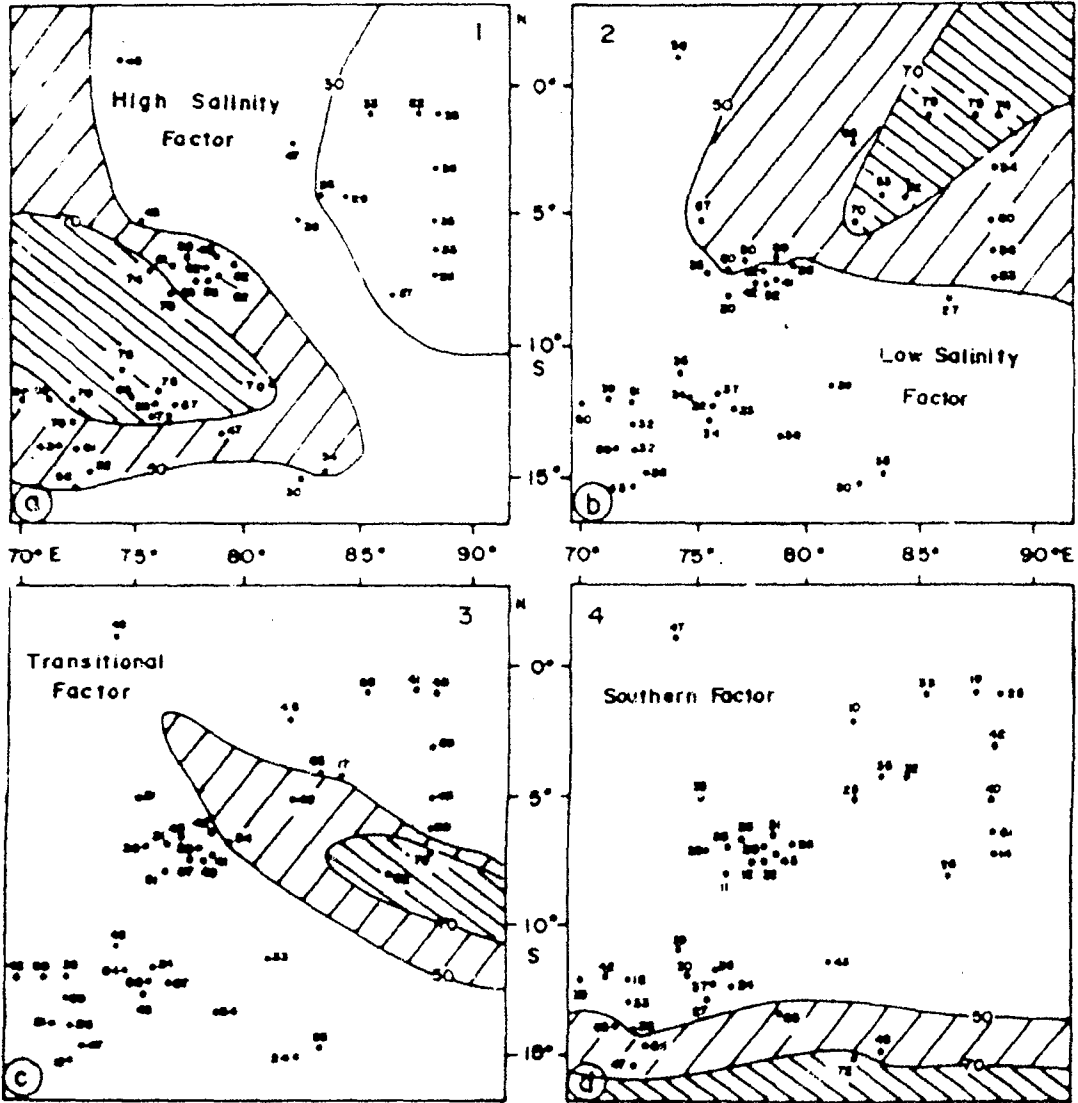


FIG. 5. 3 RADIOLARIAN FACTOR LOADINGS

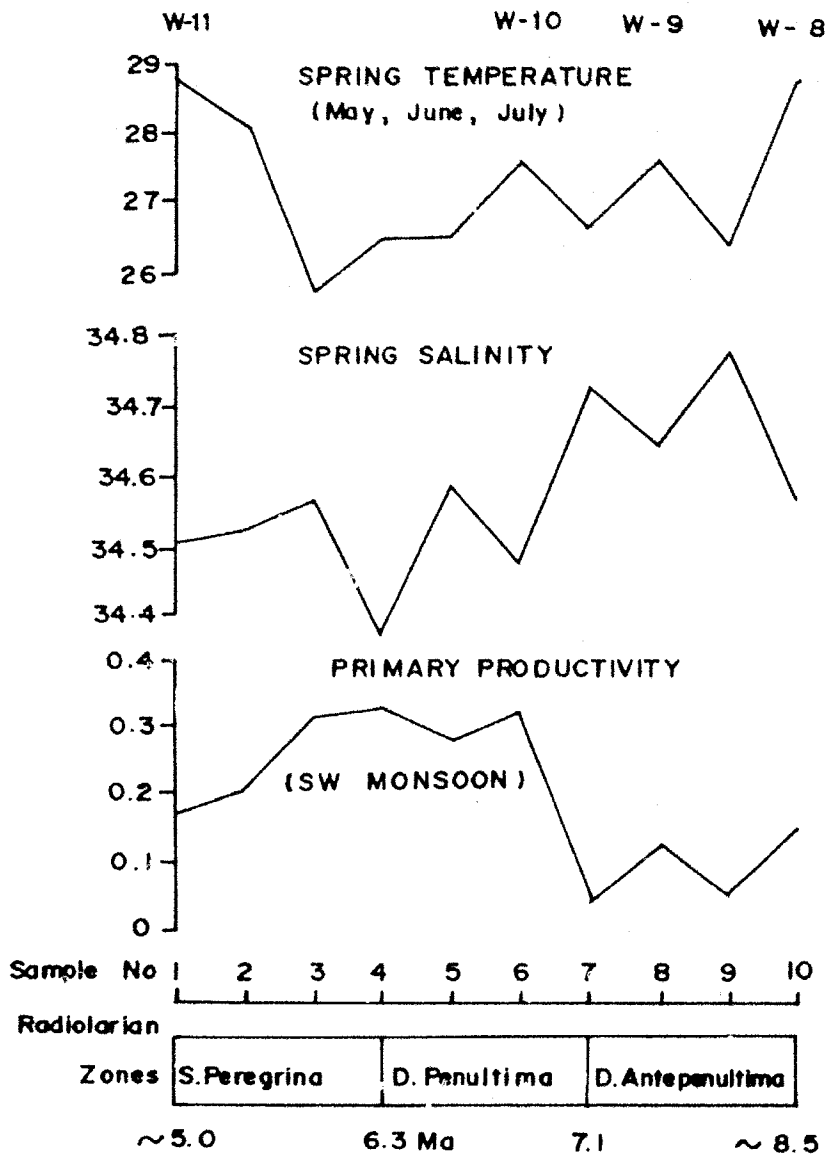


FIG. 5.4. ESTIMATES OF ENVIRONMENTAL CONDITIONS DURING LATE MIOCENE USING RADIOLARIA

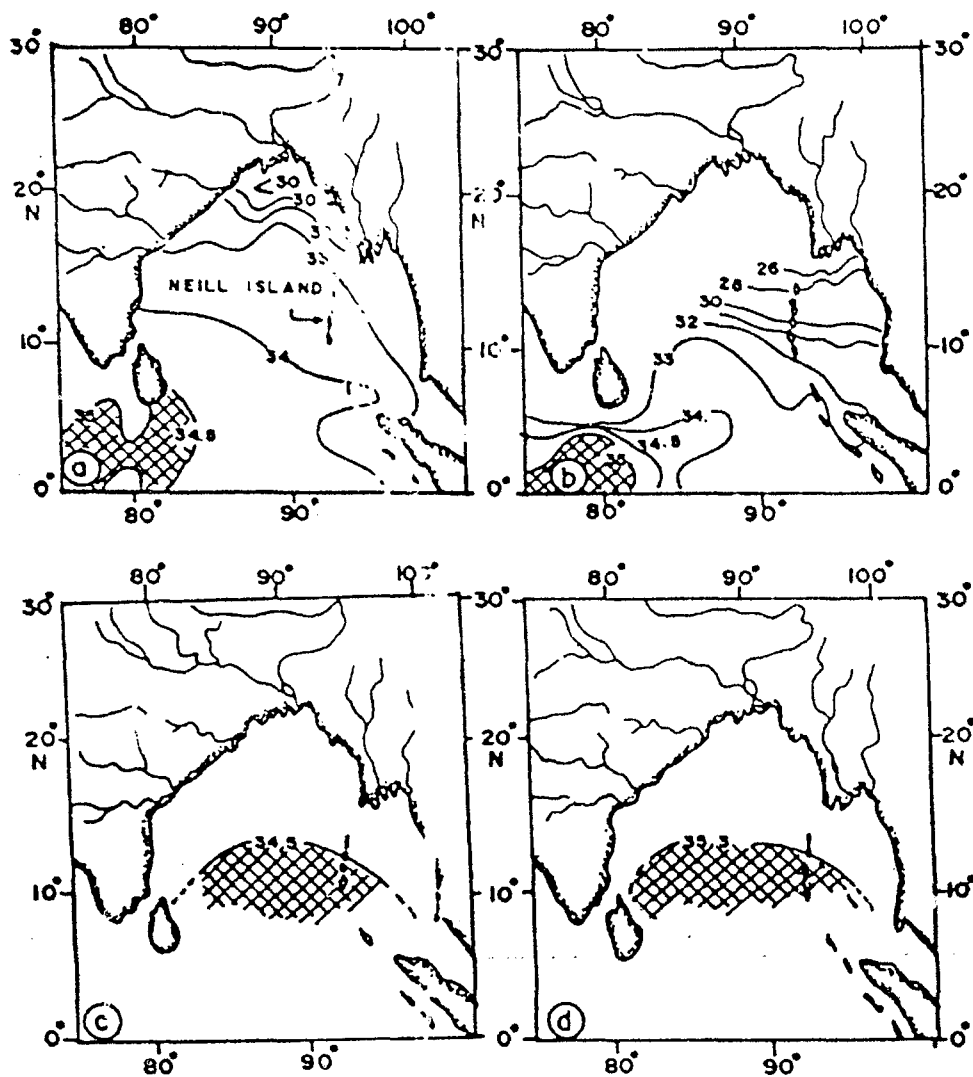


FIG. 5.5 SALINITY DURING MODERN TIMES (TOP) AND DURING LATE MIOCENE (BOTTOM) LEFT : SW MONSOON ; RIGHT : NE MONSOON

Table 5.1 : Location of radiolarian surface sediment  
(core-top) samples

SA No	Latitude deg N	Longitude deg E
01	-02.050	82.079
02	-05.000	82.090
03	-04.000	83.190
04	-04.000	84.001
05	-01.080	85.000
06	-01.125	87.020
07	-08.070	86.109
08	-07.012	88.155
09	-06.001	88.090
10	-05.075	88.180
11	-03.062	88.065
12	-01.059	88.095
13	-13.500	73.999
14	-14.002	73.001
15	-12.490	77.011
16	-05.000	75.992
17	-07.027	76.002
18	-07.444	78.954
19	-07.550	78.467
20	-07.489	78.014
21	-08.024	76.967
22	-07.021	76.980
23	-07.004	78.495
24	-07.067	79.500
25	-06.468	77.439
26	-06.500	78.945
27	-12.007	76.477
28	+01.089	74.670
29	-11.010	74.985
30	-13.006	72.984
31	-12.007	73.003
32	-12.017	73.003
33	-14.017	72.016
34	-11.999	70.990
35	-11.969	75.465
36	-12.006	76.452
37	-11.514	81.490
38	-13.510	78.979
39	-15.090	83.560
40	-15.487	82.950
41	-14.890	73.530
42	-15.500	72.991

Table 5.2 : Surface environmental parameters at the 42 core top locations. Temperature & salinity are from Levitus; Potential Primary productivity from Wyrтки's Atlas

	SALINITY		PRIMARY PRODUCTIV.		TEMPERATURE	
	Fall	Spring	NE Mon	SW Mon	Fall	Spring
1	34.88	34.56	.15	.30	28.17	29.06
2	34.45	34.46	.15	.40	28.09	28.62
3	34.49	34.51	.15	.25	28.06	28.85
4	34.43	34.51	.15	.25	28.05	28.86
5	34.67	34.58	.10	.30	28.12	29.09
6	34.55	34.53	.10	.30	28.17	29.13
7	34.30	34.21	.10	.25	28.35	27.68
8	34.25	34.36	.10	.15	28.49	28.38
9	34.28	34.42	.10	.15	28.43	28.67
10	34.31	34.47	.10	.15	28.37	28.89
11	34.40	34.53	.05	.20	28.24	29.15
12	34.48	34.49	.05	.30	28.22	29.15
13	34.82	34.28	.05	.50	26.71	26.38
14	34.97	34.37	.05	.50	26.29	25.65
15	34.40	34.18	.01	.50	27.67	26.94
16	34.63	34.35	.20	.40	28.43	28.59
17	34.42	34.17	.15	.50	28.35	28.42
18	34.24	34.23	.15	.50	28.34	28.14
19	34.25	34.20	.15	.50	28.37	28.20
20	34.28	34.18	.15	.50	28.38	28.26
21	34.30	34.11	.15	.50	28.26	28.29
22	34.36	34.17	.15	.50	28.39	28.41
23	34.30	34.23	.15	.50	28.37	28.30
24	34.26	34.28	.15	.50	28.30	28.16
25	34.39	34.22	.15	.50	28.41	28.46
26	34.35	34.29	.15	.50	28.34	28.36
27	34.42	34.14	.15	.50	27.69	27.33
28	35.14	34.75	.20	.25	28.32	29.10
29	34.54	34.14	.10	.50	27.62	27.76
30	34.94	34.34	.10	.50	26.55	26.24
31	34.88	34.32	.10	.50	26.85	26.79
32	34.89	34.32	.10	.50	26.84	26.78
33	35.11	34.44	.10	.50	26.05	25.24
34	35.25	34.48	.10	.50	26.57	26.29
35	34.54	34.15	.10	.50	27.50	27.45
36	34.42	34.14	.10	.50	27.69	27.33
37	34.14	34.42	.05	.50	27.95	25.98
38	34.34	34.39	.05	.50	27.66	25.56
39	34.44	34.76	.10	.25	27.33	24.63
40	34.47	34.76	.10	.25	27.30	24.31
41	34.94	34.37	.05	.50	26.25	25.36
42	35.01	34.43	.05	.50	25.92	24.70

Table 5.3 : List of 25 radiolarian groups exceeding 2 percent abundance in at least one core top and one pseudo core sample. Range for the groups is indicated

Group	Range
1 Collosphaera	9.57
2 Disolenia siphanosphaera	6.05
3 Acrosphaera	4.49
4 Actinomma	5.52
5 Spongodiscid	31.59
6 Spongaster Sponcore	6.56
7 Elatomma Haliomma	5.41
8 Hexacantium	8.40
9 Euch. tomids (porodiscids)	21.07
10 Stylodictya	13.79
11 Didymocyrtis (articsins)	19.52
12 Heliodiscus	4.87
13 Lethiliids	6.45
14 Otapyle & Tetrapyle (pyloniids)	24.60
15 Larcopyle Quadrangula	12.55
16 Stylosphaera Axoprimum	4.79
17 Lophophinins	3.30
18 Lophospyris phormospyris	6.76
19 Sethophormins	5.20
20 Pterocanium	6.16
21 Eucyrtidium	2.50
22 Theocorythium Theocorys	4.48
23 Anthocyrtidium	6.83
24 Lamprocyclas Cyrtis	6.16
25 Phormostichoartis	3.29

Table 5.4 : Percentage abundance of 25 radiolarian groups  
in the 42 core top samples

1	7.22	2.71	3.11	5.52	16.20	3.70	3.60	3.90	12.50	5.70
	4.80	1.00	1.20	5.50	1.40	1.90	.60	4.00	.40	2.60
	1.20	.80	1.50	.70	.30					
2	3.30	2.16	1.57	1.37	8.84	3.73	3.92	2.55	17.68	12.77
	3.92	1.18	4.32	11.79	.78	2.35	.78	5.50	.00	.59
	.59	.78	.59	.39	.00					
3	2.76	4.29	1.22	1.84	6.13	1.84	2.45	.00	18.71	13.50
	2.76	.61	2.76	13.80	.00	3.06	.92	5.83	.30	1.84
	1.84	.92	1.53	.92	.30					
4	2.66	.81	1.23	2.45	26.60	5.12	4.09	6.15	2.46	9.42
	2.46	2.46	.00	3.07	2.25	3.07	.61	6.76	.00	1.64
	.40	.82	1.63	1.02	.20					
5	2.28	.97	1.73	1.73	23.34	5.86	3.04	1.41	7.49	9.01
	8.79	2.28	1.08	4.99	2.39	2.06	.32	6.50	.10	.76
	.54	.87	1.41	.87	.30					
6	6.69	2.04	1.67	.18	31.59	4.83	1.67	2.60	7.99	10.22
	5.01	1.30	.18	3.16	.92	3.15	.18	2.78	.18	1.85
	1.11	.74	.74	.55	.37					
7	6.80	5.97	1.44	.82	4.94	1.03	.41	.61	12.16	10.92
	3.30	.20	1.23	10.10	2.26	1.03	3.30	5.77	.00	1.65
	1.44	1.23	1.85	.41	2.68					
8	9.57	4.21	1.14	.00	7.66	3.06	1.91	.00	21.07	13.79
	6.89	1.91	1.53	1.91	1.53	.76	.76	4.21	.00	3.44
	.73	1.14	.38	.00	1.53					
9	3.32	2.45	.87	.52	5.95	1.57	3.15	1.57	2.62	7.18
	8.75	.35	.87	11.90	1.92	3.15	.52	6.30	.52	3.85
	.70	3.15	6.83	3.50	1.57					
10	6.00	1.60	2.40	1.33	14.93	4.13	4.80	1.46	5.20	6.93
	4.13	2.00	1.06	3.33	1.06	3.33	1.86	4.26	1.73	5.06
	1.21	2.26	4.26	1.46	.66					
11	4.39	4.81	1.96	.65	9.40	2.18	.43	.43	8.75	7.87
	8.31	1.09	1.53	8.31	1.75	1.31	2.18	4.37	2.40	3.50
	.43	1.96	2.84	1.75	.87					
12	5.24	1.31	3.28	1.18	14.43	6.56	2.49	.65	9.18	11.67
	5.90	1.96	2.62	3.41	1.04	2.88	.91	2.75	.78	3.01
	1.04	1.31	1.57	1.18	.39					
13	7.17	4.95	2.34	.91	5.73	2.86	2.99	3.52	5.34	2.60
	12.12	1.04	2.73	18.90	5.35	.78	1.30	4.12	.65	2.73
	.91	1.30	1.30	1.43	.26					
14	6.27	.89	2.69	.89	6.72	2.24	3.13	4.03	1.79	4.93
	16.59	.89	4.93	2.69	12.55	1.34	1.79	2.24	.00	.00
	.89	4.48	4.48	2.24	.89					
15	5.82	5.64	2.91	.36	5.82	1.45	1.63	.54	5.28	3.46
	8.19	1.63	3.46	22.95	5.82	.72	1.82	5.46	1.27	2.18
	.54	.72	1.09	.18	.00					
16	3.22	.80	1.61	.40	17.74	4.00	2.82	6.85	5.64	9.67
	5.24	.00	5.45	12.09	.80	4.03	1.61	4.03	.80	1.61
	.00	.80	1.20	.40	.80					
17	6.00	1.60	2.20	.40	.80	1.00	4.80	8.40	2.40	2.00
	9.00	1.00	2.40	24.60	3.80	2.00	1.20	5.00	1.40	2.60
	1.00	.60	3.00	1.00	.00					
18	4.06	2.03	3.21	.84	7.78	2.53	3.38	2.53	3.89	4.56
	9.64	1.01	2.03	15.23	4.23	1.52	1.86	6.26	2.03	2.70
	.84	1.01	3.72	1.35	.16					

/Table 5.4 cont/

19	3.88	3.77	4.49	1.32	10.21	3.88	2.96	3.98	6.74	6.84
	8.17	1.63	2.45	5.00	1.12	1.73	.71	5.10	1.32	3.27
	1.53	1.22	3.47	1.83	.40					
20	7.69	3.37	3.29	1.24	9.60	2.78	1.68	1.90	9.16	8.35
	7.33	.80	3.22	9.16	2.05	.29	2.63	4.10	1.31	2.71
	1.09	.73	1.61	.29	1.17					
21	8.77	6.05	4.23	2.72	3.93	.75	2.11	2.72	3.47	3.78
	16.03	.90	1.81	17.09	3.47	.30	1.21	2.26	1.21	2.26
	.30	.45	1.96	.30	.15					
22	3.39	1.10	2.28	.85	8.34	3.39	5.41	4.24	7.37	7.69
	11.61	1.95	3.19	12.13	2.02	1.82	.52	2.54	.71	.91
	.97	.97	3.13	2.47	.32					
23	7.82	1.77	3.38	.35	6.93	.71	1.24	2.84	11.74	9.25
	13.35	1.60	3.55	9.78	2.66	.53	1.06	2.31	1.06	1.95
	1.60	.71	2.13	1.06	.35					
24	5.98	3.86	3.28	.57	4.82	1.35	1.93	3.47	3.66	3.47
	13.70	.77	2.89	10.03	1.73	.57	.77	6.17	1.35	1.93
	2.50	.96	4.82	1.35	.57					
25	3.73	3.23	2.48	.49	10.69	2.48	2.23	3.48	6.96	9.20
	8.20	1.49	2.98	11.69	4.47	.49	.99	4.97	.74	3.73
	.24	.24	2.23	.24	.00					
26	2.92	2.25	2.02	.67	9.90	3.60	2.02	4.50	11.93	12.83
	9.23	1.12	3.60	8.55	1.57	.22	.00	2.92	.90	3.15
	1.35	.45	2.22	.90	.00					
27	6.99	5.56	3.86	.90	2.20	.26	.26	2.33	7.64	4.79
	7.51	1.16	1.42	11.91	4.01	1.94	1.29	6.60	1.16	3.75
	.90	2.59	3.75	1.16	.13					
28	2.85	2.38	1.42	.00	3.80	2.38	2.38	.48	9.52	10.47
	11.90	.00	1.90	11.90	2.38	.00	.00	3.33	.00	.46
	1.42	1.42	4.28	1.90	.95					
29	6.90	3.62	4.46	1.68	3.02	1.88	2.68	4.46	5.61	4.61
	14.51	2.08	2.97	7.05	2.38	.74	.84	5.46	1.39	2.48
	.99	1.48	3.22	1.88	.84					
30	4.17	3.33	3.92	.83	5.25	2.16	1.81	2.30	5.89	4.76
	13.75	1.91	2.79	19.54	2.45	.73	1.27	4.66	1.03	2.25
	1.47	1.12	1.91	.73	.24					
31	6.84	1.74	2.64	1.54	5.34	3.29	3.14	2.69	9.39	9.14
	14.68	1.99	3.99	11.88	3.59	.39	1.09	1.54	.39	1.09
	.49	.74	1.44	.39	.39					
32	3.91	2.76	1.88	.40	5.66	1.61	.94	1.21	10.45	10.85
	12.33	1.95	3.77	12.67	1.28	.67	1.68	5.52	.47	2.42
	1.61	1.07	2.69	.53	.13					
33	.55	.41	.55	.00	16.41	2.34	2.48	3.03	3.86	9.37
	10.89	.68	.96	16.96	3.31	1.79	.82	4.82	.96	2.48
	.27	1.37	2.48	.96	.27					
34	4.67	2.95	1.81	.76	9.92	2.95	2.19	3.05	7.63	8.20
	11.35	1.90	1.33	15.26	2.67	.57	.19	5.62	.85	1.90
	.47	1.33	3.04	.47	.09					
35	6.11	4.47	2.38	1.64	5.14	2.16	1.93	2.01	8.79	6.26
	13.79	.89	2.01	14.16	1.41	.74	1.11	2.98	.29	2.16
	1.71	1.78	3.05	.52	.67					
36	3.69	2.26	1.78	1.19	1.30	1.78	3.33	4.16	8.92	4.76
	19.52	1.90	2.02	18.09	3.92	.71	.11	3.80	.11	1.42
	.23	1.19	1.78	.71	.23					
37	5.01	1.91	2.64	1.18	3.73	1.73	2.00	4.64	6.01	6.92
	16.77	.91	1.36	17.77	2.82	1.54	.72	4.46	.54	2.55
	.27	.91	2.37	.91	.00					

/Table 5.4 cont/



38	2.34	1.29	1.17	.94	4.69	1.87	.93	3.28	6.22	9.85
	15.25	1.87	1.17	12.44	2.34	.82	.58	5.63	1.40	3.05
	.23	1.40	3.52	3.87	.46					
39	4.87	1.98	2.88	1.14	2.64	1.08	.90	2.04	7.28	9.33
	15.95	.96	2.58	12.34	1.86	1.80	1.38	6.62	.78	2.34
	1.20	1.56	2.76	.54	.72					
40	.00	.00	1.36	.68	4.79	.68	1.36	2.05	6.16	8.90
	19.17	.68	1.36	13.01	4.10	4.79	1.36	1.36	.68	6.16
	1.36	1.36	1.36	6.16	.00					
41	2.64	1.45	2.10	.64	5.01	1.77	.91	2.04	6.63	8.24
	15.25	1.61	3.39	13.80	2.10	1.50	2.15	6.46	.37	2.10
	1.29	.86	2.31	2.15	.26					
42	1.72	.68	1.26	.68	5.97	3.21	2.98	4.13	4.24	7.69
	18.14	1.49	4.82	17.22	2.52	.45	.57	4.36	.57	2.06
	.11	1.03	3.32	.23	.11					

Table 5.5 : Percentage abundance of 25 radiolarian groups  
in 10 pseudo-core samples from Sawai Bay  
Formation, Neill Island, Andamans

1	2.81	1.58	4.39	2.10	30.60	2.10	.52	1.58	8.78	6.32
	4.74	.87	.87	7.38	1.93	2.10	2.46	1.40	1.75	3.16
	1.93	1.23	3.34	1.93	2.10					
2	4.34	.54	2.71	2.17	21.70	.81	.27	.54	9.78	2.98
	3.80	1.50	1.35	6.25	2.17	1.85	2.45	1.90	2.45	1.08
	2.17	1.63	4.07	2.45	.81					
3	2.91	1.55	2.72	1.36	16.20	.97	1.36	2.72	7.19	1.55
	1.94	2.50	2.52	5.44	1.55	.58	1.36	2.14	5.20	1.76
	1.75	1.55	1.75	1.90	2.33					
4	5.16	3.64	3.34	2.73	16.40	3.03	.00	1.82	8.81	.60
	2.43	3.03	1.21	3.95	1.82	.00	1.51	3.95	.60	1.51
	1.82	2.12	2.43	2.12	3.03					
5	2.02	2.53	3.29	2.02	16.90	1.51	3.79	4.55	8.35	1.51
	3.80	2.02	3.29	1.01	2.27	1.77	1.01	2.02	2.02	1.51
	2.27	1.77	.75	.51	3.29					
6	2.58	1.55	1.80	.77	15.50	.77	1.03	.77	8.52	1.55
	12.10	2.32	1.55	1.29	2.06	.25	.00	1.55	1.03	2.32
	2.06	2.32	3.10	.51	1.29					
7	1.56	2.15	.98	.78	29.80	.00	.78	1.76	6.66	6.47
	7.05	1.17	1.17	2.54	.58	.98	.00	1.76	2.35	1.76
	1.37	1.37	1.96	.78	2.54					
8	1.92	1.28	1.92	3.85	22.70	.00	.85	2.56	10.50	10.90
	6.85	4.06	1.49	1.28	2.14	2.35	2.14	.21	2.35	1.07
	1.71	2.14	2.78	2.14	.85					
9	3.36	.92	1.27	2.55	27.10	.34	.85	2.55	6.15	12.60
	4.87	4.87	1.09	1.97	1.04	1.97	1.16	.46	1.50	1.39
	1.16	2.32	1.16	1.27	1.62					
10	2.98	1.25	.62	1.57	24.50	.47	.62	2.98	3.93	10.70
	5.50	2.04	2.51	9.43	.47	1.41	2.35	1.10	1.25	1.41
	.78	1.72	1.25	.94	1.88					

Table 5.6 : Core top data - Factor loading matrix after varimax rotation.

Communality		Factor 1	Factor 2	Factor 3	Factor 4
.86144	1	-.47741	-.65004	-.44852	.09898
.87629	2	-.38617	-.70803	-.40199	.25349
.86572	3	-.24726	-.53067	-.63079	.35367
.89063	4	-.29106	-.82378	-.16679	.31539
.91146	5	-.32587	-.78788	-.27978	.32595
.87957	6	-.22177	-.78658	-.41872	.19065
.89504	7	-.26691	-.27413	-.82478	.26151
.86860	8	-.26158	-.53161	-.70482	.14417
.87537	9	-.32955	-.36418	-.39331	.69241
.83807	10	-.34545	-.60744	-.43951	.39571
.91742	11	-.38536	-.33708	-.69327	.41794
.91334	12	-.32799	-.73511	-.44973	.25123
.93683	13	-.72173	-.33927	-.47777	.26939
.68780	14	-.61231	-.31733	-.26013	.38014
.88063	15	-.66523	-.23442	-.57234	.23573
.79227	16	-.43174	-.67206	-.20912	.33240
.85812	17	-.74139	-.35082	-.20303	.37970
.92248	18	-.61965	-.41068	-.41431	.44520
.90265	19	-.53312	-.52796	-.48894	.31722
.94388	20	-.52815	-.42385	-.67137	.18589
.92272	21	-.77829	-.20063	-.51487	.10794
.92586	22	-.60898	-.60671	-.20632	.37991
.88516	23	-.61375	-.37346	-.55338	.25053
.87597	24	-.61855	-.26188	-.53825	.36754
.91415	25	-.59119	-.50440	-.45089	.32699
.86084	26	-.48506	-.59623	-.41634	.31100
.90312	27	-.53190	-.21895	-.66120	.36753
.80524	28	-.45336	-.38856	-.47925	.46803
.93133	29	-.69447	-.36103	-.48079	.29587
.95222	30	-.69579	-.32206	-.50242	.33458
.91740	31	-.69414	-.51251	-.37659	.17630
.92241	32	-.48775	-.38600	-.59912	.42020
.92419	33	-.42492	-.55081	-.21443	.62790
.92951	34	-.59395	-.50013	-.42112	.38635
.94471	35	-.60484	-.33927	-.60922	.30435
.91840	36	-.75998	-.37402	-.23737	.38025
.94777	37	-.70351	-.39004	-.33471	.43436
.91224	38	-.47417	-.37737	-.34235	.65406
.94385	39	-.54120	-.34848	-.54670	.48025
.75740	40	-.29804	-.30430	-.23992	.72001
.91914	41	-.51804	-.36101	-.47454	.54338
.91468	42	-.68373	-.45363	-.14932	.46809
Variance		12.13283	9.83363	9.23520	6.24425
Percentage Var		28.88770	23.41341	21.98859	14.86726
Cumulative Var		28.88770	52.30111	74.28970	89.15696

Table 5.7 : Core-top data - Factor factor score matrix after varimax rotation

GROUP	Factor1	Factor2	Factor3	Factor4
1 Collosphaera	-.27212	-.09077	-.33915	-.29179
2 Disolenia siphanosphaera	-.15192	.10592	-.51068	-.15314
3 Acrosphaera	-.37855	-.04452	-.19013	-.16683
4 Actinomma	-.10767	-.14761	-.02574	-.13577
5 Spongodiscid	.09932	-.43396	.01762	-.03441
6 Spongaster Sponcore	-.01192	-.49831	.04614	-.08668
7 Elatomma Haliomma	-.26588	-.35968	.21388	-.00975
8 Hexacantium	-.34306	-.18805	.26151	.01958
9 Euch. tomids (porodiscids)	.06300	-.20593	-.29991	-.06501
10 Stylodictya	.15791	-.37434	-.23107	.21006
11 Didymocyrtis (articsins)	-.42706	.10249	.07717	.31753
12 Heliodiscus	-.12165	-.15913	.00675	-.02425
13 Lethiliids	-.27713	-.09160	.00033	-.02971
14 Otapyle & Tetrapyle	-.37686	.09540	.02288	.22342
15 Larcopyle Quadrangula	-.20666	.03964	.04093	.07255
16 Stylosphaera Axoprunum	.16832	-.28923	.01770	.28804
17 Lophophinins	-.03439	.07242	-.29431	.09401
18 Lophospyris phormospyris	-.05553	-.14793	-.21553	.33033
19 Sethophormins	-.07316	.03615	-.05359	.06617
20 Pterocanium	.01225	-.02954	-.16860	.26739
21 Eucyrtidium	.01047	-.01623	-.31270	.08323
22 Theocorythium Theocorys	-.00515	.01730	-.09001	.25170
23 Anthocyrtidium	-.09797	.05598	-.04564	.34600
24 Lamprocyclas Cyrtis	.05572	.03603	.01976	.39794
25 Phormostichcartis	.10506	.00582	-.21500	.07059

Table 5.8 : Results of multiple regression analysis

D E P E N D E N T   V A R I A B L E   1  
 Fall salinity

1. REGRESSION EQUATION

Y( 1) =	34.54595		
	+8.62279	[ X( 1)	+ .51370 ]
	+5.35315	[ X( 2)	+ .45582 ]
	+11.88682	[ X( 3)	+ .44043 ]
	-14.27210	[ X( 4)	- .35839 ]
	+ .62394	[ X( 5)	- .28888 ]
	+4.22358	[ X( 6)	- .22072 ]
	+6.52309	[ X( 7)	- .22221 ]
	-7.29540	[ X( 8)	+ .18133 ]
	-1.72651	[ X( 9)	- .23413 ]
	+4.41419	[ X(10)	- .19061 ]
	-6.83599	[ X(11)	+ .15798 ]
	+2.69497	[ X(12)	- .21989 ]
	-9.01604	[ X(13)	+ .14955 ]
	+4.14373	[ X(14)	- .14867 ]

2. SUM OF CONSTANT TERMS IN ABOVE EQUATION = 43.80676

3. PROPORTION OF VARIANCE EXPLAINED = .15702

4. MULTIPLE CORRELATION COEFFICIENT  
 ADJUSTED FOR DEGREES OF FREEDOM = .00000

5. STANDARD ERROR OF ESTIMATE  
 ADJUSTED FOR DEGREES OF FREEDOM = .29145

Table 5.9 : Results of multiple regression analysis

DEPENDENT VARIABLE 2  
Spring salinity

1. REGRESSION EQUATION

Y( 2) =	34.36285		
	+7.78309	[ X( 1)	+ .51370 ]
	+6.07707	[ X( 2)	+ .45582 ]
	+8.29528	[ X( 3)	+ .44043 ]
	-7.19667	[ X( 4)	- .35839 ]
	+2.04991	[ X( 5)	- .28888 ]
	+3.61789	[ X( 6)	- .22072 ]
	+4.56957	[ X( 7)	- .22221 ]
	-4.00151	[ X( 8)	+ .18133 ]
	+1.36714	[ X( 9)	- .23413 ]
	+4.68777	[ X(10)	- .19061 ]
	-2.55199	[ X(11)	+ .15798 ]
	+1.82796	[ X(12)	- .21989 ]
	-5.79482	[ X(13)	+ .14955 ]
	+2.30823	[ X(14)	- .14867 ]

2. SUM OF CONSTANT TERMS IN ABOVE EQUATION = 41.00345

3. PROPORTION OF VARIANCE EXPLAINED = .55334

4. MULTIPLE CORRELATION COEFFICIENT  
ADJUSTED FOR DEGREES OF FREEDOM = .56722

5. STANDARD ERROR OF ESTIMATE  
ADJUSTED FOR DEGREES OF FREEDOM = .14367

Table 5.10 : Results of multiple regression analysis

DEPENDENT VARIABLE 3  
 North east monsoon potential primary productivity

1. REGRESSION EQUATION			
Y( 3) =	.11095		
	-.89804	[ X( 1)	+ .51370 ]
	-2.19735	[ X( 2)	+ .45582 ]
	-1.16860	[ X( 3)	+ .44043 ]
	+1.00141	[ X( 4)	- .35839 ]
	-.49090	[ X( 5)	- .28888 ]
	-.60672	[ X( 6)	- .22072 ]
	-.30943	[ X( 7)	- .22221 ]
	+.81305	[ X( 8)	+ .18133 ]
	-1.37699	[ X( 9)	- .23413 ]
	-1.33365	[ X(10)	- .19061 ]
	+.64126	[ X(11)	+ .15798 ]
	-.59262	[ X(12)	- .21989 ]
	+.39382	[ X(13)	+ .14955 ]
	-.59775	[ X(14)	- .14867 ]
2. SUM OF CONSTANT TERMS IN ABOVE EQUATION =			- .77764
3. PROPORTION OF VARIANCE EXPLAINED =			.26622
4. MULTIPLE CORRELATION COEFFICIENT			
ADJUSTED FOR DEGREES OF FREEDOM =			.00000
5. STANDARD ERROR OF ESTIMATE			
ADJUSTED FOR DEGREES OF FREEDOM =			.04433

Table 5.11 : Results of multiple regression analysis

D E P E N D E N T		V A R I A B L E		4
South west monsoon potential primary productivity				
1.	REGRESSION EQUATION			
	Y( 4) =	.40833		
		+ .62448	[ X( 1)	+ .51370 ]
		+4.19586	[ X( 2)	+ .45582 ]
		+1.69463	[ X( 3)	+ .44043 ]
		-1.18188	[ X( 4)	- .35839 ]
		- .54321	[ X( 5)	- .28888 ]
		+1.86991	[ X( 6)	- .22072 ]
		+1.46463	[ X( 7)	- .22221 ]
		-1.73159	[ X( 8)	+ .18133 ]
		+2.24074	[ X( 9)	- .23413 ]
		+1.97749	[ X(10)	- .19061 ]
		-1.84159	[ X(11)	+ .15798 ]
		+ .63055	[ X(12)	- .21989 ]
		+ .76531	[ X(13)	+ .14955 ]
		+ .07476	[ X(14)	- .14867 ]
2.	SUM OF CONSTANT TERMS IN ABOVE EQUATION =			1.68858
3.	PROPORTION OF VARIANCE EXPLAINED =			.74688
4.	MULTIPLE CORRELATION COEFFICIENT			
	ADJUSTED FOR DEGREES OF FREEDOM =			.78463
5.	STANDARD ERROR OF ESTIMATE			
	ADJUSTED FOR DEGREES OF FREEDOM =			.07863



Table 5.12 : Results of multiple regression analysis

D E P E N D E N T V A R I A B L E 5  
 Fall temperature

1. REGRESSION EQUATION

$$\begin{aligned}
 Y(5) = & 27.75143 \\
 & -54.63723 [ X(1) \quad +.51370 ] \\
 & -53.96672 [ X(2) \quad +.45582 ] \\
 & -69.40460 [ X(3) \quad +.44043 ] \\
 & +59.02314 [ X(4) \quad -.35839 ] \\
 & -15.61798 [ X(5) \quad -.28888 ] \\
 & -23.29929 [ X(6) \quad -.22072 ] \\
 & -37.92641 [ X(7) \quad -.22221 ] \\
 & +36.04641 [ X(8) \quad +.18133 ] \\
 & -14.31089 [ X(9) \quad -.23413 ] \\
 & -38.04329 [ X(10) \quad -.19061 ] \\
 & +33.40779 [ X(11) \quad +.15798 ] \\
 & -25.41920 [ X(12) \quad -.21989 ] \\
 & +33.77429 [ X(13) \quad +.14955 ] \\
 & -19.29909 [ X(14) \quad -.14867 ]
 \end{aligned}$$

2. SUM OF CONSTANT TERMS IN ABOVE EQUATION = -21.52417

3. PROPORTION OF VARIANCE EXPLAINED = .31532

4. MULTIPLE CORRELATION COEFFICIENT  
 ADJUSTED FOR DEGREES OF FREEDOM = .00000

5. STANDARD ERROR OF ESTIMATE  
 ADJUSTED FOR DEGREES OF FREEDOM = .76872

Table 5.13 : Results of multiple regression analysis

DEPENDENT VARIABLE 6  
Spring temperature

1. REGRESSION EQUATION

Y( 6) =	27.54619		
	-171.86480	[ X( 1)	+ .51370 ]
	-173.30060	[ X( 2)	+ .45582 ]
	-165.40130	[ X( 3)	+ .44043 ]
	+157.10580	[ X( 4)	- .35839 ]
	-50.57028	[ X( 5)	- .28888 ]
	-101.52900	[ X( 6)	- .22072 ]
	-100.98540	[ X( 7)	- .22221 ]
	+106.95960	[ X( 8)	+ .18133 ]
	-53.97767	[ X( 9)	- .23413 ]
	-98.40904	[ X(10)	- .19061 ]
	+90.48481	[ X(11)	+ .15798 ]
	-53.08044	[ X(12)	- .21989 ]
	+73.32769	[ X(13)	+ .14955 ]
	-51.35821	[ X(14)	- .14867 ]

2. SUM OF CONSTANT TERMS IN ABOVE EQUATION = -114.06880

3. PROPORTION OF VARIANCE EXPLAINED = .65932

4. MULTIPLE CORRELATION COEFFICIENT  
ADJUSTED FOR DEGREES OF FREEDOM = .69475

5. STANDARD ERROR OF ESTIMATE  
ADJUSTED FOR DEGREES OF FREEDOM = 1.02629

Table 5.14: Palaeoestimates of environmental conditions during Late Miocene. Modern temperature and salinity used are from Levitus while primary prod is Wyrтки's

	SALINITY		PRIM PRODUCTIVITY		TEMPERATURE	
	Fall	Spring	NE Mon	SW Mon	Fall	Spring
1	34.682	34.507	.179	.175	28.495	28.748
2	34.703	34.515	.180	.204	28.437	28.059
3	35.011	34.564	.186	.312	27.611	25.691
4	34.755	34.378	.162	.323	28.006	26.462
5	35.148	34.583	.204	.280	27.546	26.495
6	34.770	34.478	.174	.321	28.189	27.583
7	34.888	34.733	.199	.049	27.898	26.600
8	34.893	34.653	.203	.127	28.037	27.549
9	35.019	34.785	.201	.055	27.511	26.339
10	34.761	34.575	.193	.151	28.373	28.757
PVE	0.157	0.553	0.266	0.747	0.315	0.659
MCC	0.000	0.567	0.000	0.785	0.000	0.695
SEE	0.291	0.144	0.044	0.079	0.769	1.026

where,

Fall = (November, December, January)

Spring = (May, June, July)

PVV = Proportion of variance explained by regression

MCC = Multiple correlation coefficient

SEE = Standard error of estimate

N.B. MCC > 0.393 and MCC > 0.490 indicate that the palaeoestimates are reliable at 0.01 and 0.001 significance level respectively

Table 5.15: Palaeoestimates of environmental conditions during Late Miocene. Modern temperature and salinity and primary prod used is Wyrtki's

	SALINITY		PRIM PRODUCTIVITY		TEMPERATURE	
	NE Mon	SW Mon	NE Mon	SW Mon	NE Mon	SW Mon
1	35.075	34.347	.179	.175	27.915	28.401
2	35.171	34.466	.180	.204	27.904	28.193
3	35.549	34.851	.186	.312	27.270	27.331
4	35.408	34.648	.162	.323	27.778	27.278
5	35.635	34.803	.204	.280	27.111	27.616
6	35.216	34.678	.174	.321	27.866	27.801
7	35.372	34.420	.199	.049	27.458	28.087
8	35.338	34.466	.203	.127	27.527	28.244
9	35.393	34.462	.201	.055	27.258	27.914
10	35.116	34.359	.193	.151	27.795	28.527
PVE	0.670	0.803	0.266	0.747	0.182	0.536
MCC	0.706	0.834	0.000	0.785	0.000	0.543
SEE	0.203	0.125	0.044	0.079	0.644	0.930

where,

Fall = (November, December, January)

Spring = (May, June, July)

PVV = Proportion of variance explained by regression

MCC = Multiple correlation coefficient

SEE = Standard error of estimate

N.B. MCC > 0.393 and MCC > 0.490 indicate that the palaeoestimates are reliable at 0.01 and 0.001 significance level respectively

PROGRAM CUTOF5

```

*****
*   PROGRAM FOR SELECTING RADIOLARIAN GROUPS HAVING MORE THAN 2%   *
*   ABUNDANCE IN AT LEAST ONE CORE-TOP AND ONE CORE SAMPLE         *
*   Input files: SHYAMN.DAT   - (core-top data)                   *
*                   CORE-10N.DAT - (pseudo-core data)             *
*   Output files: TCT-*.DAT   - (transformed core-top)            *
*                   TC-*.DAT   - (transformed pseudo-core)        *
*   ORDER FOR RUNNING PROGRAMS:                                     *
*                   (1)CUTOF5.FOR                                  *
*                   (2)FACQ3.FOR                                   *
*                   (3)GETTAB4.FOR                                *
*                   (4)MULRAS.FOR                                 *
*                   (5)CABLESZ.FOR                               *
*****
  DIMENSION XCT(42,47),XC(10,47)
  DIMENSION YCT(42,47),YC(10,47)
  DIMENSION NCT(47),NC(47),NK(47)
  DIMENSION DUM(52),RCT(47),RC(47),RANGE(47)
  DIMENSION CTLAB(80),CLAB(80)
  CHARACTER*12  OUTFCT,OUTFC,DUM1*4,DUM2*3,FTEN*1,FUNIT*1
  OPEN(7,FILE='SHYAMN.DAT',BLANK='ZERO')
  OPEN(8,FILE='SEE')
  READ(7,1)(CTLAB(I),I=1,80)
  WRITE(8,1)(CTLAB(I),I=1,80)
  DO I=1,42
  READ(7,*)(XCT(I,J),J=1,47)
  WRITE(8,2)I,(XCT(I,J),J=1,47)
  END DO
1  FORMAT(20A4)
2  FORMAT(I5,10F7.2/(5X,10F7.2))
  CUTOFF=2.
  DO 100 J=1,47
  NCT(J)=0
  DO 200 I=1,42
  IF(XCT(I,J).GT.CUTOFF)THEN
  NCT(J)=1
  GO TO 100
  END IF
200 CONTINUE
100 CONTINUE
  OPEN(17,FILE='CORE-10N.DAT',BLANK='ZERO')
  READ(17,1)(CLAB(I),I=1,80)
  WRITE(8,1)(CLAB(I),I=1,80)
  DO I=1,10
  READ(17,'(10F7.2)')(XC(I,J),J=1,47)
  WRITE(8,2)I,(XC(I,J),J=1,47)
  END DO
  DO 500 J=1,47
  NC(J)=0
  DO 600 I=1,10
  IF(XC(I,J).GT.CUTOFF)THEN
  NC(J)=1
  GO TO 500
  END IF
600 CONTINUE
500 CONTINUE
  NCOUNT=0

```

```

DO J=1,47
IF ((NCT(J).EQ.1).AND.(NC(J).EQ.1)) THEN
NCOUNT=NCOUNT+1
NK(NCOUNT)=J
END IF
END DO
WRITE(8,*)' NCOUNT=',NCOUNT
WRITE(8,3)(NK(J),J=1,NCOUNT)
3 FORMAT(/10I5)
WRITE(8,*)' '
WRITE(8,*)' SELECTED SPECIES DATA'
WRITE(8,*)' '
WRITE(8,1)(CTLAB(I),I=1,80)
DO I=1,42
DO J=1,NCOUNT
JJ=NK(J)
YCT(I,J)=XCT(I,JJ)
END DO
WRITE(8,2)I,(YCT(I,J),J=1,NCOUNT)
END DO
WRITE(8,1)(CLAB(I),I=1,80)
DO I=1,10
DO J=1,NCOUNT
JJ=NK(J)
YC(I,J)=XC(I,JJ)
END DO
WRITE(8,2)I,(YC(I,J),J=1,NCOUNT)
END DO
WRITE(8,5)
5 FORMAT('Sp No',T10,'RCT',T17,'RC',T22,'RANGE')
DO J=1,NCOUNT
DO I=1,42
DUM(I)=YCT(I,J)
END DO
DO I=1,10
DUM(I+42)=YC(I,J)
END DO
CALL MAXMIN(DUM,1,42,AMAX,AMIN,IMAX,IMIN)
RCT(J)=AMAX
CALL MAXMIN(DUM,43,52,AMAX,AMIN,IMAX,IMIN)
RC(J)=AMAX
CALL MAXMIN(DUM,1,52,AMAX,AMIN,IMAX,IMIN)
RANGE(J)=AMAX
WRITE(8,4)J,RCT(J),RC(J),RANGE(J)
END DO
4 FORMAT(I5,3F7.2)
WRITE(8,*)' '
WRITE(8,*)' TRANSFORMED MATRICES (RANGE & NORMALIZATION)'
WRITE(8,*)' '
WRITE(8,1)(CTLAB(I),I=1,80)
DUM1='TCT-'
DUM2='TC-'
NT=NCOUNT/10
NU=MOD(NCOUNT,10)
FTEN=CHAR(NT+48)
FUNIT=CHAR(NU+48)
OUTFCT=DUM1//FTEN//FUNIT//'.DAT'
OUTFC =DUM2//FTEN//FUNIT//'.DAT'

```

```

WRITE(0,7621)OUTFCT
WRITE(0,7622)OUTFC
7621 FORMAT(3X,'Output file - CORE-TOP      : ',A12)
7622 FORMAT(3X,'Output file - PSEUDO-CORE : ',A12)
OPEN(18,FILE=OUTFCT)
WRITE(8,1)(CTLAB(I),I=1,80)
WRITE(18,1)(CTLAB(I),I=1,80)
DO I=1,42
SS=0.
DO J=1,NCOUNT
YCT(I,J)=YCT(I,J)/RANGE(J)
SS=SS+YCT(I,J)**2
END DO
SS=SQRT(SS)
DO J=1,NCOUNT
YCT(I,J)=YCT(I,J)/SS
END DO
WRITE(8,2)I,(YCT(I,J),J=1,NCOUNT)
WRITE(18,7)(YCT(I,J),J=1,NCOUNT)
END DO
WRITE(8,1)(CLAB(I),I=1,80)
OPEN(19,FILE=OUTFC)
WRITE(19,1)(CLAB(I),I=1,80)
DO I=1,10
SS=0.
DO J=1,NCOUNT
YC(I,J)=YC(I,J)/RANGE(J)
SS=SS+YC(I,J)**2
END DO
SS=SQRT(SS)
DO J=1,NCOUNT
YC(I,J)=YC(I,J)/SS
END DO
WRITE(8,2)I,(YC(I,J),J=1,NCOUNT)
WRITE(19,7)(YC(I,J),J=1,NCOUNT)
END DO
7  FORMAT(10F7.5)
STOP
END
SUBROUTINE MAXMIN(A,NB,NE,AMAX,AMIN,IMAX,IMIN)
PARAMETER (NUMPTS=47)
DIMENSION A(NUMPTS)
AMAX=-999999.
AMIN=999999.
DO 100 I=NB,NE
IF(A(I).LE.AMAX) GO TO 50
AMAX=A(I)
IMAX=I
50 IF(A(I).GE.AMIN) GO TO 100
AMIN=A(I)
IMIN=I
100 CONTINUE
RETURN
END

```

PROGRAM FACQ3

```

*****
* BLACK-BOX PROGRAM FOR Q-MODE FACTOR ANALYSIS BASED ON *
* PROGRAM SQR LISTED IN: FERNANDES A A AND R MAHADEVAN, 1982. *
* FACTOR ANALYSIS OF MULTIVARIATE DATA. NIO TECHNICAL REPORT *
* No. 2/82, NIO, DONA PAULA, GOA, OCTOBER 1982 *
* MAXIMUM ROWS PERMISSIBLE IN DATA MATRIX = 200 *
* MAXIMUM COLUMNS PERMISSIBLE IN DATA MATRIX = 50 *
* MAXIMUM NUMBER OF FACTORS PERMISSIBLE = 10 *
*
* FOR PERFORMING R-MODE FACTOR ANALYSIS: *
* 1. CHANGE DIMENSIONS OF SUBROUTINES FACTOR, EIGAN *
* AND VARMAX *
* 2. SUBROUTINE PREPAR MAY BE SUITABLY MODIED *
*****

```

```

DIMENSION A(200,50)
REAL IFMT(9), LABEL(80), IBIG(19)
CHARACTER*16 INFIL, OUTFIL
CHARACTER*1 ANS
WRITE(0,*)' *****'
WRITE(0,*)' * * * * *'
WRITE(0,*)' * MAHADEVAN and FERNANDES *'
WRITE(0,*)' * * * * *'
WRITE(0,*)' * present *'
WRITE(0,*)' * * * * *'
WRITE(0,*)' * Q- Mode FACTOR ANALYSIS *'
WRITE(0,*)' * * * * *'
WRITE(0,*)' * ## PC Version FAC-Q-P ## *'
WRITE(0,*)' * * * * *'
WRITE(0,*)' * DT. 14/8/1992 *'
WRITE(0,*)' *****'
WRITE(0,*)' ### ##'
WRITE(0, '(A\)' )' Enter name of input data file '
READ(0, '(A16)' )INFIL
OPEN (2, FILE=INFIL, ACCESS='SEQUENTIAL')
WRITE(0, '(A\)' )' Enter name of output data file '
READ(0, '(A16)' )OUTFIL
OPEN (3, FILE=OUTFIL, ACCESS='SEQUENTIAL')
WRITE(3,*)' *****'
WRITE(3,*)' * * * * *'
WRITE(3,*)' * MAHADEVAN and FERNANDES *'
WRITE(3,*)' * * * * *'
WRITE(3,*)' * present *'
WRITE(3,*)' * * * * *'
WRITE(3,*)' * Q- Mode FACTOR ANALYSIS *'
WRITE(3,*)' * * * * *'
WRITE(3,*)' * ## PC Version FAC-Q-P ## *'
WRITE(3,*)' * * * * *'
WRITE(3,*)' * DT. 14/8/1992 *'
WRITE(3,*)' *****'
WRITE(3,*)' ### ##'
CALL TIME
WRITE(0,*)
WRITE(0,*)
WRITE(3,47)
WRITE(3,47)
WRITE(0,*)
WRITE(0,*)

```



```

WRITE(3,47)
WRITE(3,47)
47  FORMAT(/)
READ(2,432)(LABEL(I),I=1,80)
432  FORMAT(20A4)
WRITE(3,433)(LABEL(I),I=1,80)
WRITE(0,433)(LABEL(I),I=1,80)
433  FORMAT(1X,20A4)
WRITE(0,'(A\)' )' IS THIS THE LABEL INFORMATION (4 LINES) OF YOUR I
+INPUT DATA ? (Y/N): '
READ(0,5)ANS
IF(ANS.EQ.'Y') THEN
    MODE=1
ELSE
    IF(ANS.EQ.'N') THEN
        STOP ' Check your input file !'
    ELSE
        STOP ' MISKEY !!!'
    ENDIF
ENDIF
WRITE(0,'(A\)' )' How many rows in matrix ? '
READ(0,*)NR
WRITE(0,'(A\)' )' How many columns in matrix ? '
READ(0,*)NC
WRITE(0,'(A\)' )' Is the data matrix in Fixed format or List direc
#ted (F/L) ?'
READ(0,5)ANS
IF(ANS.EQ.'F')THEN
    IFMT(1)='('
    IFMT(4)='F'
    IFMT(7)='.'
    IFMT(9)=')'
WRITE(0,'(A\)' )' How many values per card ? '
READ(0,5)IFMT(2),IFMT(3)
5  FORMAT(2A1)
WRITE(0,'(A\)' )' What is the field width ? '
READ(0,5)IFMT(5),IFMT(6)
WRITE(0,'(A\)' )' How many decimals to be inserted, if any ? '
READ(0,5)IFMT(8)
CALL DATA(A,NR,NC,IFMT)
CLOSE(2)
ELSE IF (ANS.EQ.'L')THEN
    CALL DATAL(A,NR,NC)
ELSE
    STOP 'MISKEY'
END IF
WRITE(0,456)
WRITE(3,456)
456  FORMAT(1X,'D A T A   M A T R I X, X')
DO I=1,2
C   WRITE(0,202)I
WRITE(0,201)I,(A(I,J),J=1,NC)
END DO
DO 200 I=1,NR
C   WRITE(3,202)I
200  WRITE(3,203)I,(A(I,J),J=1,NC)
WRITE(0,'(A\)' )' ARE THESE THE FIRST TWO LINES OF YOUR INPUT DATA
#MATRIX ROW-WISE? (Y/N): '

```

```

READ(0,5)ANS
IF(ANS.EQ.'Y') THEN
    MODE=1
ELSE
    IF(ANS.EQ.'N') THEN
        STOP ' Check your input data format !'
    ELSE
        STOP ' MISKEY !!!'
    ENDIF
ENDIF
201 FORMAT(5X,I3,2X,5E12.3/(10X,5E12.3))
203 FORMAT(5X,I3,2X,10E12.3/(10X,10E12.3))
C202 FORMAT(5X,I3/)
CALL PREPAR(A,NR,NC,DENOM,ISDEVR,IDEVR,INORM)
WRITE(0,457)
WRITE(3,457)
457 FORMAT(///1X,'M A T R I X X, A F T E R D A T A P R E P A R A
+T I O N'/)
IF(ISDEVR.NE.0)WRITE(3,*)' ROW STANDARDISATION IS PERFORMED'
IF(ISDEVR.EQ.0.AND.IDEVR.NE.0)WRITE(3,*)' ROW DEVIATION IS PERFORM
+ED'
IF(INORM.EQ.1)WRITE(3,*)' ROW NORMALISATION IS PERFORMED'
IF(INORM.EQ.3)WRITE(3,*)' ELEMENTS OF THE MATRIX ARE DIVIDED BY SQ
+RT(NS X NV)'
DO 300 I=1,NR
C WRITE(0,202)I
WRITE(0,201)I,(A(I,J),J=1,NC)
C WRITE(3,202)I
300 WRITE(3,203)I,(A(I,J),J=1,NC)
WRITE(0,'(A\)' )' Do you wish SVD or Q-mode Factor Analysis? (S/Q)
#: '
READ(0,5)ANS
IF(ANS.NE.'S'.AND.ANS.NE.'Q') STOP 'MISKEY !!!'
IF(ANS.EQ.'S')MODE=0
IF(ANS.EQ.'Q')MODE=1
WRITE(0,'(A\)' )' How many factors do you wish ? '
READ(0,*)NF
NVAL=NF
NVEC=NVAL
CALL FACTOR(A,NR,NC,NF,NVAL,NVEC,MODE)
CLOSE(3)
WRITE(0,12345)INFIL,OUTFIL
12345 FORMAT(///7X,'FILE DIARY'//2X,'INPUT FILE = ',A16/
# 2X,'OUTPUT FILE = ',A16)
STOP
END
SUBROUTINE DATA(X,NR,NC,IFMT)
DIMENSION X(200,50)
REAL IFMT(9)
CHARACTER*1 ANS
WRITE(0,'(A\)' )' Is the matrix read rowise or columnwise? (R/C): '
READ(0,'(1A1)' )ANS
IF(ANS.NE.'R'.AND.ANS.NE.'C') STOP ' MISKEY !!!'
IF(ANS.EQ.'C') GO TO 100
DO 1 I=1,NR
1 READ(2,IFMT)(X(I,J),J=1,NC)
RETURN
100 CONTINUE

```

```

DO 2 J=1,NC
2 READ(2,IFMT)(X(I,J),I=1,NR)
RETURN
END
SUBROUTINE PREPAR(X,NR,NC,DENOM,ISDEVR,IDEVR,INORM)
DIMENSION X(200,50)
CHARACTER*1 ANS
5 FORMAT(1A1)
WRITE(0,'(A\)' )' Do you require data preparation ? (Y/N):'
READ(0,5)ANS
IF(ANS.NE.'N'.AND.ANS.NE.'Y') STOP ' MISKEY !!!'
IF(ANS.EQ.'N')RETURN
ISDEVR=0
WRITE(0,'(A\)' )' Do you wish row standardisation ? (Y/N): '
READ(0,5)ANS
IF(ANS.NE.'Y'.AND.ANS.NE.'N') STOP ' MISKEY !!!'
IF(ANS.EQ.'N') GO TO 742
642 ISDEVR=1
IDEVR=1
WRITE(0,'(A\)' )' Is your row big or small ? (S/B):'
READ(0,5)ANS
IF(ANS.NE.'B'.AND.ANS.NE.'S') STOP ' MISKEY !!!'
ISMALL=1
IF(ANS.EQ.'B') ISMALL=0
GO TO 643
742 CONTINUE
IDEVR=0
WRITE(0,'(A\)' )' Do you wish row deviation ? (Y/N):'
READ(0,5)ANS
IF(ANS.NE.'Y'.AND.ANS.NE.'N') STOP ' MISKEY !!!'
IF(ANS.EQ.'N')GO TO 542
IF(ANS.EQ.'Y') IDEVR=1
542 CONTINUE
INORM=0
WRITE(0,'(A\)' )' But you wish normalisation ? (Y/N):'
READ(0,5)ANS
IF(ANS.NE.'N'.AND.ANS.NE.'Y') STOP ' MISKEY !!!'
IF(ANS.EQ.'N') GO TO 643
WRITE(0,'(A\)' )' Do you wish row or special normalisation? (R/S):
#
READ(0,5)ANS
IF(ANS.NE.'R'.AND.ANS.NE.'S') STOP ' MISKEY !!!'
IF(ANS.EQ.'R') INORM=1
IF(ANS.EQ.'S') INORM=3
643 CONTINUE
IF(IDEVR.EQ.0) GO TO 1000
IF(IDEVR.EQ.1) GO TO 500
DENOM=NR
IF(ISMALL.EQ.1) DENOM=DENOM-1
DO 400 J=1,NC
SS=0.
DO 24 I=1,NR
24 SS=SS+X(I,J)
SS=SS/NR
DO 23 I=1,NR
23 X(I,J)=X(I,J)-SS
IF(ISDEVR.EQ.0) GO TO 400
SS=0.

```

```

DO 26 I=1,NR
26 SS=SS+X(I,J)**2
   SS=SS/DENOM
   SS=SQRT(SS)
   DO 25 I=1,NR
25 X(I,J)=X(I,J)/SS
400 CONTINUE
   IF(ISDEVR.EQ.2) RETURN
500 CONTINUE
   DENOM=NC
   IF (ISMAIL.EQ.1)DENOM=DENOM-1
   DO 600 I=1,NR
   SS=0.
   DO 54 J=1,NC
54 SS=SS+X(I,J)
   SS=SS/NC
   DO 53 J=1,NC
53 X(I,J)=X(I,J)-SS
   IF(ISDEVR.EQ.0) GO TO 600
   SS=0.
   DO 56 J=1,NC
56 SS=SS+X(I,J)**2
   SS=SS/DENOM
   SS=SQRT(SS)
   DO 55 J=1,NC
55 X(I,J)=X(I,J)/SS
600 CONTINUE
   IF(ISDEVR.EQ.1) RETURN
1000 CONTINUE
   IF(INORM.EQ.0)RETURN
   IF(INORM.EQ.2)GO TO 14
   IF(INORM.EQ.3)GO TO 15
   DO 11 I=1,NR
   SS=0.
   DO 10 J=1,NC
10 SS=SS+X(I,J)**2
   SS=SQRT(SS)
   DO 11 J=1,NC
11 X(I,J)=X(I,J)/SS
   RETURN
14 CONTINUE
   DO 31 J=1,NC
   SS=0.
   DO 30 I=1,NR
30 SS=SS+X(I,J)**2
   SS=SQRT(SS)
   DO 31 I=1,NR
31 X(I,J)=X(I,J)/SS
   RETURN
15 CONTINUE
   XX=NR*NC
   XX=1./SQRT(XX)
   DO 40 I=1,NR
   DO 40 J=1,NC
40 X(I,J)=X(I,J)*XX
   RETURN
END

```

SUBROUTINE EIGAN(A,V,E,N,NVAL,NVEC,SETA)

C  
C  
C  
C  
C  
C  
C  
C

```
*****
*   DIMENSIONS OF ARRAYS IN SUBROUTINE EIGAN ARE AS FOLLOWS:   *
*   A(NV,NV),V(NV,NF),B(NV),C(NV),P(NV),Q(NV),R(NV),W(NV),IN(NV) *
*   Y(NV+2),E(NF)-PLEASE NOTE THAT DIMENSION OF Y HAS TO BE NV+2 *
*****
```

```

DIMENSION A(50,50),V(50,10),B(50),C(50),P(50),Q(50),R(50),W(50),Y(
152),IN(50),E(10)
EPA=1.E-06
EPB=1.E-20
EPC=1.E-30
EPD=1.E-10
BIG=1.E+20
NTIME=2
NITR=20
SET=0.
DO 17 J=1,N
17 SET=SET+A(J,J)
   SETA=SET
   WRITE(3,203)SET
   NMA=N-1
   NMB=N-2
   DO 18 I=1,NMB
     IPA=I+1
     SS=0.
     DO 10 J=IPA,N
10  SS=SS+A(J,I)**2
     S=SQRT(SS)
     IF(A(IPA,I).GT.0.)S=-S
     C(I)=A(I,I)
     B(I)=S

   IF S IS ZERO THEN ALPHA MUST BE ZERO

   ALPHA=0.
   TOL=1.E-20
   IF(SS.LT.TOL) GO TO 18
   ALPHA=1./ (SS-A(IPA,I)*S)
   T=A(IPA,I)-S
   A(IPA,I)=T
   W(I+1)=T
   IPB=I+2
   DO 11 J=IPB,N
11  W(J)=A(J,I)
     SET=0.
     DO 13 J=IPA,N
       T=0
       DO 12 K=IPA,N
12  T=T+A(J,K)*W(K)
       P(J)=T*ALPHA
13  SET=SET+W(J)*P(J)
       SET=SET*ALPHA*0.5
       DO 14 K=IPA,N
14  Q(K)=P(K)-SET*W(K)
       DO 15 J=IPA,N
```

C  
C  
C

```

DO 15 K=J,N
A(J,K)=A(J,K)-Q(J)*W(K)-Q(K)*W(J)
15 A(K,J)=A(J,K)
18 A(I,I)=ALPHA
C(N-1)=A(N-1,N-1)
C(N)=A(N,N)
B(N-1)=A(N-1,N)
B(N)=0.

C
C   COMPUTE THE EIGENVALUES
C
TOP=ABS(C(1))+ABS(B(1))
DO 20 I=2,N
T=ABS(C(I))+ABS(B(I))+ABS(B(I-1))
IF(T.GT.TOP) TOP=T
20 CONTINUE
DO 21 I=1,N
21 W(I)=B(I)**2
DO 22 I=1,NVAL
22 E(I)=-TOP
SUM=0.
DO 38 K=1,NVAL
BOT=E(K)
DO 40 ITER=1,NITR
24 PL=0.5*(TOP+BOT)
ERR=ABS(TOP-BOT)
IF(ERR.LT.FPA)GO TO 41
NAG=0
I=1
26 S=C(I)-PL
28 IF(S.GE.0.)NAG=NAG+1
IF(S.EQ.0.) GO TO 30
I=I+1
IF(I.GT.N) GO TO 32
S=C(I)-PL-W(I-1)/S
GO TO 28
30 I=I+2
IF(I.LE.N)GO TO 26
32 IF(NAG.GE.K) GO TO 34
TOP=PL
GO TO 40
34 BOT=PL
40 CONTINUE
41 E(K)=PL
SUM=SUM+E(K)
SS=SUM/SETA
WRITE(3,202)K,E(K),ERR,ITER,SUM,SS
38 CONTINUE
WRITE(3,204)NVAL,SUM
IF(NVEC.NE.0) GO TO 42
GO TO 80
42 DO 70 I=1,NVEC
DO 44 J=1,N
P(J)=0.
Q(J)=B(J)
R(J)=C(J)-E(I)
44 Y(J)=1.
Y(N+1)=0.

```

```

      Y(N+2)=0.
C
C   BEGIN THE GAUSSIAN ELIMINATION
C
      IF(R(1).EQ.0.)R(1)=EPC
      DO 48 J=1,NMA
      IF(ABS(R(J)).LT.ABS(B(J)))GO TO 45
      FAC=B(J)/R(J)
      IN(J)=0
      GO TO 46
45  FAC=R(J)/B(J)
      IN(J)=1
      R(J)=B(J)
      T=R(J+1)
      R(J+1)=Q(J)
      Q(J)=T
      P(J)=Q(J+1)
      Q(J+1)=0.
46  W(J)=FAC
      Q(J+1)=Q(J+1)-FAC*P(J)
      R(J+1)=R(J+1)-FAC*Q(J)
      IF(R(J+1).EQ.0.)R(J+1)=EPC
48  CONTINUE
C
C   BEGIN THE BAC- SUBSTITUTION
C
      DO 60 ITIME=1,NTIME
      DO 53 JJ=1,N
      K=N+1-JJ
      T=Y(K)
51  Y(K)=(T-Y(K+1)*Q(K)-Y(K+2)*P(K))/R(K)
      IF(ABS(Y(K)).LT.BIG)GO TO 53
      DO 52 J=1,N
52  Y(J)=Y(J)*EPD
      T=T*EPD
      GO TO 51
53  CONTINUE
C
C   THIS COMPLETES BAC- SUBSTITUTION
C   DO THE REDUCTION IN NEW R.H.S.
C
      IF(ITIME.EQ.NTIME)GO TO 60
      DO 57 J=1,NMA
      IF(IN(J).EQ.1) GO TO 56
      Y(J+1)=Y(J+1)-W(J)*Y(J)
      GO TO 57
56  T=Y(J)
      Y(J)=Y(J+1)
      Y(J+1)=T-W(J)*Y(J+1)
57  CONTINUE
60  CONTINUE
      DO 64 J=1,NMB
      T=0.
      K=N-J-1
      M=K+1
      DO 62 KK=M,N
62  T=T+A(KK,K)*Y(KK)
      T=A(K,K)*T
      DO 64 KK=M,N

```

```

64 Y(KK)=Y(KK)-T*A(KK,K)
   SS=0.
   DO 67 J=1,N
67 SS=SS+Y(J)**2
   T=1./SQRT(SS)
   DO 66 J=1,N
66 V(J,I)=Y(J)*T
70 CONTINUE
   DO 71 I=1,NVEC
   DO 71 J=I,NVEC
   A(I,J)=0.
   DO 71 M=1,N
   A(I,J)=A(I,J)+V(M,I)*V(M,J)
71 A(J,I)=A(I,J)
   WRITE(3,206)
   DO 73 J=1,NVEC
73 WRITE(3,212)J,(V(I,J),I=1,N)
   WRITE(3,207)
   DO 74 J=1,NVEC
74 WRITE(3,200)J,(A(I,J),I=1,NVEC)
80 CONTINUE
200 FORMAT(I5,10E13.4/(5X,10E13.4))
202 FORMAT(2X,15HEIGEN VALUE NO. ,I4,E13.4,2X,17HWITH ERROR LIMITS,E13
1.4,2X,5HAFTER,I4,2X,10HITERATIONS 2E13.4/)
203 FORMAT(/5X,42HSUM OF THE DIAGONAL ELEMENTS OF MATRIX A= E15.4///
1T21,1HI,T30,4HE(I),T94,8HSUM E(I),T106,15HCLOSENESS RATIO/)
204 FORMAT(5X,6HSUM OF I3,2X,13HEIGEN VALUES= ,E15.4/)
206 FORMAT(//, 5X,13HEIGEN VECTORS )
207 FORMAT(//,5X,24HMATRIX- V(TRANPOSE) X V )
212 FORMAT(I5,10E13.3/(5X,10E13.3))
   RETURN
   END
SUBROUTINE FACTOR (X,NS,NV,NF,NVAL,NVEC,MODE)

```

```

C
C *****
C *   DIMENSIONS OF ARRAYS IN SUBROUTINE FACTOR ARE AS FOLLOWS:   *
C *   X(NS,NV),R(NV,NV),V(NV,NF),T(NF,NF),E(NF),FAC(NF) AND PLEASE *
C *   NOTE: COM(NS)-FOR Q MODE ; COM(NV)-FOR R MODE                 *
C *****
C
C
C   DIMENSION X(200,50),R(50,50),V(50,10),T(10,10),FAC(10),E(10)
C   DIMENSION COM(200)
C   DO 21 I=1,NV
C   DO 21 J=1,NV
C   SS=0.
C   DO 10 K=1,NS
10  SS=SS+X(K,I)*X(K,J)
C   R(I,J)=SS
21  R(J,I)=R(I,J)
C   WRITE(3,211)
C   DO 200 I=1,NV
C   WRITE(3,202)I
200 WRITE(3,203)I,(R(I,J),J=1,NV)
203 FORMAT(5X,I3,2X,10E12.3/(10X,10E12.3))
202 FORMAT(5X,I3/)
C   CALL EIGAN(R,V,E,NV,NVAL,NVEC,SETA)
C   IF(MODE.EQ.2) GO TO 390

```



```

        IF(MODE.EQ.0) GO TO 13
        WRITE(3,258)
        WRITE(3,252)
13      IF(MODE.EQ.0) WRITE(3,259)
        DO 40 I=1,NV
        40 WRITE(3,201) I, (V(I,J),J=1,NF)
        DO 19 I=1,NS
        DO 14 J=1,NF
        FAC(J)=0
        DO 14 L=1,NV
        14 FAC(J)=FAC(J)+X(I,L)*V(L,J)
        DO 19 J=1,NF
        19 X(I,J)=FAC(J)
        IF(MODE.EQ.0) GO TO 400
        WRITE(3,257)
        DO 60 I=1,NS
        60 WRITE(3,201) I, (X(I,J),J=1,NF)
        CALL VARMAX(X,COM,NF,NS,T)
        WRITE(3,253)
        DO 20 I=1,NF
        20 WRITE(3,201) I, (T(I,J),J=1,NF)
        WRITE(3,255)
        DO 18 J=1,NV
        DO 16 I=1,NF
        FAC(I)=0.
        DO 16 L=1,NF
        16 FAC(I)=FAC(I)+V(J,L)*T(L,I)
        DO 17 I=1,NF
        17 V(J,I)=FAC(I)
        18 WRITE(3,201) J, (V(J,I),I=1,NF)
        WRITE(3,254)
        DO 51 I=1,NS
        51 WRITE(3,242) COM(I), I, (X(I,J),J=1,NF)
        DO 31 J=1,NF
        31 COM(J)=0.
        DO 34 I=1,NS
        DO 34 J=1,NF
        34 COM(J)=COM(J)+X(I,J)**2
        WRITE(3,281) (COM(I),I=1,NF)
        DO I=1,NF
        COM(I)=COM(I)/SETA*100.
        END DO
        WRITE(3,282) (COM(I),I=1,NF)

        RETURN
390     CONTINUE
        WRITE(3,260)
        DO 312 I=1,NF
        312 E(I)=SQRT(E(I))
        WRITE(3,252)
        DO 319 I=1,NS
        DO 314 J=1,NF
        FAC(J)=0
        DO 314 L=1,NV
        314 FAC(J)=FAC(J)+X(I,L)*V(L,J)
        DO 319 J=1,NF
        319 X(I,J)=FAC(J)/E(J)
        DO 360 I=1,NS

```

```

360 WRITE(3,201) I, (X(I,J), J=1, NF)
    WRITE(3,257)
    DO 335 J=1, NF
    DO 335 I=1, NV
335 V(I,J)=V(I,J)*E(J)
    DO 340 I=1, NV
340 WRITE(3,201) I, (V(I,J), J=1, NF)
    CALL VARMAX(V, COM, NF, NV, T)
    WRITE(3,253)
    DO 320 I=1, NF
320 WRITE(3,201) I, (T(I,J), J=1, NF)
    WRITE(3,255)
    DO 318 J=1, NS
    DO 316 I=1, NF
    FAC(I)=0.
    DO 316 L=1, NF
316 FAC(I)=FAC(I)+X(J,L)*T(L,I)
    DO 317 I=1, NF
317 X(J,I)=FAC(I)
318 WRITE(3,201) J, (X(J,I), I=1, NF)
    WRITE(3,254)
    DO 351 I=1, NV
351 WRITE(3,242) COM(I), I, (V(I,J), J=1, NF)
    DO 331 J=1, NF
331 COM(J)=0.
    DO 334 I=1, NV
    DO 334 J=1, NF
334 COM(J)=COM(J)+V(I,J)**2
    WRITE(3,281) (COM(I), I=1, NF)
    DO I=1, NF
    COM(I)=COM(I)/SETA*100.
    END DO
    WRITE(3,282) (COM(I), I=1, NF)
    RETURN
400 CONTINUE
    DO 70 I=1, NF
    E(I)=SQRT(E(I))
    FACC=1./E(I)
    DO 70 J=1, NS
70 X(J,I)=X(J,I)*FACC
    WRITE(3,262)
    WRITE(3,263) (I, E(I), I=1, NF)
    WRITE(3,261)
    DO 71 I=1, NS
71 WRITE(3,201) I, (X(I,J), J=1, NF)
201 FORMAT(5X, I5, 10(2X, F9.5))
211 FORMAT(//1X, 23HMATRIX X(TRANSPPOSE) X /)
212 FORMAT(10F12.4/)
281 FORMAT(//5X, 'SUM OF THE SQUARES OF EACH COLUMN OF THE ABOVE FACTOR
LOADING MATRIX' /
5X, 'i.e. THE VARIANCE
2EXPLAINED BY EACH FACTOR ARE GIVEN BELOW' /10X, 10(2X, F9.5))
282 FORMAT(//5X, 'PERCENTAGE VARIANCE EXPLAINED BY EACH FACTOR ARE GIVEN
IN BELOW' /10X, 10(2X, F9.5))
242 FORMAT(5X, F9.5, I6, 10(1X, F9.5))
252 FORMAT(// 5X, 19HFACTOR SCORE MATRIX /)
253 FORMAT(// 5X, 23HVARIMAX ROTATION MATRIX /)
254 FORMAT(// 5X, 44HFACTOR LOADING MATRIX-AFTER VARIMAX ROTATION /5X,
1 72HSUM OF THE SQUARES OF THE ELEMENTS OF EACH ROW IS ALONG THE FI

```

```

2RST COLUMN /)
255 FORMAT(/ / 5X,42HFACTOR SCORE MATRIX AFTER VARIMAX ROTATION /)
257 FORMAT(/ / 5X,21HFACTOR LOADING MATRIX /)
258 FORMAT(/ 20X,10HQQQQQQQQQQ 3X,22HQ-MODE FACTOR ANALYSIS 3X,
110HQQQQQQQQQQ /)
259 FORMAT(/ 20X,10HSSSSSSSSSS 3X,28HSINGULAR VALUE DECOMPOSITION
1 3X,10HSSSSSSSSSS / 31X,26HX = U . GAMA . V-TRANSPOSE / / 5X,
2 18HCOMPONENT MATRIX-V /)
260 FORMAT(/ 20X,10HRRRRRRRRRR 3X,22HR-MODE FACTOR ANALYSIS 3X,
110HRRRRRRRRRR /)
261 FORMAT(/ / 5X,18HCOMPONENT MATRIX-U /)
262 FORMAT(/ / 5X,33HDIAGONAL ELEMENTS OF GAMMA MATRIX /)
263 FORMAT(10X,I5,E15.4)
RETURN
END
SUBROUTINE VARMAX(F,COM,NF,NN,T)

```

```

C
C *****
C * FOR Q-MODE ANALYSIS THE DIMENSIONS OF ARRAYS IN SUBROUTINE
C * VARMAX ARE AS FOLLOWS: F(NS,NV),COM(NS),T(NF,NF)
C *
C * FOR R-MODE ANALYSIS THE DIMENSIONS OF ARRAYS IN SUBROUTINE
C * VARMAX ARE AS FOLLOWS: F(NV,NF),COM(NV),T(NF,NF)
C * SUBROUTINE VARMAX IS NOT CALLED FOR SINGULAR VALUE VALUE
C * DECOMPOSITION
C *****
C
C

```

```

DIMENSION F(200,50),COM(200),T(10,10)
EPS=0.06993
DO 11 I=1,NF
DO 10 J=1,NF
10 T(I,J)=0.
11 T(I,I)=1.
DO 13 I=1,NN
COM(I)=0.
DO 12 J=1,NF
12 COM(I)=COM(I)+F(I,J)**2
COM(I)=SQRT(COM(I))
DO 13 J=1,NF
13 F(I,J)=F(I,J)/COM(I)
NFA=NF-1
14 NROT=0
DO 40 M=1,NFA
K=M+1
DO 40 L=K,NF
A=0.
B=0.
C=0.
D=0.
DO 15 I=1,NN
U=F(I,M)**2-F(I,L)**2
V=F(I,M)*F(I,L)*2
A=A+U
B=B+V
C=C+U**2-V**2
15 D=D+U*V*2
QNUM=D-2.*A*B/NN

```

```

QDEN=C-(A**2-B**2)/NN
IF (ABS(QNUM)+ABS(QDEN).EQ.0.)GO TO 30
IF (ABS(QNUM)-ABS(QDEN))17,24,21
17 R=ABS(QNUM/QDEN)
IF (R.LT.EPS)GO TO 19
CS4TH=COS(ATAN(R))
SN4TH=SIN(ATAN(R))
GO TO 25
19 IF(QDEN.GE.0.)GO TO 30
SNPHI=0.70710678
CSPHI=SNPHI
GO TO 31
21 R=ABS(QDEN/QNUM)
IF (R.LT.EPS)GO TO 23
SN4TH=1./SQRT(1.+R**2)
CS4TH=SN4TH*R
GO TO 25
23 CS4TH=0.
SN4TH=1.
GO TO 25
24 CS4TH=0.70710678
SN4TH=CS4TH
25 R=SQRT((1.+CS4TH)*.5)
CSTH=SQRT((1.+R)*0.5)
SNTH=SN4TH/(4.*CSTH*R)
IF(QDEN.GE.0.)GO TO 27
CSPHI=.70710678*(CSTH+SNTH)
SNPHI=.70710678*(CSTH-SNTH)
GO TO 28
27 CSPHI=CSTH
SNPHI=SNTH
28 IF(QNUM.GE.0.)GO TO 31
SNPHI=-SNPHI
GO TO 31
30 NROT=NROT+1
GO TO 40
31 DO 32 J=1,NN
R=F(J,M)*CSPHI+F(J,L)*SNPHI
F(J,L)=F(J,L)*CSPHI-F(J,M)*SNPHI
F(J,M)=R
IF(J.GT.NF)GO TO 32
TP=T(J,M)
T(J,M)=TP*CSPHI+T(J,L)*SNPHI
T(J,L)=-TP*SNPHI+T(J,L)*CSPHI
32 CONTINUE
40 CONTINUE
IF(NROT.LT.NF*NFA/2)GO TO 14
DO 42 I=1,NN
DO 41 J=1,NF
41 F(I,J)=F(I,J)*COM(I)
42 COM(I)=COM(I)**2
RETURN
END
SUBROUTINE TIME
CALL GETTIM(IHR,IMIN,ISEC,I100TH)
CALL GETDAT(IYR,IMON,IDAY)
WRITE(0,1)IDAY,IMON,IYR
WRITE(0,2)IHR,IMIN

```

```

WRITE(3,1) IDAY, IMON, IYR
WRITE(3,2) IHR, IMIN
1  FORMAT(T10, 'DATE', 2X, I2.2, '/', I2.2, '/', I4)
2  FORMAT(T10, 'TIME ', I3, ':', I2.2, 3X, 'HO'RS'////)
RETURN
END
SUBROUTINE DATAL(X, NR, NC)
DIMENSION X(200, 50)
CHARACTER*1 ANS
WRITE(0, '(A\)\') ' Is the matrix read rowise or columnwise? (R/C): '
READ(0, '(1A1)\') ANS
IF(ANS.NE.'R'.AND.ANS.NE.'C') STOP ' MISKEY !!'
IF(ANS.EQ.'C') GO TO 100
DO 1 I=1, NR
1  READ(2, *) (X(I, J), J=1, NC)
RETURN
100 CONTINUE
DO 2 J=1, NC
2  READ(2, *) (X(I, J), I=1, NR)
RETURN
END

```

PROGRAM GETTAB4

```

*****
* PROGRAM TO CONVERT THE FOUR FACTORS OF THE FACTOR SCORE *
* MATRIX INTO 14 QUADRATIC TERMS *
* Input file : IND-VAR.DAT *
* Output file: IND-V-T.DAT *
*****
    DIMENSION BC(42,50)
    REAL LABEL(80)
    NR=42
    NC=4
    OPEN(7, FILE='IND-VAR.DAT', STATUS='OLD')
    OPEN(8, FILE='IND-V-T.DAT')
    READ(7, '(20A4)') (LABEL(I), I=1, 80)
    WRITE(8, '(20A4)') (LABEL(I), I=1, 80)
10  FORMAT(20X, 4F10.5)
20  FORMAT(I10, 14F10.5)
30  FORMAT(14F10.5)
    DO I=1, NR
    READ(7, 10) (BC(I, J), J=1, NC)
C   WRITE(8, 20) I, (BC(I, J), J=1, NC)
    END DO
    NCOL=NC
    DO L=1, NC
    DO M=L, NC
    NCOL=NCOL+1
    DO I=1, NR
    BC(I, NCOL)=BC(I, L)*BC(I, M)
    END DO
    END DO
    END DO
    WRITE(*, *) ' NCOL=', NCOL
    DO I=1, NR
    WRITE(8, 30) (BC(I, J), J=1, NCOL)
    END DO
    STOP
    END

```

PROGRAM MULRAS

```

*****
*   BLACK-BOX PACKAGE FOR PERFORMING MULTIPLE REGRESSION   *
*   ANALYSIS                                               *
*   MAXIMUM SAMPLE SIZE           = 500                   *
*   MAXIMUM INDEPENDENT VARIABLES = 20                    *
*   MAXIMUM DEPENDENT VARIABLES   = 10                    *
*   TEST DATA FOR PROGRAM IMPLICITLY INCLUDED           *
*****
PARAMETER (NRG=500,NG=20,MG=10,NG2MG=NG+2*MG,NGMG=NG+MG)
DIMENSION X(NRG,NG2MG),B(NG,NGMG),AX(NGMG)
CHARACTER*15 NAMEX,NAMEY,XFMT,YFMT,OUTFIL
COMMON NR,N,M,NAMEX,NAMEY,XFMT,YFMT,OUTFIL
CALL PARAM(ICODE)
EPS=1.0E-08
MN=N+M
NP1=N+1
MM=M+M
IF(ICODE.EQ.0)CALL DATA0(X,NR,N,M,NAMEX,XFMT)
IF(ICODE.NE.0)CALL DATA1(X,NR,N,M,NAMEX,XFMT,NAMEY,YFMT)
DO 780 J=1,MN
AX(J)=0.
DO 781 K=1,NR
AX(J)=AX(J)+X(K,J)
781 CONTINUE
AX(J)=AX(J)/NR
DO 782 K=1,NR
X(K,J)=X(K,J)-AX(J)
782 CONTINUE
780 CONTINUE
DO 783 J=1,N
DO 783 I=1,N
B(I,J)=0.
DO 784 K=1,NR
B(I,J)=B(I,J)+X(K,I)*X(K,J)
784 CONTINUE
783 CONTINUE
DO 785 NK=NP1,MN
DO 785 I=1,N
DO 785 K=1,NR
B(I,NK)=B(I,NK)+X(K,I)*X(K,NK)
785 CONTINUE
CALL MATINV(-1,B,N,M,DET,EPS)
CALL PRED(AX,B,X,NR,N,M)
MNM=MN+M
WRITE(25,1345)
1345 FORMAT(1H1/' ORIGINAL AND PREDICTED VALUES OF Y'//)
CALL OUT(X,NR,NP1,MNM)
WRITE(0,567)OUTFIL
567 FORMAT(//5X,'Your output file is.... ',A20)
STOP
END
SUBROUTINE PRED(AX,B,Y,NR,N,M)
PARAMETER (NRG=500,NG=20,MG=10,NG2MG=NG+2*MG,NGMG=NG+MG)
DIMENSION Y(NRG,NG2MG),B(NG,NGMG),AX(NGMG),YYBAR(NGMG)
DIMENSION YKJJ2(NGMG),BX(NGMG)
NP1=N+1
MP1=M+1

```

```

MN=M+N
MNM=MN+M
MM=M+M
DO 786 J=NP1,MN
YKJJ2(J)=0.
JJ=J-N+MN
DO 786 K=1,NR
DO 787 I=1,N
Y(K,JJ)=Y(K,JJ)+B(I,J)*Y(K,I)
787 CONTINUE
YKJJ2(J)=YKJJ2(J)+Y(K,JJ)**2
Y(K,JJ)=Y(K,JJ)+AX(J)
786 CONTINUE
DO 788 J=1,MN
YYBAR(J)=0.
DO 789 K=1,NR
YYBAR(J)=YYBAR(J)+Y(K,J)**2
Y(K,J)=AX(J)+Y(K,J)
789 CONTINUE
788 CONTINUE
DO 880 I=1,MN
BX(I)=-AX(I)
880 CONTINUE
DO 884 J=1,M
NPJ=N+J
WRITE(25,1)J
1 FORMAT(///10X,'DEPENDENT VARIABLE',I2//)
WRITE(25,2)J,AX(NPJ)
2 FORMAT(5X,'1. REGRESSION EQUATION'/13X,'Y(',I2,')=',F14.5)
DO 881 I=1,N
WRITE(25,3)B(I,NPJ),I,BX(I)
881 CONTINUE
3 FORMAT(25X,SP,F14.5,2X,'[ X(',SS,I2,')',SP,F14.5,2X,']',SS)
XXX=AX(NPJ)
DO 882 I=1,N
XXX=XXX-B(I,NPJ)*AX(I)
882 CONTINUE
WRITE(25,4)XXX
4 FORMAT(/5X,'2. SUM OF CONSTANT TERMS IN ABOVE EQUATION =',F14.5)
XXX=YKJJ2(NPJ)/YYBAR(NPJ)
WRITE(25,5)XXX
5 FORMAT(/5X,'3. PROPORTION OF VARIANCE EXPLAINED =',F14.5)
XXX=(YYBAR(NPJ)-YKJJ2(NPJ))/(NR-N-1)
YYY=YYBAR(NPJ)/(NR-1)
IF(XXX.GT.YYY)XXX=YYY
ZZZ=SQRT(1.-XXX/YYY)
WRITE(25,6)ZZZ
6 FORMAT(/5X,'4. MULTIPLE CORRELATION COEFFICIENT'/
#13X,'ADJUSTED FOR DEGREES OF FREEDOM =',F14.5)
ZZZ=SQRT(XXX)
WRITE(25,7)ZZZ
7 FORMAT(/5X,'5. STANDARD ERROR OF ESTIMATE'/
#13X,'ADJUSTED FOR DEGREES OF FREEDOM =',F14.5)
WRITE(25,8)
8 FORMAT(/5X,'6. STANDARD PARTIAL REGRESSION COEFFICIENTS')
DO 883 I=1,N
XXX=B(I,NPJ)*SQRT(YYBAR(I)/YYBAR(NPJ))
WRITE(25,9)I,XXX

```



```

9      FORMAT(13X,'FOR INDEPENDENT VARIABLE ',I2,' = ',F14.5)
883   CONTINUE
884   CONTINUE
      RETURN
      END
      SUBROUTINE MATINV(IJOB,C,N,M,DET,EP)
C *****
C *      PURPOSE
C *      THIS ROUTINE COMPUTES THE SOLUTION OF A SYSTEM OF
C *      EQUATIONS CX=U, WHERE C IS THE MATRIX OF COEFFI
C *      CIENTS, X IS THE SOLUTION VECTOR AND U IS THE RIGHT
C *      HAND SIDE VECTOR.
C *      THIS ROUTINE CAN ALSO BE USED TO FIND THE DETERMINANT
C *      AND/OR INVERSE OF A MATRIX.
C *      USAGE
C *      CALL MATINV(IJOB,C,N,M,DET,EP)
C *      DESCRIPTION OF PARAMETERS
C *
C *      C-IS THE COEFFICIENT MATRIX AUGMENTED WITH VECTOR U
C *      APPENED TO IT
C *      IJOB- WHEN IJOB=-1, THE SYSTEM OF SIMULTANEOUS EQUATIONS
C *      CX=U IS SOLVED
C *      - WHEN IJOB= 0, THE INVERSE OF THE MATRIX X IS
C *      DETERMINED
C *      - WHEN IJOB= 1, THE DETERMINANT OF THE MATRIX X IS
C *      DETERMINED
C *      M -IS THE NUMBER OF COLUMN VECTORS APPENED TO MATRIX C.
C *      FOR THIS PROBLEM M IS CHOSEN AS 1.
C *      N -NUMBER OF EQUATIONS .EQ. NUMBER OF UNKNOWNNS
C *      C -IS THE COFFICIENT MATRIX AUGMENTED WITH THE VECTOR
C *      U APPENED TO IT
C *      METHOD
C *      GAUSSIAN ELIMINATION
C *****
      PARAMETER (NG=20,MG=10,NGMG=NG+MG)
      DIMENSION C(NG,NGMG)
30  FORMAT(5X,'THE DETERMINANT OF THIS SYSTEM EQUALS ZERO'/
15X,'THE PROGRM CANNOT HANDLE THIS CASE')
      DET=1.0
      NP1=N+1
      NPM=N+M
      NM1=N-1
      IF(IJOB) 2,1,2
1    DO 3 I=1,N
20   DO 20 J=NP1,NPM
      C(I,J)=0.
      IPN=I+N
3    C(I,IPN)=1.
2    DO 66 J=1,NM1
      E=ABS(C(J,J))
      JP1=J+1
      DO 105 I=JP1,N
      D=ABS(C(I,J))
      IF(E-D) 6,105,105
6    DET=-DET
      DO 7 K=J,NPM
      F=C(I,K)
      C(I,K)=C(J,K)

```

```

7      C(J,K)=F
      E=D
105    CONTINUE
      IF (ABS(C(J,J))-EP) 14, 15, 15
14     DET=0.0
      IF (IJOB) 16, 16, 17
16     WRITE(25,30)
17     RETURN
15     DO 4 I=JP1,N
      CONST=C(I,J)/C(J,J)
      DO 4 K=JP1,NPM
      C(I,K)=C(I,K)-CONST*C(J,K)
4      CONTINUE
66     CONTINUE
      IF (ABS(C(N,N))-EP) 41, 18, 18
41     DET=0.0
      IF (IJOB) 61, 61, 71
61     WRITE(25,30)
71     RETURN
18     DO 11 I=1,N
11     DET=DET*C(I,I)
      IF (IJOB) 10, 10, 171
10     DO 12 I=1,N
      K=N-I+1
      KP1=K+1
      DO 12 L=NP1,NPM
      S=0.0
      DO 13 J=KP1,N
      IF (J .GT. N) GOTO 12
13     S=S+C(K,J)*C(J,L)
12     C(K,L)=(C(K,L)-S)/C(K,K)
171    RETURN
      END
      SUBROUTINE DATA0(X,NR,N,M,NAMEX,XFMT)
      PARAMETER (NRG=500,NG=20,MG=10,NG2MG=NG+2*MG)
      DIMENSION X(NRG,NG2MG)
      DIMENSION ALAB(80)
      CHARACTER*15 NAMEX,XFMT
CC     WRITE(0,*) 'TINE DATA0'
      OPEN(12,FILE=NAMEX,ACCESS='SEQUENTIAL')
      READ(12,23)(ALAB(I),I=1,80)
      WRITE(25,24)(ALAB(I),I=1,80)
      MN=N+M
23     FORMAT(20A4)
24     FORMAT(1X,20A4)
      WRITE(25,1)NR,N,M
1      FORMAT(5X,'I N P U T   M A T R I X'//
#         5X,'NUMBER OF DATA POINTS           :',I3/
#         5X,'NUMBER OF INDEPENDENT VARIABLES X :',I3/
#         5X,'NUMBER OF DEPENDENT VARIABLES   Y :',I3)
      DO 780 I=1,NR
      READ(12,XFMT)(X(I,J),J=1,MN)
780    CONTINUE
      CALL OUT(X,NR,1,MN)
      RETURN
      END
      SUBROUTINE DATA1(X,NR,N,M,NAMEX,XFMT,NAMEY,YFMT)
      PARAMETER (NRG=500,NG=20,MG=10,NG2MG=NG+2*MG)

```

```

DIMENSION X(NRG,NG2MG)
DIMENSION ALAB(80),BLAB(80)
CHARACTER*15 NAMEX,NAMEY,XFMT,YFMT
CC      WRITE(0,*)'TINE DATA1'
OPEN(12,FILE=NAMEX,ACCESS='SEQUENTIAL')
OPEN(13,FILE=NAMEY,ACCESS='SEQUENTIAL')
READ(12,23)(ALAB(I),I=1,80)
READ(13,23)(BLAB(I),I=1,80)
MN=N+M
NP1=N+1
23      FORMAT(20A4)
24      FORMAT(1X,20A4)
WRITE(25,1)NR,N
1       FORMAT(5X,'I N D E P E N D E N T   V A R I A B L E S'//
#         5X,'NUMBER OF DATA POINTS           :',I3/
#         5X,'NUMBER OF INDEPENDENT VARIABLES X  :',I3)
WRITE(25,24)(ALAB(I),I=1,80)
DO 780 I=1,NR
READ(12,XFMT)(X(I,J),J=1,N)
780     CONTINUE
CALL OUT(X,NR,1,N)
WRITE(25,2)NR,M
2       FORMAT(///5X,'D E P E N D E N T   V A R I A B L E S'//
#         5X,'NUMBER OF DATA POINTS           :',I3/
#         5X,'NUMBER OF DEPENDENT VARIABLES Y   :',I3)
WRITE(25,24)(BLAB(I),I=1,80)
DO 781 I=1,NR
READ(13,YFMT)(X(I,J),J=NP1,MN)
781     CONTINUE
CALL OUT(X,NR,NP1,MN)
RETURN
END
SUBROUTINE OUT(X,NR,NP1,MN)
PARAMETER (NRG=500,NG=20,MG=10,NG2MG=NG+2*MG)
DIMENSION X(NRG,NG2MG)
DO 780 I=1,NR
WRITE(25,31)I,(X(I,J),J=NP1,MN)
C31     FORMAT(I6,6X,8E15.5/(12X,8E15.5))
31      FORMAT(I2,3X,14F7.3)
780     CONTINUE
RETURN
END
SUBROUTINE PARAM(ICODE)
COMMON NR,N,M,NAMEX,NAMEY,XFMT,YFMT,OUTFIL
CHARACTER*15 DUMMY,NAMEX,NAMEY,XFMT,YFMT,OUTFIL
CHARACTER*1 ANS
1       WRITE(0,678)
678     FORMAT(1X,'HAVE YOU CREATED YOUR SPECIFICATION FILE? (Y/N):',S)
READ(0,234)ANS
234     FORMAT(A1)
IF (ANS.EQ.'Y') THEN
OPEN(7,FILE='MULT-REG.SPC',ACCESS='SEQUENTIAL')
READ(7,265)ICODE
READ(7,255)OUTFIL
READ(7,265)NR
READ(7,265)N
READ(7,265)M
READ(7,255)NAMEX,NAMEY

```

```

READ(7,255)XFMT,YFMT
265  FORMAT(35X,I3)
255  FORMAT(35X,2A15)
OPEN(25,FILE=OUTFIL,ACCESS='SEQUENTIAL',STATUS='UNKNOWN')
C   OPEN(25,FILE='MULT-REG.RES',ACCESS='SEQUENTIAL')
WRITE(0,126)NR,N,M
126  FORMAT(5X,'Number of data points=',I3/
#     5X,'Number of X variables=',I3/
#     5X,'Number of Y variables=',I3)
IF(NR.GT.500)WRITE(0,*)'Number of data points is more than 500'
IF(N.GT.20)WRITE(0,*)'Number of X variables is more than 20'
IF(M.GT.10)WRITE(0,*)'Number of Y variables is more than 10'
IF((NR.GT.500).OR.(N.GT.20).OR.(M.GT.10))STOP
WRITE(0,125)NAMEX,NAMEY,XFMT,YFMT
125  FORMAT(5X,'Name of input data file..... ',A20,5X,A20/
#     5X,'Name of input data format.... ',A20,5X,A20)
ELSEIF (ANS.EQ.'N')THEN
OPEN(7,FILE='MULT-REG.SPC',ACCESS='SEQUENTIAL',STATUS='UNKNOWN')
WRITE(7,25)
25  FORMAT( 'C TAB 36,51'/
#     'Name of output file (A15 format) :MULT-REG.RES'/
#     'Number of data points           :018'/
#     'Number of independent variables, X:003'/
#     'Number of dependent variables, Y :002'/
#     'Name of input file               :SNED-435.DAT'/
#     'Format for input file            :(5F6.3)')
OPEN(12,FILE='SNED-435.DAT',ACCESS='SEQUENTIAL',STATUS='UNKNOWN')
WRITE(12,26)
26  FORMAT( 'CTAB S7 6                               '/
#     'SNEDECOR                                     '/
#     'PG 435                                         '/
#     '.....'/
#     '1.4   53.   158.  64.   93.  '/
#     '1.4   23.   163.  60.   73.  '/
#     '3.1   19.   37.   71.   38.  '/
#     '1.6   34.   157.  61.  109.  '/
#     '4.7   24.   59.   54.   54.  '/
#     '1.7   65.   123.  77.  107.  '/
#     '9.4   44.   46.   81.   99.  '/
#     '10.1  31.  117.  93.   94.  '/
#     '11.6  29.  173.  93.   66.  ')
WRITE(12,27)
27  FORMAT( '12.6  58.   112.  51.  126.  '/
#     '10.9  37.   111.  76.   75.  '/
#     '23.1  46.   114.  96.  108.  '/
#     '23.1  50.   134.  77.   90.  '/
#     '21.6  44.   73.   93.   72.  '/
#     '23.1  56.   168.  95.   90.  '/
#     '1.9   36.   143.  54.   82.  '/
#     '26.8  58.   202.  168.  128.  '/
#     '29.9  51.   124.  99.  120.  ')
WRITE(0,*)'TWO FILES HAVE BEEN CREATED'
WRITE(0,*)' 1. SPECIFICATION FILE.....MULT-REG.SPC'
WRITE(0,*)' 2. INPUT DATA FILE.....SNED-435.DATA'
WRITE(0,*)'PLEASE SEE THEM VIA @PED COMMAND'
WRITE(0,*)' '
WRITE(0,*)'NOW RUN THE PROGRAM TO GET RESULTS '
WRITE(0,*)'FOR ABOVE EXAMPLE'

```

```

STOP
ELSE
    GO TO 1
END IF
RETURN
END

```

Test data for multiple regression analysis  
 Source: G W Snedecor. Statistical methods applied to  
 experiments in agriculture and biology.  
 Allied Pacific, Bombay, 1961 (See PG 435)

X1	X2	X3	Y1	Y2
3.1	19.	37.	71.	38.
4.7	24.	59.	54.	54.
1.7	65.	123.	77.	107.
9.4	44.	46.	81.	99.
10.1	31.	117.	93.	94.
11.6	29.	173.	93.	66.
12.6	58.	112.	51.	126.
10.9	37.	111.	76.	75.
23.1	46.	114.	96.	108.
23.1	50.	134.	77.	90.
21.6	44.	73.	93.	72.
23.1	56.	168.	95.	90.
1.9	36.	143.	54.	82.
26.8	58.	202.	168.	128.
29.9	51.	124.	99.	120.

X1: inorganic phosphorus I  
 X2: organic hydrolysed phosphorus I(indep var)  
 X3: organic unhydrolysed phosphorusI

Y1: plant available phosphorus at 20 deg C I  
 Y2: plant available phosphorus at 35 deg C I (dep var)

Program results:

D E P E N D E N T V A R I A B L E 1

1. REGRESSION EQUATION

Y( 1) = 81.27778  
 +1.78478 [ X( 1) -11.94444 ]  
 -.08340 [ X( 2) -42.11111 ]  
 +.16113 [ X( 3) -123.00000 ]

2. SUM OF CONSTANT TERMS IN ABOVE EQUATION = 43.65220

3. PROPORTION OF VARIANCE EXPLAINED = .54934

4. MULTIPLE CORRELATION COEFFICIENT  
 ADJUSTED FOR DEGREES OF FREEDOM = .67288

5. STANDARD ERROR OF ESTIMATE  
 ADJUSTED FOR DEGREES OF FREEDOM = 19.97051

6. STANDARD PARTIAL REGRESSION COEFFICIENTS  
 FOR INDEPENDENT VARIABLE 1 = .67134  
 FOR INDEPENDENT VARIABLE 2 = -.04209  
 FOR INDEPENDENT VARIABLE 3 = .27303

D E P E N D E N T   V A R I A B L E   2

1. REGRESSION EQUATION  

$$Y(2) = 90.22222 + .16189 [ X(1) -11.94444 ] + 1.19570 [ X(2) -42.11111 ] + .11547 [ X(3) -123.00000 ]$$
2. SUM OF CONSTANT TERMS IN ABOVE EQUATION = 23.73373
3. PROPORTION OF VARIANCE EXPLAINED = .63019
4. MULTIPLE CORRELATION COEFFICIENT  
 ADJUSTED FOR DEGREES OF FREEDOM = .74225
5. STANDARD ERROR OF ESTIMATE  
 ADJUSTED FOR DEGREES OF FREEDOM = 16.41213
6. STANDARD PARTIAL REGRESSION COEFFICIENTS  
 FOR INDEPENDENT VARIABLE 1 = .06712  
 FOR INDEPENDENT VARIABLE 2 = .66518  
 FOR INDEPENDENT VARIABLE 3 = .21566

PROGRAM CABLESZ

```

*****
* PROGRAM FOR OBTAINING PALAEO ESTIMATES OF ENVIRONMENTAL *
* CONDITIONS (This is the final stage of computations) *
* Input files: TC-25.DAT (transformed core data) *
* FACRES.25 (factor score matrix) *
* REGRES.25 (regression results) *
* Output file: SEE (palaeo estimates) *
*****
C DIMENSION X(10,47),F(47,3),BC(10,9),ALAB(80),Z(10,6)
  DIMENSION X(10,47),F(47,4),BC(10,14),ALAB(80),Z(10,6)
C DIMENSION COEFF(9,6),BCMEAN(9)
  DIMENSION COEFF(14,6),BCMEAN(14)
  REAL MEAN(6)
  CHARACTER*4 DUMMY
  OPEN(7,FILE='TC-25.DAT',BLANK='ZERO')
  OPEN(8,FILE='FACRES.25',BLANK='ZERO')
  OPEN(10,FILE='REGRES.25',BLANK='ZERO')
  OPEN(9,FILE='SEE')

  READ(7,2)(ALAB(I),I=1,80)
  WRITE(9,2)(ALAB(I),I=1,80)
2  FORMAT(20A4)
  DO I=1,10
  READ(7,71)(X(I,J),J=1,25)
  WRITE(9,101)I,(X(I,J),J=1,25)
  END DO
101 FORMAT(I6,10F10.5/(6X,10F10.5))
C71 FORMAT(10F11.5)
  71 FORMAT(10F7.2)
81 FORMAT(10X,4F11.5)
C DO 11 I=1,10
C SS=0.
C DO 10 J=1,25
C10 SS=SS+X(I,J)**2
C SS=SQRT(SS)
C DO 11 J=1,25
C11 X(I,J)=X(I,J)/SS

  READ(8,2)(ALAB(I),I=1,80)
  WRITE(9,2)(ALAB(I),I=1,80)
  DO I=1,25
  READ(8,81)(F(I,J),J=1,4)
  WRITE(9,101)I,(F(I,J),J=1,4)
  END DO

  DO 21 I=1,10
  DO 21 J=1,4
  BC(I,J)=0.
  DO 21 K=1,25
21 BC(I,J)=BC(I,J)+X(I,K)*F(K,J)

  DO I=1,10
  WRITE(9,101)I,(BC(I,J),J=1,4)
  END DO

  NCOL=4
  DO L=1,4

```

```

DO M=L,4
NCOL=NCOL+1
  DO I=1,10
    BC(I,NCOL)=BC(I,L)*BC(I,M)
  END DO
END DO
END DO

DO I=1,10
WRITE(9,101)I,(BC(I,J),J=1,14)
END DO

DO J=1,6
DO I=1,4
READ(10,'(1A4)')DUMMY
END DO
READ(10,'(20X,F14.5)')MEAN(J)
WRITE(9,1200)J,MEAN(J)
1200 FORMAT(' MEAN VALUE OF',I2,' DEP VARIABLE =',F11.6)
DO I=1,14
READ(10,510)COEFF(I,J),BCMEAN(I)
WRITE(9,510)COEFF(I,J),BCMEAN(I)
BCMEAN(I)=-BCMEAN(I)
END DO
DO I=1,30
READ(10,'(1A4)')DUMMY
END DO
END DO
51 FORMAT(9F11.5)
510 FORMAT(28X,F11.5,10X,F14.5)
DO I=1,10
DO J=1,6
  Z(I,J)=MEAN(J)
  DO K=1,14
    Z(I,J)=Z(I,J)+(BC(I,K)-BCMEAN(K))*COEFF(K,J)
  END DO
END DO
END DO
END DO

```



C TAB F;()1:72

PROGRAM READL

```
*****
* PROGRAM FOR SELECTING DATA IN A SPECIFIED RECTANGLE FROM *
* LEVITUS SEASONAL DATA FILE (TEMPERATURE/ SALINITY) *
* INPUT: Levitus data file copied from tape supplied by NOAA *
* OUTPUT: *.LEV *
* THE FOLLOWING PROGRAMS HAVE TO BE CONSECUTIVELY RUN TO BUILD *
* UP THE TABLE GIVING MODERN ENVIRONMENTAL CONDITIONS AT THE *
* 42 CORE-TOP SITES *
* (1) READL:SYMB ON ND-570, Output *.LEV *
* (2) GETLEV.FOR ON PC, Output *.DAT *
* (3) OBJA4.FOR ON PC, Output *.FAT *
* (4) LEVT2.FOR ON PC, Output DEP2-LEV.DAT *
*****
```

DIMENSION IPAR(24)

CHARACTER\*1 DUMMY

OPEN(7, FILE='(--2:NOR)FER-160-3:DATA', ACCESS='R', BLANK='ZERO')

OPEN(8, FILE='FAL-SAL:LEV', ACCESS='SEQUENTIAL')

OPEN(9, FILE='FER-ERROR-STAT', ACCESS='SEQUENTIAL')

LLH=100

LLL=60

LTH=100

LTL=70

WRITE(8,10)LLH,LLL,LTH,LTL

10 FORMAT(2X,'FALL SALINITY'/

# 2X,'LONGITUDE: LLH=',I5,5X,'LLL=',I5/

# 2X,'LATITUDE : LTH=',I5,5X,'LTL=',I5/

# 2X,'\_\_\_\_\_')

DO FOR I=1,3

READ(7, '(A1)')DUMMY

END DO

WRITE(1,\*)'##'

DO 100 L=1,100000

READ(7,41) (IPAR(K),K=1,11),N1,JLL1,JLT1

WRITE(1,567)L,JLL1,JLT1

READ(7, '(A1)')DUMMY

READ(7, '(A1)')DUMMY

IF(N1.NE.1)CALL ERRORN(L,JLL1,JLT1)

IF(JLL1.GT.LLH)STOP

IF(JLL1.LT.LLL)GO TO 100

IF((JLT1.LT.LTL).OR.(JLT1.GT.LTH))GO TO 100

WRITE(8,42)IPAR(1),N1,JLL1,JLT1

100 CONTINUE

41 FORMAT(14I5)

42 FORMAT(4I5)

567 FORMAT('+ Record No: ',i6,3X,'Long : ',i4,3X,'Lat: ',i4)

200 STOP

END

SUBROUTINE ERRORN(L,JLL1,JLT1)

WRITE(9,10)L,JLL1,JLT1

10 FORMAT(2X,'ERROR IN GRID No.=' ,I6,5X,'JLL=' ,I5,5X,'JLT=' ,I5)

RETURN

END

DO I=1,10

WRITE(9,102)I,(Z(I,J),J=1,6)

END DO

```
102  FORMAT(I6,6F10.3)  
      STOP  
      END
```

C TAB F; ()1:72

PROGRAM GETLEV

```
*****  
* PROGRAM FOR CREATING DATA MATRIX FROM LEVITUS DATA *  
* THE INPUT FOR THIS PROGRAM IS CREATED BY READL:SYMB *  
* THE OUTPUT OF THIS PROGRAM IS INPUT FOR OBJA4.FOR *  
*****
```

CHARACTER\*12 INFIL,OUTFIL,DUMMY

DIMENSION X(31,41)

DO I=1,31

DO J=1,41

X(I,J)=-99.0

END DO

END DO

LLL=60

LLH=100

LTL=70

LTH=100

WRITE(0,111)

111 FORMAT(' Enter input file name: ',§)

READ(0,'(A12)')INFIL

WRITE(0,'(1X,A12)')INFIL

OUTFIL=INFIL(1:7)//'.DAT'

WRITE(0,'(1X,A12)')OUTFIL

OPEN(7,FILE=INFIL,ACCESS='SEQUENTIAL',BLANK='ZERO')

OPEN(8,FILE=OUTFIL,ACCESS='SEQUENTIAL')

INUM=LTH-LTL+1

JNUM=LLH-LLL+1

NREAD=100000

DO I=1,4

READ(7,'(A12)')DUMMY

END DO

DO 6 N=1,NREAD

READ(7,1,END=1000)KDATA,KL1,LL1,LT1

IF(KL1.NE.1)WRITE(0,2)N,KL1

1 FORMAT(4I5)

2 FORMAT(' N= ',I4,5X,'KL1= ',I5)

IF(KDATA.EQ.0) GO TO 6

I=LTH-LT1+1

J=-LLL+LL1+1

X(I,J)=(FLOAT(KDATA))/1000.-10.

6 CONTINUE

1000 CONTINUE

WRITE(8,20)INFIL,LLL,LLH,LTL,LTH

DO I=1,INUM

WRITE(8,10)(X(I,J),J=1,JNUM)

END DO

10 FORMAT(10F7.2)

20 FORMAT('INPUT FILE= ',A12/'LLL= ',I3,5X,'LLH= ',I3/

#'LTL= ',I3,5X,'LTH= ',I3/'#####')

STOP

END

```

PROGRAM OBJA4
*****
* PROGRAM FOR INTERPOLATING MODERN TEMPERATURE AND SALINITY *
* FROM SEASONAL LEVITUS DATA *
*****
DIMENSION GLAT(75),GLON(75),XLAT(100),XLON(100),YY(100),NQ(100)
DIMENSION WM(200),XX(200),X(31,41),ALAB(80)
CHARACTER*11 INFIL,OUTFIL
NK=42
NR=31
NC=41
RR=1.212
NM=4
GLAT0=100.
GLON0=60.
WRITE(0,'(A\)' )' ENTER INPUT FILE NAME: '
READ(0,'(1A11)' )INFIL
OUTFIL=INFIL(1:7)//'.FAT'
WRITE(0,'(1X,1A11)' )OUTFIL
OPEN(3,FILE='SEE')
OPEN(1,FILE='ERR-ST.RES')
OPEN(8,FILE=INFIL,BLANK='ZERO')
READ(8,30)(ALAB(I),I=1,80)
WRITE(3,30)(ALAB(I),I=1,80)
30 FORMAT(20A4)
DO I=1,NR
READ(8,40)(X(I,J),J=1,NC)
WRITE(3,40)(X(I,J),J=1,NC)
END DO
40 FORMAT(10F7.2)
OPEN(7,FILE='LAT-LON.DAT',BLANK='ZERO')
READ(7,30)(ALAB(I),I=1,80)
WRITE(3,30)(ALAB(I),I=1,80)
DO K=1,NK
READ(7,50)KG,XLAT(K),XLON(K)
WRITE(3,50)KG,XLAT(K),XLON(K)
IF(KG.NE.K)WRITE(0,90)K
END DO
90 FORMAT(' ERROR IN LAT-LONG # No: ',I2)
50 FORMAT(I2,2F10.3)
DO I=1,NR
GLAT(I)=GLAT0-(I-1)-90.5
END DO
DO J=1,NC
GLON(J)=GLON0+(J-1)-0.5
END DO

DO K=1,NK
DO J=2,NC

IF(XLON(K).LT.GLON(J))THEN
JJ=J
GO TO 100
END IF
END DO
100 CONTINUE
IF(XLON(K).LT.GLON(1).OR.XLON(K).GE.GLON(NC))THEN
WRITE(1,10)K,XLAT(K),XLON(K)

```

```

END IF

DO I=2,NR

IF (XLAT(K) .GT. GLAT(I)) THEN
II=I
GO TO 200
END IF
END DO
200 CONTINUE
IF (XLAT(K) .GT. GLAT(1) .OR. XLAT(K) .LE. GLAT(NR)) THEN
WRITE(1,20) K, XLAT(K), XLON(K)
END IF

10 FORMAT(2X, 'POINT No =', I2, 3X, 'LAT =', F7.2, 3X, 'LONG =', F7.2, 3X,
# 'IS OUTSIDE LONGITUDE BOUNDS')
20 FORMAT(2X, 'POINT No =', I2, 3X, 'LAT =', F7.2, 3X, 'LONG =', F7.2, 3X,
# 'IS OUTSIDE LATITUDE BOUNDS')

IP1=II+NM
IM1=II-NM
IM1I=0
IP1I=0
IF (IM1 .LT. 1) THEN
IM1=1
IM1I=1
END IF
IF (IP1 .GT. NR) THEN
IP1=NR
IP1I=1
END IF

JP1=JJ+NM
JM1=JJ-NM
JM1J=0
JP1J=0
IF (JM1 .LT. 1) THEN
JM1=1
JM1J=1
END IF
IF (JP1 .GT. NC) THEN
JP1=NC
JP1J=1
END IF

ICOUNT=1
C WRITE(3,*) ' IM1, IP1=', IM1, IP1
C WRITE(3,*) ' JM1, JP1=', JM1, JP1
WRITE(3,92)
92 FORMAT('No', T10, 'DIST', T20, 'WT', T28, 'VAL')
DO 1000 I=IM1, IP1
DO 2000 J=JM1, JP1
IF (X(I, J) .LT. -98.) GO TO 2000
XLATK=XLAT(K)
XLONK=XLON(K)
GLATI=GLAT(I)
GLONJ=GLON(J)
RMIC=DIST(XLATK, XLONK, GLATI, GLONJ)

```

```

IF(RMIC.GT.RR) GO TO 2000
  PIC=X(I,J)
  WM(ICOUNT)=1./RMIC**2
  WRITE(3,91) ICOUNT,RMIC,WM(ICOUNT),PIC
  XX(ICOUNT)=X(I,J)
  ICOUNT=ICOUNT+1
2000 CONTINUE
1000 CONTINUE
91  FORMAT(I2,3X,F7.2,F10.3,F7.2)
  ICOUNT=ICOUNT-1
  NQ(K)=ICOUNT
  YY(K)=OBJ(WM,XX,ICOUNT)
  WRITE(3,80) XLON(K),XLAT(K),YY(K),K,NQ(K)
  END DO
  OPEN(4,FILE=OUTFIL)
  DO K=1,NK
  WRITE(4,80) XLON(K),XLAT(K),YY(K),K,NQ(K)
  END DO
80  FORMAT(3F7.2,2I7)
  STOP
  END
  FUNCTION DIST(X1,Y1,X2,Y2)
  DIST=SQRT((X1-X2)**2+(Y1-Y2)**2)
  RETURN
  END
  FUNCTION OBJ(WM,XX,ICOUNT)
  DIMENSION WM(200),XX(200)
  WTT=0.
  XTT=0.
  DO N=1,ICOUNT
  WTT=WTT+WM(N)
  XTT=XTT+WM(N)*XX(N)
  END DO
  OBJ=XTT/WTT
  RETURN
  END

```

```

PROGRAM LEVT2
*****
* PROGRAM FOR ASSIMILATING MODERN ENVIRONMENTAL CONDITIONS*
* INPUT FOR THIS PROGRAM IS OUTPUT OF OBJA4.FOR *
*****
DIMENSION X(6)
CHARACTER*80 DUMMY
OPEN(2,FILE='FAL-SAL.FAT',BLANK='ZERO')
OPEN(3,FILE='SPR-SAL.FAT',BLANK='ZERO')
OPEN(4,FILE='DEP2-VAR.DAT',BLANK='ZERO')
OPEN(5,FILE='FAL-TEM.FAT',BLANK='ZERO')
OPEN(6,FILE='SPR-TEM.FAT',BLANK='ZERO')
OPEN(7,FILE='DEP2-LEV.DAT')
DO I=1,4
READ(4,'(1A80)')DUMMY
WRITE(7,'(1A80)')DUMMY
END DO
10 FORMAT(16X,F5.2)
20 FORMAT(18X,2F9.3)
DO I=1,42
READ(2,10)X(1)
READ(3,10)X(2)
READ(4,20)X(3),X(4)
READ(5,10)X(5)
READ(6,10)X(6)
WRITE(7,'(6F9.2)')(X(K),K=1,6)
END DO
STOP
END

```