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GEOCHEMICAL APPLICATIONS OF LINEAR
PROGRAMMING

by

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SUMMARY

Rock compositions may be expressed in terms of non-negative proportions of end-members by use of linear programming methods, in which one maximises the sum of these proportions; linear programming may in many cases be a preferable alternative to both Q-mode factor analysis (in which end-member proportions are not constrained to non-negative values) and traditional norm computation (where linear programming has the advantage of generality).

A general purpose computer program has been written to do this, with an option to identify, iteratively, the most divergent rock compositions from within the data matrix, and include them as additional end-members. KEY WORDS: linear programming, geochemistry, norm computation, factor analysis.

INTRODUCTION

Linear programming is used to optimize linear functions where the variables are subject to a number of linear constraints (inequalities). In general, one seeks to maximize z , given by the relation:

$$z = c_1x_1 + c_2x_2 + c_3x_3 + \dots + c_nx_n,$$

subject to the constraints $x_i \geq 0$ and

$$a_{11}x_1 + a_{12}x_2 + \dots + a_{1n}x_n \leq b_1$$

$$a_{21}x_1 + a_{22}x_2 + \dots + a_{2n}x_n \leq b_2$$

.....

$$a_{m1}x_1 + a_{m2}x_2 + \dots + a_{mn}x_n \leq b_m,$$

where a_{ij} , b_i , and c_j are given constants (Harbaugh & Bonham-Carter, 1970).

Frequently in geochemical and petrological studies, we wish to characterize a rock as a mixture of 'end-member' compositions, which may be idealized mineral compositions, as in norm computation, or extreme rock compositions or hypothetical rock compositions as in Q-mode factor analysis (Imbrie, 1963). In each case, a number of constraints are implied in the model. If one considers a chemical analysis of m elements, of which the i th element gives a percentage value p_i , and one wishes to split the observed composition into proportions x_j of n end-members, each of composition given by a vector of percentage values a_{ij} , the situation will fit the general case by substitution p for b , and setting $c_j = 1$. Each constraint,

$$a_{i1}x_1 + a_{i2}x_2 + \dots + a_{in}x_n \leq p_i,$$

has the simple meaning that the sum of contributions to each variable by each end-member cannot exceed the observed value of that variable: i.e., end-member scores must be non-negative, and the 'error' term, given by

$$e_i = p_i - \sum_{j=1}^n a_{ij}x_j$$

must also be non-negative - This contrasts with normal multivariate techniques, such as least-squares optimization, where the error term is allowed to take negative values. There is one additional constraint, since

$$1x_1 + 1x_2 + \dots + 1x_n \leq 1.0,$$

the sum of proportions of end-members cannot exceed 1. Normally, with linearly independent end-members, this constraint is superfluous and may be ignored, but in badly formulated problems containing redundant variables, and in norm calculations involving extensive mineral lists, it would be advisable to include this constraint in the formulation of the problem.

SIMPLEX SOLUTION OF LINEAR PROGRAMMING PROBLEMS

This method is described in practical detail by Harbaugh & Bonham-Carter (1970) and, as the explanations involved are rather complicated the reader is commended to their excellent treatment, and also to the account by Vajda (1961). Harbaugh & Bonham-Carter present a FORTRAN computer program for solution of linear programming problems, and this has been modified (Appendix 1) for application to problems of rock chemistry.

TWO-COMPONENT EXAMPLE

Consider that one has obtained a number of chemical analyses within the K-Al-Si-O system and wishes to express the data in terms of quartz and kaliophyllite. Two end-member vectors could be set up as follows:

	Q	Kp
Si	33.33	14.29
Al	0	14.29
K	0	14.29
O	66.67	57.14

A sample with a composition corresponding to orthoclase could then be allotted a position between the two, and expressed in terms of proportions of Q and Kp. Since negative proportions are disallowed, one may write the following inequalities:

$$33.33p_q + 14.29p_{kp} \leq 23.08 \quad (\text{Si})$$

$$Op_q + 14.29p_{kp} \leq 7.69 \quad (\text{Al})$$

$$Op_q + 14.29p_{kp} \leq 7.69 \quad (\text{K})$$

$$66.67p_q + 57.14p_{kp} \leq 61.65 \quad (\text{O})$$

The sum of p_q and p_{kp} cannot exceed 1, and thus one may write a further inequality:

$$1p_q + 1p_{kp} \leq 1$$

By application of the simplex method to maximize the objective function,

$$z = p_q + p_{kp},$$

one immediately finds that $z_{\max} = 1$, $p_q = 0.40$ and $p_{kp} = 0.60$. Since only two end-members are involved, this solution can be represented graphically in two-dimensional space (Fig. 1), which may clarify a little the principles of linear programming.

NORM COMPUTATION

The essence of norm calculation is the transformation of a chemical analysis vector by a mineral composition matrix to a vector of mineral proportions. Expressed in these terms, it becomes somewhat analogous to factor analysis, since in both methods one is attempting to transform a set of observations into a set of more readily interpretable variables. Computer programs for norm computation do not normally reflect this theoretical simplicity, however, being generally rather long and untidy, due to the many 'special cases' which must be allowed for (e.g., the problem of partitioning iron and magnesium among the femic minerals). Most of the constraints in norm computation are linear, and thus one may use linear programming methods of solution. In simple cases, where partitioning problems do not arise and mineral compositions are linearly independent, the general model will invariably give correct results, but attempts to apply it to more complex problems may lead either to incorrect results, or to cyclic solutions (Beale, 1954), in which there is no decision among several incorrect results.

When pairs of solid solution series are involved, it is possible to set up additional constraints concerning them. To consider the case of coexisting orthopyroxene and olivine, let the molar percentages of MgSiO_3 and FeSiO_3 be x_{en} and x_{fs} respectively, and the percentages of Mg_2SiO_4 and Fe_2SiO_4 be x_{fo} and x_{fa} . Also let the ratios of Mg to Fe in the two minerals be equal. Then

$$x_{\text{en}}/x_{\text{fs}} = x_{\text{fo}}/x_{\text{fa}} = r,$$

where r is the ratio Mg/Fe .

This equality may be expressed as two constraints:

$$x_{\text{en}} - rx_{\text{fs}} = 0$$

$$x_{\text{fo}} - rx_{\text{fa}} = 0$$

If olivine and pyroxene are the only normative minerals containing iron and magnesium, r may be computed beforehand and these constraints applied directly (by use of the 'Big M' method - Harbaugh & Bonham-Carter, 1970). However, the presence of any minerals in which iron and magnesium are treated separately (e.g. pyrite, dolomite) invalidates this approach, as the proportions of residual Fe and Mg cannot be determined beforehand. It is possible to remove r from the constraints by a rearrangement of the equations, but the resulting constraint,

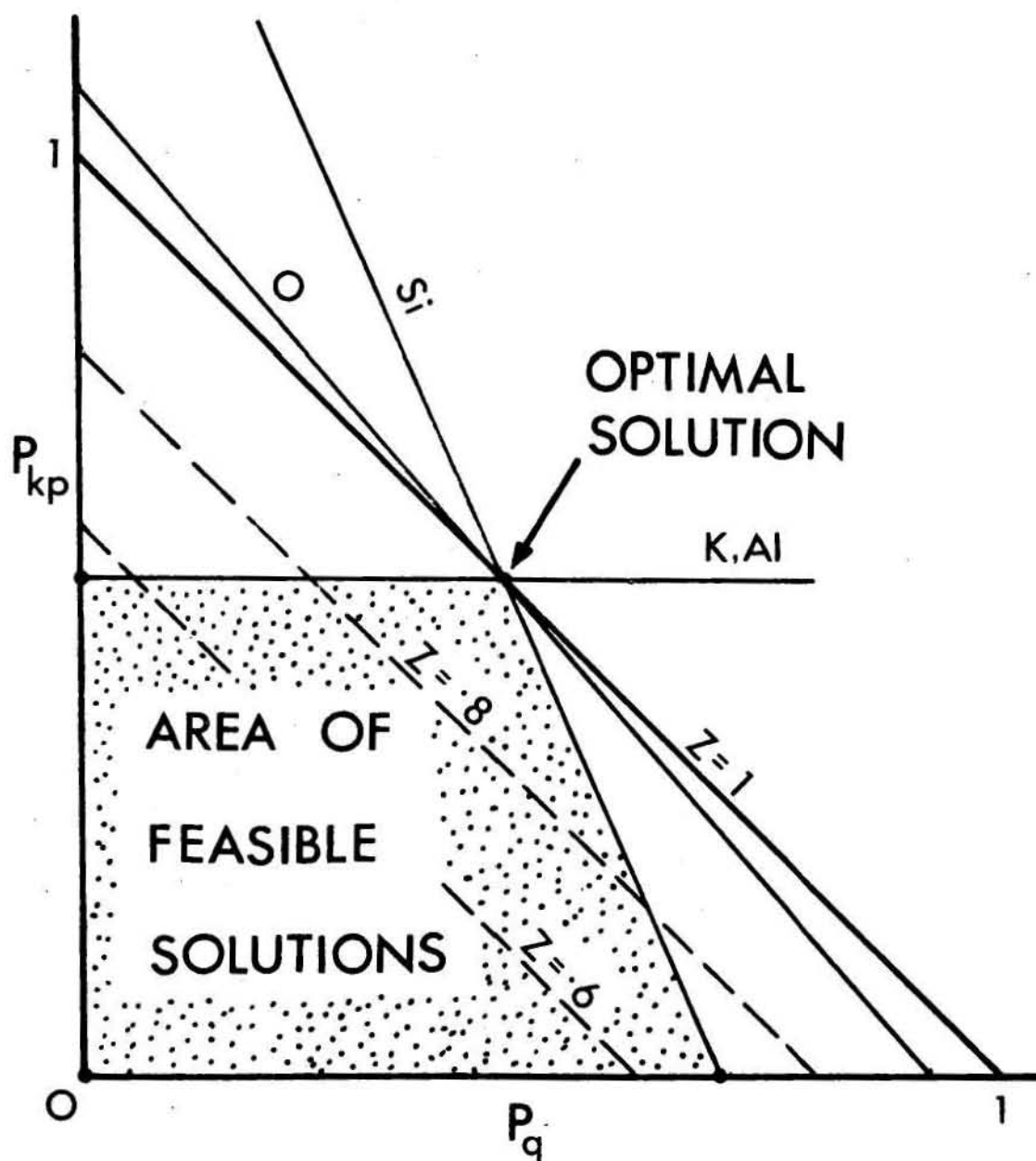
$$x_{\text{en}}x_{\text{fa}} = x_{\text{fs}}x_{\text{fo}},$$

is nonlinear, and thus linear programming methods can no longer be used.

If such a case arises, it might be possible to remove the constituents containing Fe and Mg alone or in fixed ratios first, then compute r and carry out the main part of the norm computation. If this is not possible, one could resort to more sophisticated programming methods (e.g., dynamic programming), or return to the specialised forms of norm computation. Despite this disadvantage of such a generalised method, its great advantage over the traditional types of norm computation lies in the variety of mineral end-members which one may incorporate into the problem without alteration of the computer program.

FIGURE 1. Representation of orthoclase as molar proportions of quartz (q) and kaliophyllite (kp). The sum of p_q and p_{kp} cannot exceed 1; thus the objective function $z = p_q + p_{kp} \leq 1$ is one constraint. Additional constraints are imposed by the relative proportions of the analysed elements in the minerals. e.g. the sum of $p_q Si_q$ and $p_{kp} Si_{kp}$ cannot exceed $Si_{or} = 23.08$.

These constraints, together with the requirement that all values be non-negative, define a field (stippled) of feasible solutions. The optimal solution is that in which $z = p_q + p_{kp}$ is maximised.



LINEAR PROGRAMMING AND FACTOR ANALYSIS

The factor analysis model (Harman, 1967) may be defined as:

$$z_{ji} = \sum_{p=1}^m a_{jp} F_{pi} + d_j U_{ji},$$

where z is the value of variable j for individual or sample i , and each of the m terms $a_{jp} F_{pi}$ represents the contribution of the corresponding factor to the value of z_{ji} , while $d_j U_{ji}$ is the 'residual error' in the theoretical representation of z_{ji} . The F 's and U 's are usually taken to be linearly independent, and are assumed to have zero means and unit variances; thus in any individual sample, the term containing U could take a negative value, so that no physical significance can be ascribed to the solution unless (as is often the case) one assumes that U_{ji} approximates to zero.

By re-definition of all the components of a , F , and U as non-negative (a reasonable definition in view of the fact that we are dealing with a set of non-negative observations), one may re-write the model as an inequality:

$$z_{ji} \geq \sum_{p=1}^m a_{jp} F_{pi},$$

leading to a set of constraints in a model in which one seeks to maximize $\sum_{p=1}^m F_{pi}$.

PSEUDO FACTOR ANALYSIS

Q-mode factor analysis, as carried out by Imbrie (1963), involves the selection of the most divergent rock compositions from a data matrix, followed by computation of the relative proportions (scores) of these hypothetical end-members in each sample.

Definition of the most divergent compositions is an area in which linear programming appears at first sight to be of little relevance. However, one may adopt an iterative approach, by first selecting a single end-member, in which, for example, the variable of highest variance (e.g. silica) has

maximum (or minimum) value. Applying linear programming methods to a set of analyses, one may now select the sample with poorest fit to the chosen composition, to become the second end-member. And so the process might continue, obtaining as many end-members as desired, to a maximum of m (the number of variables).

A computer program has been developed to carry out this type of analysis, and a listing, together with a worked example, is included in Appendices B and C. Operating instructions are given in Appendix A.

LIMITATIONS

Apart from the limitations of the method with respect to norm calculation, discussed above, linear programming suffers perhaps by being principally a deterministic technique, though Vajda (1961) has discussed 'stochastic linear programming' in which one assumes that the constants (or 'technological coefficients' as they are termed by Vajda) are random variables.

The main difficulties in introducing random variables concern the estimation of type and parameters of the distribution function of the objective function optimum. The method used in the present paper has been based on Madansky's (1960) 'Wait-and-See' principle, by which one does not try to estimate the distribution parameters, but simply takes the available observation (or waits for an observation) and solves the non-stochastic linear programming problem resulting.

POSSIBLE APPLICATIONS

The use of linear programming techniques has the virtue of generality, compared with classical methods of norm computation: empirical mineral compositions may be slotted in as required, without the necessity of writing a special computer program for each.

Further uses might be seen in the realms of experimental geochemistry (construction of phase diagrams, etc.), and in studies of magmatic differentiation, metasomatism, sedimentology, and ore-deposit paragenesis.

An interesting application might be the calculation of ternary diagram co-ordinates. Apart from the conventional triangular diagram, one could also envisage a diagram with two components plus an 'unknown' or 'remainder' component. In Fig. 1, for example, one might plot the optimal points for a number of samples in the triangle defined by 1.0q, 1.0kp, and the origin, which represents simply zero quartz, plus zero kaliophyllite, plus 100% of something else. Such a plot could be useful in studies of contamination of igneous rocks, or in economic geochemical surveys (analogous to the communality maps recommended by Krumbein & Graybill, 1965).

ACKNOWLEDGMENTS

The ideas developed in this paper were inspired by Harbough & Bonham-Carter (1971). The CSIRO CDC 3600 computer was used for development of the program.

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APPENDIX 1

PROGRAM ENDMEM : OPERATING INSTRUCTIONS, LISTING, AND SAMPLE OUTPUT.

1) Operating instructions

The data input format has been kept as simple as possible, but the user can easily include additional options if desired.

Card 1: Variable format card for input of analytical data. It consists of a FORTRAN format definition, in brackets, allowing an initial alphanumeric field for identification, e.g. (A8, 2X, 14F4.2).

Card 2: Columns 1-3 (right-justified) M, the number of variables.

4-6 (right-justified) N, the number of end-members supplied.

N may be punched as a negative number, in which case -N end-members are supplied, and additional end-members are extracted from the data matrix until every sample composition is accounted for to at least TOL percent (set at 95 at present) by linear combinations of the end-members.

Cards 3 to N + 2 (or -N + 2): End-member compositions in the format specified on card 1.

Cards N + 3 (or -N + 3) onward: Data cards in the format specified on card 1.

Last card: End-of-file marker; format of this card will vary with the computer system; the CDC3600 format is ⁸₇EOF.

	PROGRAM ENDMEM	ENDM0001
	DIMENSION KEYS(50),SCORES(200,50),PROP(200),ID(20),EM(70,50),X(71	ENDM0002
),EMM(70,50),XX(20,200),IDXX(200),FMT(10)	ENDM0003
	COMMON/KQZCOM/KQZSRX,KQZB00,KQZB06	ENDM0004
C		ENDM0005
C	WRITTEN BY S. HENLEY BMR 1972	ENDM0006
C		ENDM0007
C	CONVERTED AUTOMATICALLY TO ANSI FORTRAN FROM CDC3600 FORTRAN	ENDM0008
C		ENDM0009
C	SEPARATES A ROCK ANALYSIS INTO A SET OF END-MEMBERS BY THE SIMPLEX	ENDM0010
C	METHOD OF LINEAR PROGRAMMING IN SUCH A WAY AS TO MAXIMISE THE SUM	ENDM0011
C	OF PROPORTIONS OF THE END-MEMBERS,	ENDM0012
C	OPTIONALLY, SUBSEQUENT END-MEMBERS (MOST DIVERGENT COMPOSITIONS	ENDM0013
C	WITHIN THE DATA SET) MAY BE IDENTIFIED AND INCLUDED IN FURTHER	ENDM0014
C	ANALYSIS.	ENDM0015
C		ENDM0016
C		ENDM0017
20	FORMAT(10A8)	ENDM0018
	KQZB00#32	ENDM0019
	KQZB06#8	ENDM0020
	READ(5,20) FMT	ENDM0021
	READ(5,170) M,N	ENDM0022
	NS=0	ENDM0023
	MM=M+1	ENDM0024
	NUMBER=0	ENDM0025
	NUMCYC=0	ENDM0026
	LL=0	ENDM0027
	IF(N.GT.0) GOTO 160	ENDM0028
	N=N	ENDM0029
	LL=1	ENDM0030
	TOL=.95,C	ENDM0031
	X(71)=0.0	ENDM0032
160	CONTINUE	ENDM0033
170	FORMAT(2I3)	ENDM0034
	IF(1.GT.N) GOTO 189	ENDM0035
	DO 188 I=1,N	ENDM0036
	EM(MM,I)=1.0	ENDM0037
	READ(5,FMT) ID(I),(EM(J,I),J=1,M)	ENDM0038
188	CONTINUE	ENDM0039
189	CONTINUE	ENDM0040
210	CONTINUE	ENDM0041
	X(MM)=1.0	ENDM0042
	IF(LL.EQ.1.AND.NUMCYC.GT.0) GOTO 270	ENDM0043
	READ(5,FMT) IDX,(X(I),I=1,M)	ENDM0044
	CALL KQZEOF(5)	ENDM0045
	GOTO(490,300),KQZSBX	ENDM0046
270	NIM=NUMBER+1	ENDM0047
	IF(1.GT.M) GOTO 289	ENDM0048
	DO 288 I=1,M	ENDM0049
	X(I)=XX(I,NIM)	ENDM0050
288	CONTINUE	ENDM0051
289	CONTINUE	ENDM0052
300	CONTINUE	ENDM0053
	IF(NUMCYC.GE.1) GOTO 370	ENDM0054
	NIM=NUMBER+1	ENDM0055
	IDXX(NIM)=IDX	ENDM0056
	IF(1.GT.M) GOTO 359	ENDM0057
	DO 358 I=1,M	ENDM0058
	XX(I,NIM)=X(I)	ENDM0059
358	CONTINUE	ENDM0060
359	CONTINUE	ENDM0061
370	IF(1.GT.N) GOTO 379	ENDM0062

	DO 378 I=1,N	ENDMU0063
	IF(1,GT,MM) GOTO 389	ENDMU0064
	DO 388 J=1,MM	ENDMU0065
	EMM(J,I)=EM(J,I)	ENDMU0066
386	CONTINUE	ENDMU0067
389	CONTINUE	ENDMU0068
378	CONTINUE	ENDMU0069
379	CONTINUE	ENDMU0070
	CALL SIMLEX(X,EMM,MM,N,KEYS,OBJFUN)	ENDMU0071
	NUMBER=NUMBER+1	ENDMU0072
	PROP(NUMBER)=OBJFUN*100,0	ENDMU0073
	IF(1,GT,N) GOTO 439	ENDMU0074
	DO 438 I=1,N	ENDMU0075
	IF(KEYS(I),LT,1) GOTO 470	ENDMU0076
	KQZ001=KEYS(I)	ENDMU0077
	SCORES(NUMBER,I)=X(KQZ001)	ENDMU0078
470	CONTINUE	ENDMU0079
438	CONTINUE	ENDMU0080
439	CONTINUE	ENDMU0081
	IF(.NOT.(NUMBER,EQ,NS)) GOTO 210	ENDMU0082
490	CONTINUE	ENDMU0083
	NS=NUMBER	ENDMU0084
	WRITE(6,720)	ENDMU0085
	PMIN=100,1	ENDMU0086
	IF(1,GT,NUMBER) GOTO 539	ENDMU0087
	DO 538 I=1,NUMBER	ENDMU0088
	IF(PMIN,LT,PROP(I)) GOTO 580	ENDMU0089
	PMIN=PROP(I)	ENDMU0090
	NMIN=I	ENDMU0091
580	CONTINUE	ENDMU0092
	WRITE(6,730) IDXX(I),PROP(I),(SCORES(I,J),J=1,N)	ENDMU0093
538	CONTINUE	ENDMU0094
539	CONTINUE	ENDMU0095
	IF(11,EQ,0.OR,PMIN,GT,TOL) GOTO 750	ENDMU0096
	NIM=NMIN	ENDMU0097
	WRITE(6,740) NIM,PMIN	ENDMU0098
	N=N+1	ENDMU0099
	IF(1,GT,M) GOTO 669	ENDMU0100
	DO 668 I=1,M	ENDMU0101
	EM(I,N)=XX(I,NIM)	ENDMU0102
668	CONTINUE	ENDMU0103
669	CONTINUE	ENDMU0104
	EM(MM,N)=1.0	ENDMU0105
	NUMBER=0	ENDMU0106
	NUMCYC=NUMCYC+1	ENDMU0107
	GOTO 210	ENDMU0108
720	FORMAT(8H1SUMMARY,8H OF SIMP,8HLEX L.P.,8H CLASSIF,7HICATION//	ENDMU0109
	,8H0SAMPLE ,8H PERCENT,6H ACCTD,7X,8HPROPORTI,8HONS OF E,	ENDMU0110
	,8HND-MEMBE,2HRS)	ENDMU0111
730	FORMAT(1H ,AB,F10,2,10X,10F10,4,(/29X,10F10,4))	ENDMU0112
740	FORMAT(8H0 SAMPLE,14,8H SELECT,8HED AS NE,8HXT EVD=M,5HMEMBER/	ENDMU0113
	,8H PERCENT,8HT ACCOUN,8HTED FOR ,8HBY EXIST,8HING END-,8HMEMBERS	ENDMU0114
	,,2HIS,F10,2)	ENDMU0115
750	CALL EXIT	ENDMU0116
	END	ENDMU0117
	SUBROUTINE SIMLEX(RTSID,COEF,MM,NN,KEYS,OBJFUN)	SIMP0001
	DIMENSION COEF(70,50),WEIGHT(70),IBASIC(50),RTSID(70),KEYS(50)	SIMP0002
	COMMON/KQZCOM/KQZSRX,KQZB00,KQZB06	SIMP0003
C		SIMP0004
CSIMPLEX METHOD OF LINEAR PROGRAMMING	SIMP0005
C	PROGRAM FROM HARBAUGH AND BONHAM-CARTER , COMPUTER SIMULATION IN	GSIMP0006
C	MODIFIED BY S. HENLEY FOR USE AS AN OPTIMISATION SUBROUTINE IN	SIMP0007
C	PROGRAM ENDMEM	SIMP0008

	NVAR=NN	SIMP0009
	NEQU=MM	SIMP0010
	IF(1,GT,NN) GOTO 49	SIMP0011
	DO 48 I=1,NN	SIMP0012
	KEYS(I)=0	SIMP0013
	WEIGHT(I)=-1,0	SIMP0014
48	CONTINUE	SIMP0015
49	CONTINUE	SIMP0016
	OBJFUN=0,0	SIMP0017
	IF(1,GT,MM) GOTO 89	SIMP0018
	DO 88 I=1,MM	SIMP0019
	MI=I+NN	SIMP0020
	IF(1,GT,MM) GOTO 109	SIMP0021
	DO 108 J=1,MM	SIMP0022
	COEF(J,MI)=0,0	SIMP0023
108	CONTINUE	SIMP0024
109	CONTINUE	SIMP0025
	COEF(I,MI)=1,0	SIMP0026
	KEYS(MI)=I	SIMP0027
	IBASIC(I)=MI	SIMP0028
88	CONTINUE	SIMP0029
89	CONTINUE	SIMP0030
	NVAR=MI	SIMP0031
	NTIM=25	SIMP0032
	IF(1,GT,NTIM) GOTO 259	SIMP0044
	DO 258 NT=1,NTIM	SIMP0045
	SMALL1=WEIGHT(1)	SIMP0046
	JENTER=1	SIMP0047
	IF(2,GT,NVAR) GOTO 289	SIMP0048
	DO 288 J=2,NVAR	SIMP0049
	IF(WEIGHT(J),GE,SMALL1) GOTO 330	SIMP0050
	SMALL1=WEIGHT(J)	SIMP0051
	JENTER=J	SIMP0052
330	CONTINUE	SIMP0053
288	CONTINUE	SIMP0054
289	CONTINUE	SIMP0055
	SMALL2=9999999,9	SIMP0056
	IF(1,GT,NEQU) GOTO 359	SIMP0057
	DO 358 I=1,NEQU	SIMP0058
	IF(COEF(I,JENTER),LE,0,000) GOTO 430	SIMP0059
	RATIO=RTSID(I)/COEF(I,JENTER)	SIMP0060
	IF(RATIO,GE,SMALL2) GOTO 430	SIMP0061
	SMALL2=RATIO	SIMP0062
	ILEAVE=I	SIMP0063
430	CONTINUE	SIMP0064
358	CONTINUE	SIMP0065
359	CONTINUE	SIMP0066
	JLEAVE=IBASIC(ILEAVE)	SIMP0067
	IF(SMALL2,GT,11111,1,OR,SMALL1,GE,0,0) GOTO 670	SIMP0068
	CON=COEF(ILEAVE,JENTER)	SIMP0069
	IF(1,GT,NVAR) GOTO 489	SIMP0070
	DO 488 J=1,NVAR	SIMP0071
	COEF(ILEAVE,J)=COEF(ILEAVE,J)/CON	SIMP0072
488	CONTINUE	SIMP0073
489	CONTINUE	SIMP0074
	RTSID(ILEAVE)=RTSID(ILEAVE)/CON	SIMP0075
	IF(1,GT,NEQU) GOTO 519	SIMP0076
	DO 518 I=1,NEQU	SIMP0077
	IF(I,EQ,ILEAVE) GOTO 580	SIMP0078
	CON=COEF(I,JENTER)	SIMP0079
	IF(1,GT,NVAR) GOTO 559	SIMP0080
	DO 558 J=1,NVAR	SIMP0081
		SIMP0082

	COEF(I,J)=COEF(I,J)-CON*COEF(ILEAVE,J)	SIMP0083
558	CONTINUE	SIMP0084
559	CONTINUE	SIMP0085
	RTSID(I)=RTSID(I)-CON*RTSID(ILEAVE)	SIMP0086
580	CONTINUE	SIMP0087
518	CONTINUE	SIMP0088
519	CONTINUE	SIMP0089
	CON=WEIGHT(JENTER)	SIMP0090
	IF(1,GT,NVAR) GOTO 609	SIMP0091
	DO 608 J=1,NVAR	SIMP0092
	WEIGHT(J)=WEIGHT(J)-CON*COEF(ILEAVE,J)	SIMP0093
608	CONTINUE	SIMP0094
609	CONTINUE	SIMP0095
	OBJFUN=OBJFUN-CON*RTSID(ILEAVE)	SIMP0096
	KEYS(JENTER)=ILEAVE	SIMP0097
	IBASIC(ILEAVE)=JENTER	SIMP0098
258	CONTINUE	SIMP0099
259	CONTINUE	SIMP0100
	GOTO 690	SIMP0101
670	CONTINUE	SIMP0102
690	RETURN	SIMP0103
	END	SIMP0104

3) Output

Major element data on 24 altered clastic sediments from the Holywell Bay - Mitchell area of Cornwall were supplied. One sample, a highly siliceous sandstone, chosen for its dissimilarity with the other 23 rocks, was used as the first end-member. The second sample, 165, is the rock differing most from the first, being a slate containing much basic tuffaceous material. The third sample extracted by the program, is again an unusual rock, being a metasomatised slate with 12.8% K_2O and 27% Al_2O_3 . Original analyses may be seen in Henley, 1970 (PhD thesis, University of Nottingham) or will be sent, on request to the author.

SUMMARY OF SIMPLEX L.P. CLASSIFICATION

SAMPLE	PERCENT ACCTD	PROPORTIONS OF END-MEMBERS
101	65.34	0.6534
136	64.86	0.6486
137	56.76	0.5676
155	74.21	0.7421
156	85.09	0.8509
157	66.67	0.6667
158	70.84	0.7084
159	58.33	0.5833
160	66.67	0.6667
161	72.94	0.7294
162	71.57	0.7157
163	38.89	0.3889
164	70.07	0.7007
165	18.63	0.1863
181	69.38	0.6938
182	71.72	0.7172
183	74.81	0.7481
192	78.27	0.7827
193	78.40	0.7840
194	75.15	0.7515
197	76.58	0.7658
198	77.27	0.7727
199	66.67	0.6667

SAMPLE 14. SELECTED AS NEXT END-MEMBER
 PERCENT ACCOUNTED FOR BY EXISTING END-MEMBERS IS 18.63

SUMMARY OF SIMPLEX L.P. CLASSIFICATION

SAMPLE	PERCENT ACCTD	PROPORTIONS OF END-MEMBERS	
101	65.36	0.6530	0.0006
136	64.86	0.6486	0.0000
137	56.76	0.5676	0.0000
155	75.68	0.7178	0.0390
156	87.60	0.8091	0.0669
157	66.67	0.6667	0.0000
158	71.82	0.6919	0.0264
159	58.33	0.5833	0.0000
160	66.67	0.6667	0.0000
161	83.60	0.5521	0.2839
162	77.93	0.6100	0.1693
163	38.89	0.3889	0.0000
164	80.62	0.5252	0.2811
165	100.00	0.0000	1.0000
181	70.92	0.6681	0.0410
182	80.61	0.5692	0.2369
183	85.01	0.5784	0.2718
192	85.32	0.6653	0.1879
193	78.75	0.7783	0.0091
194	80.88	0.6561	0.1527
197	83.69	0.6476	0.1893
198	79.21	0.7404	0.0518
199	66.67	0.6667	0.0000

SAMPLE 12 SELECTED AS NEXT END-MEMBER
 PERCENT ACCOUNTED FOR BY EXISTING END-MEMBERS IS 38.89

SUMMARY OF SIMPLEX L.P. CLASSIFICATION

SAMPLE	PERCENT ACCTD	PROPORTIONS OF END-MEMBERS		
101	77.03	0.4242	0.0005	0.3456
136	64.86	0.6486	0.0000	0.0000
137	56.76	0.5676	0.0000	0.0000
155	78.77	0.6188	0.0347	0.1536
156	93.25	0.7563	0.0593	0.0969
157	67.39	0.6522	0.0000	0.0217
158	76.80	0.5945	0.0263	0.1472
159	69.68	0.5112	0.0000	0.1856
160	72.00	0.5600	0.0000	0.1599
161	85.68	0.5110	0.2811	0.0647
162	83.58	0.4819	0.2112	0.1538
163	100.00	0.0000	0.0000	1.0000
164	85.64	0.4261	0.2744	0.1558
165	100.00	0.0000	1.0000	0.0000
181	78.87	0.5123	0.0410	0.2353
182	90.10	0.3833	0.2368	0.2809
183	89.23	0.4951	0.2662	0.1311
192	92.73	0.5190	0.1780	0.2303
193	85.86	0.6390	0.0091	0.2106
194	86.71	0.5411	0.1450	0.1809
197	93.52	0.4534	0.1763	0.3056
198	85.74	0.6124	0.0517	0.1933
199	73.84	0.5232	0.0000	0.2151

SAMPLE 3 SELECTED AS NEXT END-MEMBER

PERCENT ACCOUNTED FOR BY EXISTING END-MEMBERS IS 56.76