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A COMPARISON OF SYNOPTIC CLASSIFICATION SCHEMES BASED ON 'OBJECTIVE' PROCEDURES

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ABSTRACT

Various 'objective' methods of classifying the atmospheric circulation are compared in order to determine whether the different methods result in similar groupings of circulation types, and also to examine the question of how much subjectivity is present in each of the typing schemes. The results indicate a high degree of subjectivity within each approach and that the different classification schemes do give rise to the production of different synoptic types. A method which groups days based on the sum of squares difference between cases (Kirchhofer method) gives the best overall classification, but only classifies 80 per cent of the days. A technique that clusters days based on principal component scores gives a larger mean sum of squares difference between the type patterns and the individual cases, but classifies all of the days.

KEY WORDS Synoptic climatology Objective typing schemes

1. INTRODUCTION

Synoptic typing schemes have long been used as a descriptive tool for summarizing typical modes of the atmospheric circulation associated with a particular region. Synoptic typing schemes also offer the potential for reducing data volumes, provide a framework for the grouping/analysis of other surface and atmospheric parameters, where their occurrence is related to the atmospheric circulation, and may be of use for statistical prediction of circulation patterns.

An historical overview of the development of synoptic typing methods is given by Barry and Perry (1973), updated in short progress reports by Barry (1980) and Perry (1983). Early schemes were essentially subjective in nature, grouping days by a visual examination of the circulation patterns (e.g. Lamb, 1972). Recently, there has been the development of more 'objective' quantitative classification methods. Objective typing schemes may take one of several forms. The major approaches use either correlation coefficients or sums of squared differences as a measure of similarity between pairs of maps, or alternatively use empirical orthogonal functions (EOFs) to extract the principal spatial patterns inherent in the data. As well as these, discriminant analysis (McCutchan, 1978, 1980) and cluster analysis (Kruizinga, 1979; McCutchan, 1980) have also been used to classify circulation types, and attempts have been made to fit pressure fields to predefined mathematical functions (White *et al.*, 1958).

Although subjective methods are still being used for particular applications (e.g. Alt, 1978; Stenning *et al.*, 1981), for a long period of record such analyses tend to be very time consuming. There is the

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further drawback that the subjectivity involved makes replication of the results difficult, as the identification of types by any two analysts may well differ. The major advantage of the objective typing schemes, aside from the fact that they are well suited to computer processing, is that they supposedly remove the subjective element from the analysis. Subjective and objective schemes have been compared by Ladd and Driscol (1980). Our purpose here, however, is to examine the question of just how objective an 'objective' typing scheme really is. In order to do so, we concentrate on two of the more popular techniques, the sum of squares method developed by Kirchhofer (1973), and a method that employs principal component analysis (EOFs), and cluster analysis.

2. BACKGROUND

The first method described here is one developed by Kirchhofer (1973) to classify patterns of 500 mb heights over Europe. Pairs of daily map grids are compared, their similarity is evaluated, and the day with the most other days similar to it is designated as the key day for type 1. These days are removed from the data set and the process is repeated for type 2, etc. The process of extracting key days continues until all of the remaining days have less than the minimum number of similar days required per type, as specified by the analyst. The remaining days are considered unclassified. As the days are removed once they have been associated with a key day, a final step recomputes the similarity between every case and each key day and reassigns those days that have a greater similarity with a group other than the one to which they had previously been assigned.

The technique uses a sum of squares of differences between normalized grid point values, which are computed for each pair of days and compared to a previously set threshold. If too low a threshold is used, numerous well-defined but infrequently occurring types are obtained. Conversely, if too high a threshold is used, few types with considerable internal variance result. Here lies the most subjective part of the methodology; the analyst chooses the particular typing scheme that seems most realistic, or that best fits the application. The choice of minimum group size is a further area of subjectivity that influences the number of groups derived by the analysis. This is discussed further in Section 4.

Initially, each daily grid is normalized by

$$Z_i = (X_i - \bar{X})/s$$

where Z_i is the normalized value of the ith grid point, X_i is the original value of the ith grid point, $\bar{X}$ is the mean of the grid point values, and s is the standard deviation of the grid. In the normalization process, the spatial pattern is retained, but the effects of pressure/height magnitude are removed. This is often assumed to remove the seasonal cycle from the data. This is only true, however, where the cycle is constant over the entire spatial domain. If different parts of the region have very different seasonal cycles, this approach reduces, but does not completely remove, the seasonal signal from the data set.

The similarity between any two circulation patterns is the sum of squares of the differences in pressure/height at each grid point. This score (S) is given by

$$S = \sum_{i=1}^{n} (Z_{ai} - Z_{bi})^2$$

where Z_{ai} is the normalized grid value at point i on day a, Z_{bi} is the normalized grid value at point i on day b, and n is the number of grid points.

The similarity between each pair of grids is computed for the overall grid as well as for any number of latitudinal and meridional zones. The overall score for each zone must not be greater than their respective threshold values for the patterns to be accepted as similar. Thus it is possible for the overall score to be less than the threshold for the map as a whole, but one or more zone scores may exceed the zone thresholds. In such a case, the two maps would not be accepted as similar. Zone thresholds eliminate the possibility that two grids which are similar over most of their area but are very different in one zone will be regarded as the same type. Zone thresholds may also serve as a means to weight

different geographical areas, allowing more variability between maps in some areas than in others. For a complete description of the technique and a listing of the Kirchhofer program (Fortran) see Yarnal (1984).

The second method to be discussed involves the use of principal components analysis combined with cluster analysis. Principal components analysis is essentially a data transformation technique; transforming the original data into a new set of composite variables (principal components). The transformation is such that the same amount of variability is described using the same number of variables, but with the first component accounting for the maximum possible proportion of the total variance. Succeeding components, in turn, account for as much of the residual variance as possible, subject to the constraint that they be orthogonal to the previous components. The method has had extensive application in climatology, and the techniques are described in numerous papers (e.g. Kutzbach, 1970; Trenberth, 1980).

The eigenvalues are extracted from a square similarity matrix. There has been some discussion as to whether it is preferable to extract the eigenvalues from the correlation matrix or the variance–covariance matrix. Essentially, the correlation matrix weights each grid equally and the first component will tend to reflect the mean pattern, whereas the use of the covariance matrix will emphasize the regions of greatest variance.

The eigenvectors, or the loading (correlation) of each grid point on each component, gives the spatial representation of the components. These would be interpreted in terms of height or pressure distributions and, like the 'key days' from the Kirchhofer scheme, would be used to represent each synoptic type. Component scores give a value for each case on each component, obtained by summing the products of the grid point values and the eigenvectors for each component, so that

$$P_{ik} = \sum_{i=1}^{n} D_{ij} L_{jk}$$

where D_{ij} is the standardized value of variable j for case i, L_{jk} is the loading of variable j on component k, P_{ik} is the score of case i on component k, and the summation is over all n variables (Johnston, 1978).

The scores are standardized by dividing the loadings (L_{jk}) by the eigenvalue for that component. A time sequence of the component scores shows time periods for which a particular component is more, or less, dominant. The implication is that any particular day or case could then be assigned to a group according to the component on which it has the highest score. A major objection to this approach is that the components are 'unrealistic'. On any one day, the height or pressure field will be made up of some combination of the components and it is highly unlikely that a single component will actually resemble the 'real' field.

Map typing using principal components can be considerably improved by employing a rotated principal components analysis (Richman, 1981; Horel, 1981), but this technique is not discussed here. An alternative approach is to use the simple unrotated solution, and then to classify days by clustering the component scores. The circulation types are formed by grouping days which have similar scores on all components. Use of this method involves various assumptions about the data. For example, both the principal components analysis and the cluster routine assume multivariate normal distributions. In using the principal components analysis, we are also assuming that the interrelations among the variables are adequately described by linear functions. To this point, the only subjectivity introduced by the analyst is in deciding which similarity matrix to use to extract the eigenvalues. Before proceeding further with the classification, however, the analyst has also to decide on the number of components to retain for the analysis, and the type of clustering scheme to be used. How these decisions influence the outcome of the final classification is discussed below.

3. DATA AND METHODOLOGY

National Meteorological Center (NMC) grid point analyses of the 700 mb height fields are available from the U.S. National Center for Atmospheric Research (NCAR). Of the 1977 grid points contained within

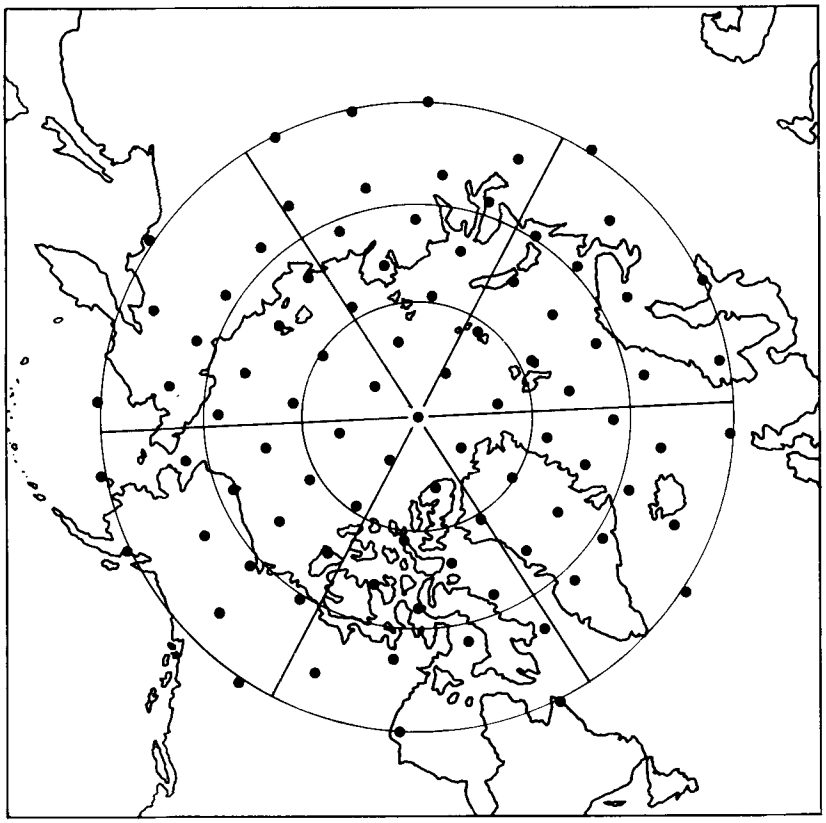

Figure 1. NMC grid points used for the synoptic classifications

the NMC octagon, 93 grid points centred on the North Pole and covering the area north of 60°N are used for the present analysis (Figure 1). This grid gives sufficient detail to detect synoptic variability, while keeping processing demands modest.

For the purpose of comparing the various typing schemes, the analyses are performed on daily grids (1200Z) for the July months of the ten years 1973–1982. The restricted data set again reduces the processing time needed and also, to a large extent, removes any problem with variations in the seasonal cycle across the polar basin.

Parameter testing

The parameter testing goes through several stages. Two parameters may be altered which will affect the final typing scheme in the Kirchhofer technique: the similarity threshold and the minimum group size. For the present paper the zone and grid thresholds are kept equal, but are varied from 1·0 to 1·9 per grid point. The minimum group size is varied from 5 to 15 days (1·7 to 5 per cent of the total sample size). From these results an 'optimum' solution is decided upon, and this solution is further compared to the results from the cluster analysis.

For the principal components and cluster analyses, the same data are used and the eigenvalues are simply extracted from the correlation matrix. The clustering is then based on the component scores. Two clustering techniques are employed; both are procedures contained in the CLUSTAN statistical package (Wishart, 1978, 1982). The first, 'Relocate', employs an iterative procedure to obtain a local optimum for a designated number of clusters; in the present case, the error sum of squares is used as a similarity measure. The error sum of squares is the sum of the squared Euclidean distances from each case to the centre of the cluster to which the case belongs.

Initially, the cases are randomly assigned to m clusters and an interative procedure is used to relocate cases between clusters by testing the similarity between the case and the cluster centroids. After each relocation occurs, the group centroids are recomputed to account for the change in location. Once an optimum solution for m clusters is reached, the two closest clusters are combined and the relocation procedure is repeated for $m - 1$ clusters. For comparison purposes, the terminal number of clusters is chosen to be the same as the number of groups obtained from the 'optimum' Kirchhofer classification.

The second procedure 'Normix' obtains maximum likelihood estimates of the parameters of a multivariate normal mixture of distributions (Wishart, 1982). The procedure begins with a single large cluster and then, at each step, subdivides the data by adding a further cluster. Within each step, an iterative procedure is again used to optimize the distribution of cases between clusters. In actual fact, Normix does not assign a case exclusively to a particular cluster, rather it gives a probability of membership to each of the clusters for every point in the sample. Where a case lies midway between two clusters it will contribute equally to the estimation of the parameters of both clusters. At each step, the number of clusters increases by one, and the procedure is terminated when a Chi-square test shows that a classification of $r + 1$ types is no more likely than a classification or r types. Unlike Relocate, Normix itself determines the 'best' number of terminal clusters.

Relocate and Normix, therefore, use very different methods for clustering cases. In the present paper, the results obtained from both Relocate and Normix are compared as examples of different clustering techniques. The analysis is also repeated retaining different numbers of components as the input variables to the cluster routines, in order to determine what effect this may have on the classifications obtained.

4. RESULTS

Kirchhofer classification

In the Kirchhofer typing scheme, changing the threshold value(s) can have an effect on the key day chosen for each type. Table I, as a hypothetical case, illustrates why this might occur. Table I(a) contains the score per grid point for each of ten days on two days, A and B, which we will assume will be the first and second key days in either order. Table I(b) shows that with a threshold of 1·3, day A has most days similar to it, and will be designated as the first key day. If, however, the threshold is 1·6, day B will be the first key day and day A the second. Table I(b) also shows, as one would expect, that changing the threshold value also changes the group size and the number of days that are classified.

Table I. Change of key days as a function of threshold: (a) scores per grid point for each of ten days on two key days; (b) resulting order of key days in the hypothetical typing scheme

(a)

Key day	Day number 1	2	3	4	5	6	7	8	9	10
A	1·4	1·7	0·8	0·9	1·0	1·5	2·0	1·9	1·8	1·7
B	1·4	1·5	1·7	2·0	1·9	1·0	0·8	1·4	1·6	2·1

(b)

Threshold	Number of days similar to (A)	Number of days similar to (B)	Key day 1	Key day 2
1·3	3	2	A	B
1·6	5	6	B	A

Table II. Results obtained by varying the threshold and the minimum number of days used in the Kirchhofer typing scheme

Minimum group size (days)	Threshold	Number of types	Percentage classified	Percentage of days (group 1)	Key day: No. 1	No. 2	No. 3
5	1·0	18	56·7	7·9	7-10-73	7-3-75	7-14-79
5	1·3	17	78·4	16·8	7-21-81	7-10-73	7-19-76
5	1·6	14	87·3	29·6	7-21-81	7-7-79	7-28-79
5	1·9	10	95·5	47·8	7-22-81	7-12-73	7-9-77
10	1·0	5	27·8	7·9	7-10-73	7-3-75	7-14-79
10	1·3	6	52·9	16·8	7-21-81	7-10-73	7-19-76
10	1·6	7	82·1	29·6	7-21-81	7-7-79	7-28-79
10	1·9	6	86·3	47·8	7-22-81	7-12-73	7-9-77
15	1·0	3	20·3	7·9	7-10-73	7-3-75	7-14-79
15	1·3	4	45·7	16·8	7-21-81	7-10-73	7-19-76
15	1·6	4	59·8	29·6	7-21-81	7-7-79	7-28-79
15	1·9	4	77·7	47·8	7-22-81	7-12-73	7-9-77

Table II shows the effect of varying the threshold from 1·0 to 1·9 and the minimum group size from 5 to 15, for the ten years of July 700 mb heights (sample size = 291 days). Changing the minimum group size parameter does not change the key days for each type, but it does change the number of types generated. Lowering this value allows days with fewer days similar to them to constitute a new type. For each threshold–group-size combination, the table gives the number of groups obtained, the percentage of days classified, the percentage (of the total number of days) accounted for by the first type, and the dates of the first three key days. Note that the percentage of days in the first group and the first three key days are the same for any given threshold, regardless of the minimum group size. As the minimum group size increases, however, the total number of days classified decreases.

As the threshold increases, the total number of days classified increases, as does the number of days contained within the first group (group one increasingly reflects the mean pattern). More importantly, as the threshold increases, it changes the key days. The effect this has is illustrated in Figures 2–4, which show the 700 mb patterns for the first three key days at each threshold. In some cases, as with thresholds of 1·3 and 1·6, the key days show similar patterns between the two thresholds. For threshold values of 1·0 and 1·3, even though the individual key day patterns may not be similar, the three key days for each threshold seem to account for the same general patterns, but not in the same order of 'importance'. When the threshold is set to 1·9 key day 1 is fairly similar to the previous cases, but key days 2 and 3 appear to have very little in common with the results from the other thresholds, particularly in the western hemisphere. In this case it is obvious that the same 'objective' typing scheme (as with a subjective classification) may still exhibit considerable variability in its determination of types and number of days classified, depending on the threshold criteria selected.

Relocate and Normix

Both programs were run using 5, 11 and 17 components as the variables to be used in the clustering of the types. Figure 5 shows a plot of the cumulative percentage of variance explained by the first 65 components. The first 5 components explain 53·7 per cent of the variance (component 5 = 6·9 per cent); for 11 and 17 components the variances explained are 79·9 per cent (component 11 = 2·9 per cent) and 89 per cent (component 17 = 1·1 per cent), respectively.

All of the analyses produce patterns that look synoptically reasonable. For the procedure Relocate, the number of groups specified is 7 and in each case all of the days are classified. All three analyses

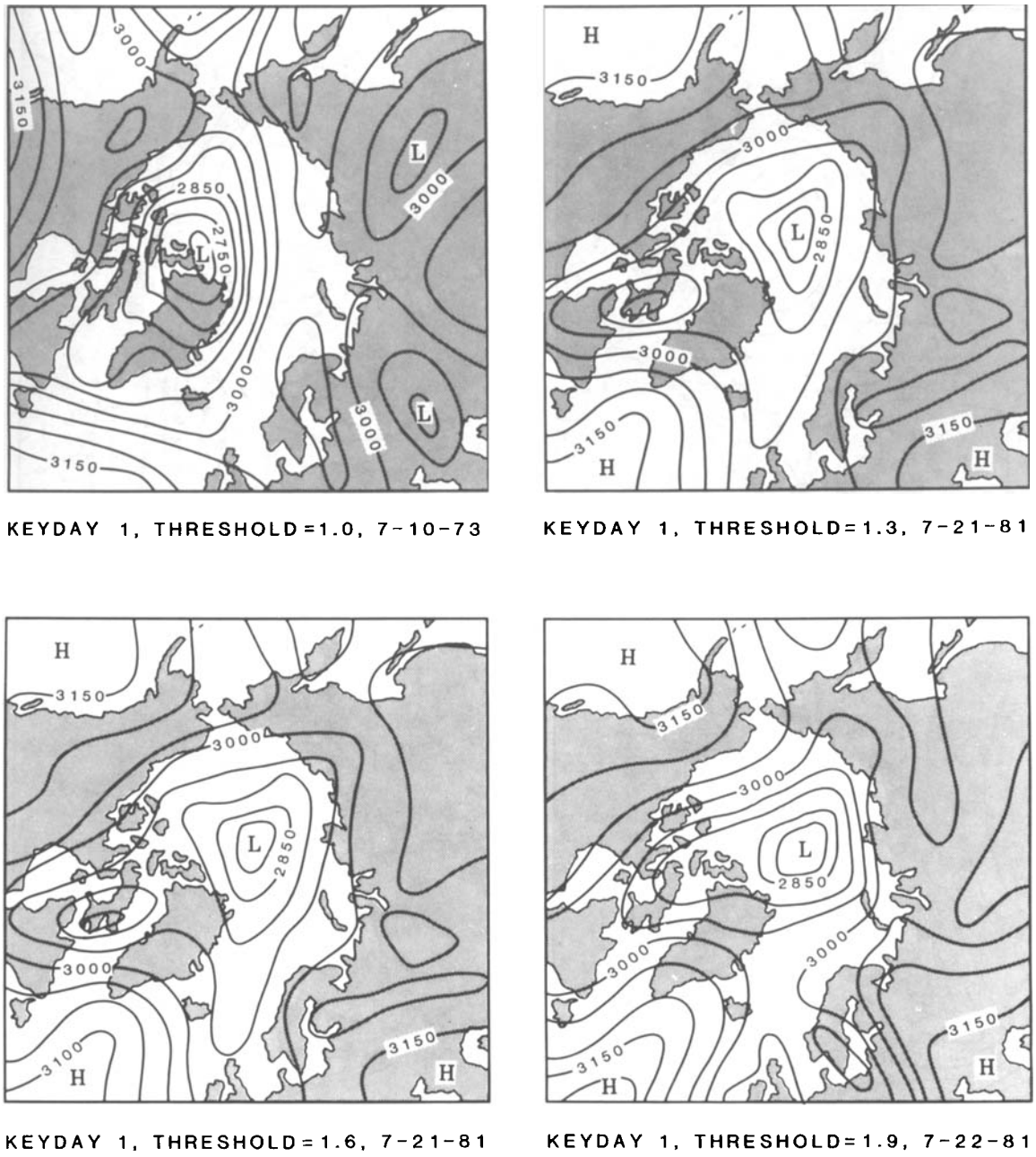

Figure 2. 700 mb heights for key day 1 using thresholds of 1·0, 1·3, 1·6 and 1·9. Contour interval = 50 m

show similar group size distributions; however, as the number of components used increases, the error sum of squares also increases. Tables III and IV are contingency tables that compare the groupings of days using 5 components and 11 components (Table III), and 11 and 17 components (Table IV). Picking a group in any row or column shows how the days in that group are distributed between groups in the other analysis. Each element in the table shows the number of days common to the two groups. In Table III, for example, of the 52 days that make up group 1 of the 5 component analysis, 17 of these days are found in group 5 of the 11 component analysis, 16 in group 6, 9 in group 7 etc. These

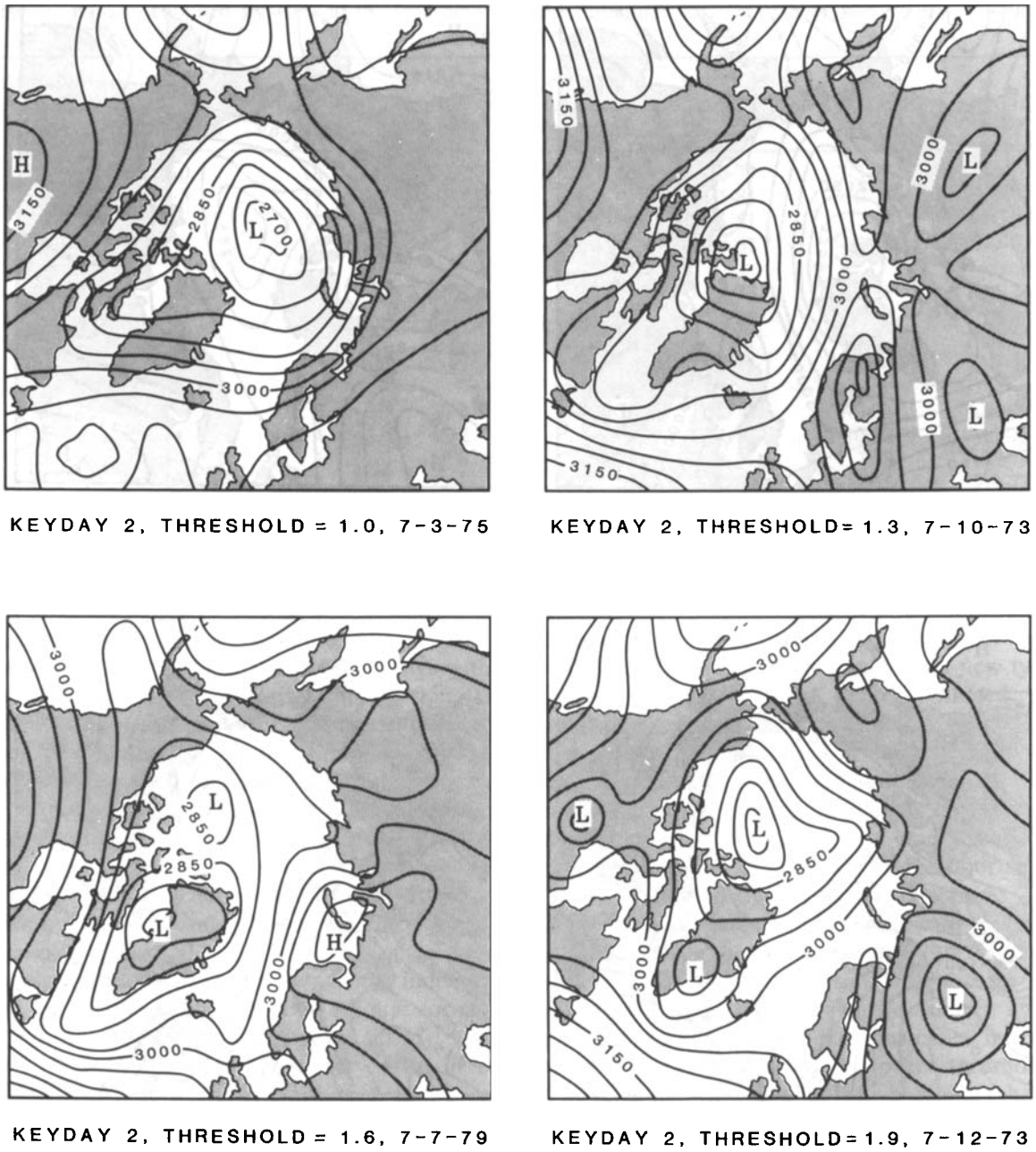

Figure 3. 700 mb heights for key day 2 using thresholds of 1·0, 1·3, 1·6 and 1·9. Contour interval = 50 m

comparisons indicate that the different analyses result in very different classification schemes. The comparison is slightly better for the groupings using 11 and 17 components (Table IV): group 1 with the 11 components is similar to group 6 with the 17 components, group 2 is similar to group 7, group 3 to group 5 etc. Even so, although the typing schemes give broadly similar results, for any group in either of the schemes, there is still considerable dispersion of the days in the group over several of the groups in the other analysis.

The results from the Normix procedure are tabulated in similar fashion in Tables V and VI. As with

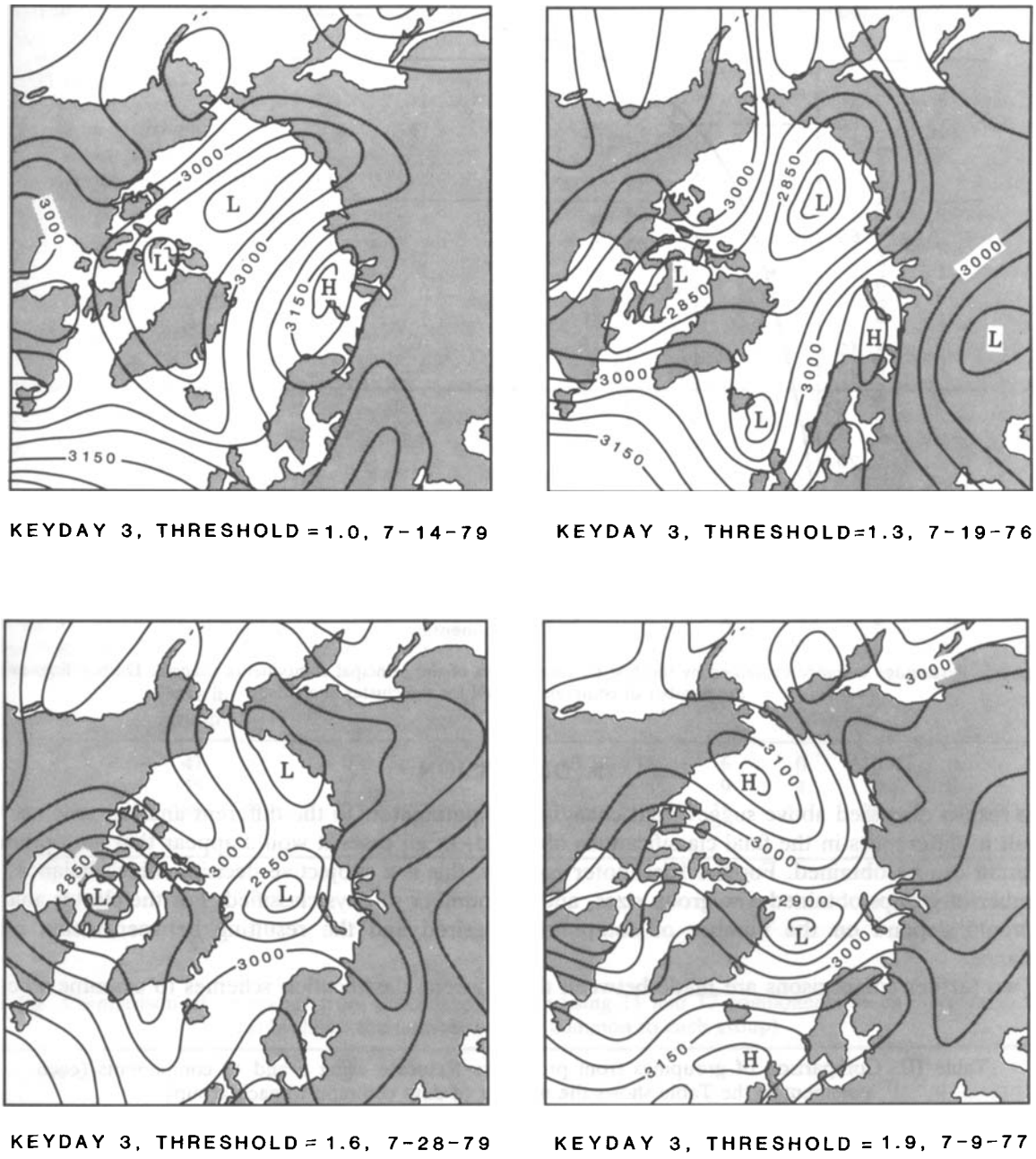

Figure 4. 700 mb heights for key day 3 using thresholds of 1·0, 1·3, 1·6 and 1·9. Contour interval = 50 m

the procedure Relocate, this method also classifies all of the days in the sample. In this case, however, the number of groups obtained and the sizes of the groups vary according to the number of components used in the analysis. Again it is obvious from Tables V and VI that using a different number of components results in a very different grouping of days. Using 11 or 17 components (Table VI) results in similar numbers of groups, of similar sizes, but the distribution of days among the groups show very little agreement.

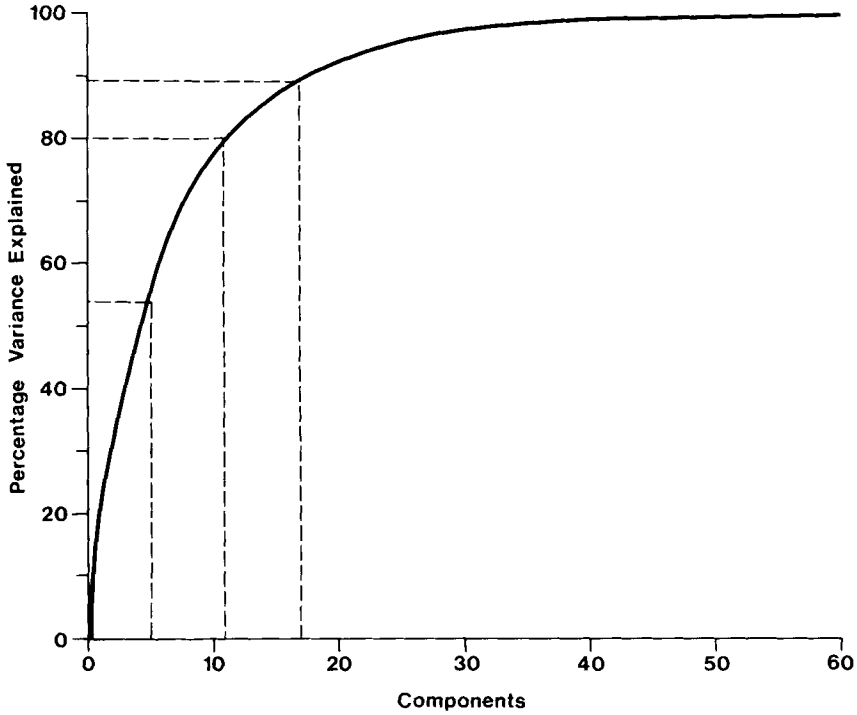

Figure 5. Percentage variance explained by the first 65 components of the principal components analysis. Dashed lines indicate the number of components used for the cluster analyses

5. DISCUSSION

The results discussed above suggest that changing the parameters in the different analysis schemes will result in differences in the final classifications obtained. In all cases it would appear that an 'optimum' solution can be obtained. For the Kirchhofer analysis, this is a subjective decision which balances the number of groups obtained, the group sizes, and the number of days classified. For the cluster analysis it would depend on the number of components desired and the resulting between/within group variance.

Two further comparisons are made between the different classification schemes to examine whether

Table III. Comparison of groupings from procedure Relocate using 5 and 11 components (each element in the Table shows the number of days common to each group)

5 *Components*								
Group		1	2	3	4	5	6	7
Days in group		52	41	34	40	48	39	37
11 *Components*								
Group	Days in group							
1	47	9	16	3	0	19	0	0
2	33	0	10	9	3	3	3	5
3	36	1	2	15	4	11	0	3
4	51	0	0	7	26	3	4	11
5	42	17	11	0	0	8	0	6
6	51	16	2	0	7	4	22	0
7	31	9	0	0	0	0	10	12

Table IV. Comparison of groupings from procedure Relocate using 11 and 17 components (each element in the Table shows the number of days common to each group)

11 components								
Group		1	2	3	4	5	6	7
Days in group		47	33	36	51	42	51	31
17 components								
Group	Days in group							
1	64	6	3	0	7	28	8	12
2	51	7	0	4	9	8	14	9
3	35	1	2	0	30	0	1	1
4	37	0	8	1	0	0	28	0
5	29	7	4	12	0	5	0	1
6	44	20	1	11	5	1	0	6
7	31	6	15	8	0	0	0	2

Table V. Comparison of groupings from procedure Normix using 5 and 11 components (each element in the Table shows the number of days common to each group)

11 components											
Groups		1	2	3	4	5	6	7	8	9	10
Days in group		7	64	21	17	24	50	20	45	20	23
5 components											
Group	Days in group										
1	47	0	7	0	0	16	6	0	15	0	3
2	55	7	5	6	7	5	9	4	6	4	2
3	189	0	52	15	10	3	35	16	24	16	18

Table VI. Comparison of groupings from procedure Normix using 11 and 17 components (each element in the Table shows the number of days common to each group)

11 components											
Group		1	2	3	4	5	6	7	8	9	10
Days in Group		7	64	21	17	24	50	20	45	20	23
17 components											
Group	Days group										
1	25	0	3	10	1	1	8	0	2	0	0
2	12	0	2	0	7	0	2	1	0	0	0
3	28	2	2	7	0	0	9	5	2	1	0
4	21	0	2	3	1	1	2	0	1	2	9
5	45	0	9	0	0	10	1	1	15	6	3
6	62	2	37	0	0	4	5	1	12	0	1
7	35	3	6	0	0	3	8	0	9	5	1
8	39	0	1	1	1	5	12	1	4	5	9
9	24	0	2	0	7	0	3	11	0	1	0

there is any similarity in groupings obtained, and to determine which scheme gives the 'best' grouping. Table VII compares the Kirchhofer classification with the 1·6 threshold (which appeared to give the 'optimum' Kirchhofer grouping), and the Relocate analysis with 11 components. Once again, although Relocate is using the same input data, and is constrained to find the same number of groups as Kirchhofer, the two typing schemes result in very different synoptic classifications.

The 'fit' of the synoptic type patterns to the data is tested by calculating the sum of squares difference between each case and the designated type pattern for that case, for each of the classification schemes. The analyses used are the Kirchhofer scheme (threshold = 1·6, minimum group size = 10), comparing the cases with the 'key day' patterns; the same Kirchhofer analysis, but using the mean pattern for each type; Normix, using 11 components; and Relocate with 11 components.

The results are shown in Table VIII, which compares the mean sum of squares difference between the cases and the synoptic types, and also shows the percentage of cases assigned to each typing scheme. That is, the percentage number of times a particular synoptic typing scheme has the lowest sum of squares difference between the daily pattern and the synoptic type, on a case-by-case basis.

The worst score is obtained by the Kirchhofer analysis which uses key days to represent the types. This analysis also has the fewest cases assigned to the scheme. The lowest mean sum of squares difference, however, is obtained by the same Kirchhofer analysis using the mean pattern for each synoptic type rather than the key day. Normix and Relocate have slightly larger mean sum of squares differences, but also have the larger number of cases assigned to them.

Table VII. Comparison of Groupings using Relocate (11 components) and Kirchhofer (threshold = 1·6) (each element in the Table shows the number of days common to each group)

Kirchhofer									
Group		1	2	3	4	5	6	7	0*
Days in group		62	54	29	33	26	26	19	42
Relocate									
Group	Days in group								
1	47	11	11	2	4	13	2	0	4
2	33	9	6	1	0	4	9	0	4
3	36	8	19	0	4	2	0	2	1
4	51	11	5	10	0	1	3	15	6
5	42	13	8	5	10	0	4	0	2
6	51	5	2	9	4	2	6	1	22
7	31	5	3	2	11	4	2	1	3

* Unclassified.

Table VIII. Summary comparison of the three different typing schemes

Typing scheme	Mean sum of squares difference†	Percentage of cases assigned to typing scheme‡
Kirchhofer	5040	6·5
Kirchhofer*	2974	20·3
Normix (11 components)	3596	34·4
Relocate (11 components)	3377	38·8

* Uses the mean pattern for each group rather than the key day for the group.
† Mean sum of squares difference between each case and the synoptic type pattern to which it was assigned in each classification scheme.
‡ Percentage number of times a particular typing scheme has the lowest sum of squares difference on a case-by-case basis. The column total adds to 100 per cent.

In terms of the overall mean sum of squares difference, therefore, the best classification is obtained by the Kirchhofer analysis using the mean grids. On the other hand, the synoptic types obtained from Relocate have the largest number of cases where individual daily grids are best represented by the Relocate synoptic types, compared to the other analyses. This is probably explained by the fact that Relocate and Normix classify 100 per cent of the cases, whereas the mean sum of squares difference for the Kirchhofer analysis is based on only the 80 per cent of the cases that are classified, resulting in a lower overall variance.

6. SUMMARY AND CONCLUSIONS

Several objective typing schemes have been tested in order to determine whether the subjectivity introduced by user-controlled parameters within each scheme can result in different synoptic type classifications for the same data set. Three different typing schemes have been examined, one of which compares the similarity between days using the sum of squares difference between cases (Kirchhofer method), whereas the other two involve different methods of clustering principal component scores (using procedures Relocate and Normix from CLUSTAN). The analysis shows that the results from a single typing scheme can vary, depending on the parameters chosen, and that an intercomparison of the different schemes reveals large differences in the synoptic classifications produced. For the data examined here, it would appear that the Kirchhofer approach gives the best overall classification, if group means are used to depict the synoptic types rather than the 'key days'. Twenty per cent of the days in the sample, however, remain unclassified. The procedure Relocate has a slightly larger overall mean sum of squares difference between the type patterns, but does classify all of the days.

The results indicate that when attempting to classify synoptic circulation features there is unlikely to be a single unique solution. The different classification schemes all result in the production of different synoptic types, and each scheme may give several equally valid classifications, suggesting that some subjectivity will always be present in this type of analysis.

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