NOTES AND CORRESPONDENCE

Preliminary Results of a Statistical Long-Range Forecasting Attempt

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ABSTRACT

By statistical methods an attempt was made to obtain long-range predictions of large-scale circulation parameters for the Northern Hemisphere. Using lag relationships going back in time up to 50 months and attempting to predict coefficients of monthly sea level pressure eigenvectors, statistically significant results could be obtained in a set of independent data.

1. Introduction

This is a first report on results of a long-range forecasting attempt of large-scale atmospheric parameters by a statistical technique. The results reported below should be viewed as preliminary; additional research will have to be undertaken to establish the potential value of these or equivalent approaches. However, I feel that these preliminary results are indicative of some progress and thus may be of value to workers in this field of research.

In recent years the increased interest in climatic changes and their potentially major effect on human endeavors has stimulated research into the time domain behavior of a variety of climatic variables. In such studies it has been noted that there seems to exist a certain amount of variance above that expected if only random factors were operating, especially for time period regions between several months and up to four or more years. Especially noted by various researchers was the evidence for quasibiennial fluctuations in a variety of large-scale circulation features such as location and central pressure of centers of action on mean monthly sea level pressure fields of the Northern Hemisphere (e.g., Angell and Korshover, 1974).

Such long-term fluctuations could be interpreted in very general terms in two ways. First, it is possible that the atmosphere undergoes very long-term, large-scale oscillations the nature of which we do not yet understand. Second, it could be argued that the long-term fluctuations are the results of feedback into the atmospheric circulation of processes in the oceans and/or the cryosphere with long time constants. For the latter possibility the results of studies by Namias (1969) related to the effect of long-lasting sea surface temperature anomalies on subsequent large-scale circulation patterns are a good example.

In both cases, however, it may be possible to utilize the behavior of antecedent conditions of the large-scale sea level pressure field (a poor substitute for the three-dimensional general circulation of the atmosphere) to obtain indications of subsequent developments of the same or other related quantities. If the fluctuations are inherent in the atmosphere itself, this is obvious. If, on the other hand, the feedback assumptions are correct, one can argue that the oceanic or cryosphere anomalies are linked to antecedent circulation states which can be used in the absence of sufficient information about the feedback systems themselves. My current attempts are essentially based on these considerations, namely that there may be some predictability for future states of the circulation in a careful evaluation of antecedent conditions.

2. The database

Until we understood the physical basis for these long-term fluctuations, a statistical approach to this forecast problem can serve as a first step. The necessary prerequisite is the existence of a sufficiently long data record, in view of both the low frequency of these oscillations and especially the anticipated high noise content of the system. It also is clear that this record should be related to the large-scale features of the general circulation rather than local or regional parameters which are essentially the result of changes of the hemispheric patterns. These considerations essentially limit the choice of parameters to mean monthly sea level pressure patterns—the only set of hemispheric data spanning a time interval of now better than 70 years. The data used in this study thus are the monthly average maps of sea level pressure based on the Historical Series (1899–1938) extended by various groups into the 1950's and continued to the present by utilizing
the NMC daily analyses. This data set was available in the form of a 5° latitude by 10° longitude diamond grid, from 90°N to 20°N. In the eigenvector calculations a subset of the above, consisting of 180 points in a 10° by 10° grid (20°-50°N) and 10°×20° grid (60, 70°N), was employed to represent the large-scale monthly patterns.

A number of derived data were used in several attempts of achieving forecasts. Initially, we abstracted from the data above the monthly latitudinal position and the average value of the zonally averaged sea level pressure for the subtropical highs and the subpolar lows (i.e., the maximum and minimum of the monthly N-S profile). As a second attempt, we obtained a similar quantity in the two oceanic sectors, averaging separately over the Atlantic and Pacific Oceans.

Some results will be given later. In general, these initial results were somewhat encouraging but by no means convincing. There appeared to exist some predictability in forecasting the features of the subtropical highs but no success was apparent for the subpolar lows. It then was decided to go to a new set of variables which would allow the more complete use of the hemispheric pressure field than was made by only concentrating on the major features of subtropical highs and subpolar lows alone.

Kutzbach (1970) had represented the sea level pressure field (monthly averages) by means of eigenvectors based on the 180 point grid mentioned earlier. Using six eigenvectors the fraction of total variance explained by this representation ranges from values of 65 to 70% in winter to slightly over 50% in the summer months; by expanding the representation to the first 10 eigenvectors the total explained variance can be increased to more than 80% in the winter and to approximately 65% in the summer months. In Kutzbach’s calculations, separate sets of eigenvectors were derived for each month. This is statistically the most efficient way of representing the monthly patterns with a minimum of eigenvectors. It has, however, several drawbacks which relate to the fact that from month to month the specific pattern of a particular eigenvector may change quite drastically. In fact, what is eigenvector pattern \( x \) in one month may become very similar to the pattern of eigenvector \( y \) in another month, simply due to the fact that the amount of variance explained by eigenvector \( x \) has become less than that of eigenvector \( y \) which changes the number of the eigenvectors (which are selected sequentially by the computer program with decreasing values in explained variance).

3. Choice of forecast method

If one wishes to establish relationships between a number of time series which might be useful for forecasting, a variety of methods are available from rather simple to quite sophisticated ones. The choice made here—namely to use a contingency table method—was based on a number of considerations. A major factor was the realization that the expectation of success of this attempt was easier believed to be marginal at best, based on the failure of many previous long-range forecast attempts. Second, the method chosen was very inexpensive in terms of time and computer requirements, an important factor since only limited funding was available. Finally, the method is rather simple and robust; success in this attempt certainly would be an encouragement to expand research into more sophisticated approaches.

The basic method of using contingency tables for forecasting schemes has been described in an Air Force Technical Report (Lund and Wahl, 1955). It requires the data to be classified into a number of mutually exclusive classes, then establishes from the dependent data set a number of contingency tables between a desired predictor set and the chosen predictand sets in the form of lag relations (relating antecedent class values of the predictors to subsequent class value of the predictand). The availability of data essentially dictates the number of classes into which predictor and predictand records can be subdivided. In our particular case a three-class classification was used.

The best way to establish the success or failure of a particular forecast method is the actual forecasting in an independent set of data. In order to be able to do this, each basic data set was divided into a dependent set using data from January 1899 to December 1964 and an independent set, comprising the subsequent data to the end of the available record. The derivation of the class limits for predictors and predictands as well as the establishment of the forecast contingency tables was done using the dependent data sets only.

There is one minor complication which should be mentioned here. When using Kutzbach’s eigenvector data, the individual monthly eigenvector patterns were originally derived for the whole set of data (1899 through part of 1971). To be totally independent in the set from 1965 through 1971, one should have determined the patterns from the dependent set only. However, experience with these patterns has shown that the change in pattern would have been small (66 of the 71 years belong to the dependent set) and probably would have influenced the eigenvector coefficients only in a very minor way, especially since the coefficients subsequently were used in classified form. Thus I do not believe that this minor problem is seriously influencing the results presented below.

4. Contingency table forecast method

As mentioned before, the basic method of using contingency tables as a tool for forecasting was published earlier; this particular paper is probably difficult to obtain. Therefore, a brief description is compiled, with some recent refinements added to the previous method. The basic idea is to obtain the relationships of a par-
ticular predictand to suitably chosen predictors which essentially are variables of antecedent conditions (i.e., lag relationships).

For example, if one wishes to forecast the class of the eigenvector 1 coefficient for month February, one might use as a predictor the class values of this same eigenvector 1 (EV1) for the preceding month January (=lag 1, EV1). Let $O_{ij}$ be the observed number of simultaneous occurrences of predictor values in class $i$ ($i=1, \ldots, k$) and of predictand values in class $j$ ($j=1, \ldots, l$) with the total number of occurrences in predictor class $i$ being $S_i$ and in predictand class $j$ being $S_j$. The total number of pairs is $N$. The value one would expect to occur in class combination $(i, j)$ if no relationship between predictor and predictand exists is then given by the "expected" value:

$$E_{ij} = \frac{S_i S_j}{N}. \quad (1)$$

We now derive a contingency ratio

$$R_{ij} = \frac{O_{ij}}{E_{ij}} \quad (2)$$

which will be $>1$ if more than the expected number of pairings $(i, j)$ occur than one would expect, and $<1$ if less are occurring.

Since it is not always possible to have all $S_i$ and/or $S_j$ exactly equal to each other (i.e., the $E_{ij}$ will vary) and also, since various predictors which one wishes to use together may have different total number of available pairs $N$, one can normalize the contingency ratios by choosing the largest $N$ value of all predictors to be used, called $N_0$, and by obtaining a "normal" expected value

$$E_0 = \frac{N_0}{kl}. \quad (3)$$

The normalized contingency ratio $R'_{ij}$ then is obtained from

$$R'_{ij} = 1 + (R_{ij} - 1)\left(\frac{E_{ij}}{E_0}\right)^{1/4}. \quad (4)$$

In our particular case, $k=l=3$, $N_0=66$ (the maximum number of years in the dependent data set).

In view of the rather limited record ($E_0=7.33\ldots$, hardly exceeding the recommended minimum for $E$ of 5 cases) a final smoothing procedure was used to ameliorate somewhat the large noise in the $O_{ij}$ introduced by classifying the data which becomes particularly noticeable when one wishes to combine many predictor tables. This smoothing was done by weighted averaged within the three predictand columns of the $R'_{ij}$ table, defining

$$R''_{ij} = \frac{1}{4}(3R'_{ij} + R''_{ij}) \\
R''_{ij} = \frac{1}{4}(R'_{ij} + 2R'_{ij} + R''_{ij}) \quad (5)$$

Finally, the departure of each $R''_{ij}$ from its column average $\frac{1}{4} \sum_i R''_{ij}$ was obtained to establish the forecast table values

$$\Delta_{ij} = (R''_{ij} - \frac{1}{4} \sum_i R''_{ij}). \quad (6)$$

A typical forecast table is given in Table 1.

Finally, the actual forecast is obtained by combining all appropriate $\Delta_{ij}$ of the chosen predictors. Each predictor has an observed class value (since it occurred prior to the month to be predicted). From each forecast table the $\Delta_{ij}$ for $j=1, 2$ and 3 are obtained and summed up for each predictand class over all predictors; as the predicted class is chosen the class with the highest positive sum. This means that many predictors favor the particular class (since in order to obtain a positive sum a good number of the $\Delta_{ij}$ have to be positive, i.e., individually indicate a surplus of $(i,j)$ pairs over the expected random number in the dependent data set). As an example, the following is the final sum (EV1) for February 1965:

Sum of 22 predictors: Class (1) $-2.6404$, (2) $-2.0298$, (3) $+4.7269$.

Forecast Class 3, actual observed class was also 3. One of the predictors was lag 14, EV2; the observed value of this predictor 14 months back (December 1963) was 3 and the contribution to this sum were the values on the line 3 of Table 1.

5. Selection of predictors

At this point one has to decide first of all how many lags one wishes to include in the forecast scheme; second, one wishes to include in the forecast scheme only those predictors which, in the dependent data set, show some useful relationship to the predictand. 

A priori one can assume with high degree of certainty that any "useful" relationships between a given predictand and some antecedent predictor will be at best very weak indeed. It appears to be highly unlikely that current and antecedent pressure fields of a whole hemisphere show any strong relationships; if they did exist they most likely would have been detected and used before. Thus any secondary relationships (equivalent to interrelationships between predictors themselves) can safely be ignored since they would be even weaker in their effect on the forecast than the first-order effects given by the forecast tables.
The answer to the first question was by no means obvious; in fact, no clear answer is possible at this time. Since I postulated initially that rather long-term relationships over many months may exist, I chose to test all possible lags up to 30 months back. Whether even more lags would have been more advantageous has not yet been established but the possibility cannot be rejected. For any given predictand this meant that a total of 50 times the number of different predictors could be used—giving, for the eigenvector forecasts, for example, a total of 300 potential forecast contingency tables. Obviously, only a much smaller number of predictors might have any useful connection to the predictand; the problem is to select those which are useful and leave out the others which most likely would contribute only noise to the system.

Statistically, this selection can be based on a criterion of significance for the predictand/predictor relationship. If any of these relationships, for example, can be found to be statistically significant at the 95% level, one can then decide to use only those particular lag relationships. However, in a random set of data, one would expect at least about 15 such values (out of 300) to occur by chance; a successful forecast scheme should show a larger number of such tables so that one could be reasonably certain that at least some of the apparent relationships are real and not the result of random data fluctuations.

A common method of testing the significance of a contingency table is the $X^2$ test. In this forecast method a closely related quantity was used instead, the so-called “information ratio” based on information theory and used there to establish the content of data relationships. A discussion of this concept was published both in the earlier mentioned Air Force Survey Report and by Wahl (1955). It is also sometimes called the entropy ratio (Shannon, 1948; Holloway, 1955).

The calculated information ratio $I_e$ for a given contingency table with frequency counts $O_{ij}$, row and column totals $S_i$ and $S_j$, respectively, and total number of pairs $N$ is defined by

$$I_e = \frac{1}{N} \sum_{i=1}^{k} \sum_{j=1}^{l} O_{ij} \ln O_{ij} - \sum_{i=1}^{k} S_i \ln S_i - \sum_{j=1}^{l} S_j \ln S_j + N \ln N$$

where $D_e$ is the denominator of $I_e$. Obviously a value of $I_e$ close to or even less than $I_E$ signifies a random case, useless for forecasting; large positive differences $(I_e - I_E)$, on the other hand, may indicate nonrandom data.

The numerator of $I_E$ has been shown to be distributed as $\frac{1}{2}X^2$; the denominator of $I_e$ (and $I_E$), on the other hand, depends only on $N$ and the climatology (distribution) of the predictand, i.e., is nearly constant for all tables for this predictand. On this basis one can obtain confidence limits for $I_E$ from $X^2$ tables. For example, for a $3 \times 3$ table (4 degrees of freedom), the 95% confidence limit from the $X^2$ tables equals 9.4877. Thus one can calculate the upper 95% limit above $I_E$ which will be exceeded by $I_e$ only in 5% of all cases if the basic data were random, by obtaining

$$L(I_E) = \frac{\frac{1}{2}X^2}{D_e} = 4.74$$

One then sets up a threshold value $I_e = I_E + L(I_E)$ for the desired significance level. Calculating $I_E$ from the data and obtaining $\rho = I_e/I_E$ gives a criterion which can be used to select or reject predictors. If $\rho > 1$, then $I_e$ indicates a relationship which is significant at a level better than the chosen threshold and one would select that particular predictor; if $\rho < 1$ the predictor can be rejected. This obviously does not mean that one can be certain that the so-called “significant” relationship truly is physically real; in fact, one would expect in such a large number of potential predictors quite a few which in spite of the large $\rho$ value are totally useless. However, by combining a reasonably large number of predictors in the forecast scheme the randomly occurring useless $\Delta$’s will hopefully tend to cancel out, while those tables which result from actual physical relationships will eventually prevail in a correct indication of the value of the predictand to be expected.

The above selection procedure allows an objective choice of predictors from among those considered as potentially useful. Under certain circumstances additional rules must be established. For example, where the predictors represented the latitude and central pressure values of the subtropical highs and subpolar lows one had to decide which of the variables for a given lag should be used. If two or more are possible according to the above criteria only the one with the highest $\rho$ value was used since the values of the variables for the same month are highly correlated. In case of the eigenvector coefficients this caution was not required since by definition the individual eigenvector coefficients are orthogonal to each other, at least in the strict linear sense. Just to be sure that this independence is also preserved in the contingency table (which can take into account at least partially some nonlinearities) the contingency tables between the eigenvectors of lag 0 (same month) were obtained for four months and tested by the $X^2$ test. None of the tables
showed any significant relationships exceeding even the 70% confidence limits, in fact many (70%) fell below the 50% confidence limit indicating a high probability of no correlation (i.e., very low values of $x^2$).

Since the predictors are chosen according to a statistical selection process it is quite likely that in some cases the forecast will not require the knowledge of any predictor in the immediate past, say at lag 1 (the preceeding month). In this case the forecast actually can be obtained several months in advance. Thus, strictly speaking, the method is not a one-month forecast scheme. For example, in the 72 cases (forecasts for 12 months each for 6 EV's) only 25 cases required lag 1. Furthermore, even in those cases where low lags were in the chosen predictor set they usually only make up a small number of all chosen predictors. Thus one can simply eliminate them from the set and attempt a forecast using only predictors with lags larger than a set number. This was done, eliminating all lags $\leq 6$ thus attempting a 7 month forecast. Results will be reported below.

6. Results of forecasts in the independent data set

The results of forecasts using the data set beginning in January 1965 are presented in Tables 2-5. These results will be discussed now.

The first attempt was the forecasting of derived circulation parameters, essentially the latitude and strength of the major centers of action of the hemisphere:

<table>
<thead>
<tr>
<th>PH</th>
<th>Maximum pressure of subtropical high</th>
</tr>
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<tbody>
<tr>
<td>$\phi H$</td>
<td>Latitude of PH</td>
</tr>
<tr>
<td>PL</td>
<td>Minimum pressure of subpolar low</td>
</tr>
<tr>
<td>$\phi L$</td>
<td>Latitude of PL</td>
</tr>
</tbody>
</table>

Table 2 under A shows the results for the zonally averaged quantities, essentially the highest and lowest value of the N-S profile of sea level pressure. The results are hardly convincing, however, it is interesting to note that at least the variables related to the subtropical highs are better than those related to the subpolar lows. The two figures (e.g., PH 38, 40) refer to forecasts using 1) predictors with $\rho \geq 1.00$ and 2) with $\rho \geq 0.90$. This attempt was made since, in some cases, the number of predictors chosen with $\rho \geq 1.0$ was considered too small and thus the $\rho$ limit was lowered to find more predictors. Apparently this slightly improved the forecast results.

Meteorologically these four variables are a simple but also rather poor representation of the large-scale circulation. Both the subtropical high and especially the subpolar low variables are seriously affected by the monsoon circulation. It was thought possible that a restriction to the regions where these variables are most pronounced would be advantageous. Thus, we subdivided the same variables into values for the two major oceanic sectors of the Pacific and Atlantic, indicated by a prefix P or A in the variable designation.

| Table 2. Results of independent forecasts of circulation parameters showing the number of correct forecasts out of 100 attempted forecasts. (Random expected 33.3%) (A) Zonally averaged parameters; (B) Pacific, Atlantic separately; (C) as in B, only with "high" parameters used as predictors and predictands. |
|-----|-------|-------|
| A   | B     | C     |
| PH 38, 40 | PPH 34 | PPH 30 |
| $\phi H$ 40, 44 | P$\phi H$ 40 | P$\phi H$ 43 |
| PL 27, 34 | APL 35 | APL 32 |
| $\phi L$ 34, 31 | A$\phi H$ 36 | A$\phi H$ 42 |

For example, A$\phi H$ means the latitude of the Atlantic subtropical high, etc. Table 2B gives the results. Actually no improvement is seen; in fact, the best results seem to occur for the subtropical high latitude. Since the subpolar lows apparently cannot be forecast with this method, a third attempt was made trying only to forecast the "high" parameters, using also only "high" variables as predictors. Table 2C shows these results; again the latitudes of the subtropical highs seem to give the best forecasts. However, even these forecast results are not significant at any reasonable confidence level. Even the best (P$\phi H$ in Table 2C with 43% success) barely exceeds the 65% limit, while the best in the A column, PH, exceeds the 80% limit (the two $x^2$ values are 4.58 and 6.24, respectively, with 4 degrees of freedom).

The next attempt then was the forecasting of the class of the eigenvector coefficients EV1 through EV6. These quantities describe the total pressure field, not just a particular part, and thus may be more valuable, especially if one uses them as predictors. Results are given in the next tables. Here only 78 forecasts could be made since the EV coefficients had been calculated only through July 1971 (with June 1970 missing due to lack of data when Kutzbach obtained the values here used). However, since the individual EV's of a given month are by definition orthogonal to each other, a total of $6 \times 78 = 468$ independent forecasts are obtained which obviously constitutes a much better sample to judge success or failure of this attempt. Table 3 first of all shows that all EV forecasts exceed the expected percentage of random forecasts (33.3%); apparently the best forecasts can be obtained for the low order EV's which in general represent large-scale features of the circulation. Especially EV1 with 51.3% of correct forecasts is quite successful which is also indicated by the $x^2$ value and significance level of 98.8% in Table 4. If one successively adds the EV's (i.e. increases the number of independent forecasts), $x^2$ increases markedly to highly significant levels even after only the first two EV's.
TABLE 3. Forecasts of eigenvector class values showing the number and percent of correct forecasts (78 forecasts—expected $\frac{3}{4}=26$) (a) using all lags (predictors chosen when confidence level $\geq 95\%$) and (b) using only lags $>6$ months.

<table>
<thead>
<tr>
<th></th>
<th>(a)</th>
<th>(b)</th>
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<tbody>
<tr>
<td>EV1</td>
<td>40=51.3%</td>
<td>36=46.2%</td>
</tr>
<tr>
<td>EV2</td>
<td>35 44.9</td>
<td>36 46.2</td>
</tr>
<tr>
<td>EV3</td>
<td>35 44.9</td>
<td>31 39.7</td>
</tr>
<tr>
<td>EV4</td>
<td>28 33.9</td>
<td>31 39.7</td>
</tr>
<tr>
<td>EV5</td>
<td>31 39.7</td>
<td>29 37.2</td>
</tr>
<tr>
<td>EV6</td>
<td>28 35.9</td>
<td>29 37.2</td>
</tr>
</tbody>
</table>

In Tables 3 and 4, the first result column under (a) represents the results using all available lags. This means in some months that lag 1 (the class value of the preceding month) may be required to obtain the forecast. The second result column (b) gives the results when all lags six months back or less were not used; in this case the forecast can be made six months ahead (when the value of lag 7 is known at the end of this month). It is quite interesting to note that the loss of accuracy is rather small (from 51 to 46% correct forecasts for EV1). This apparently means that much of the information needed to make a correct forecast is already available quite some time before the actual occurrence of this particular large-scale pressure pattern. To follow up this somewhat further, a set of forecasts were obtained, for EV1–3 only, omitting all predictors with lags $\leq 12$ months. This would then be a true one-year forecast. The results are given in Table 5.

It appears that higher order eigenvectors, being more irregular and explaining small amounts of variance, cannot be forecast as well as the low-order ones. Also, the long-term information transmitted in the forecast from large lags seems to affect the low-order EV's more than the higher order ones—the addition of lags 1–12 gives a rather small improvement in EV1 but seems to be nearly solely responsible for the result of 33 correct forecasts (i.e., nine more than expected by chance) in EV3.

7. Concluding remarks

The reason that this result is presented in this paper as preliminary is essentially that I cannot yet claim

TABLE 4. Cumulative $x^2$ and confidence limits for results in Table 3.

<table>
<thead>
<tr>
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<th>(a)</th>
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<tbody>
<tr>
<td></td>
<td>$x^2$</td>
<td>Confidence limit</td>
</tr>
<tr>
<td>EV1</td>
<td>12.931</td>
<td>98.8</td>
</tr>
<tr>
<td>EV1-2</td>
<td>14.857</td>
<td>99.4</td>
</tr>
<tr>
<td>EV1-3</td>
<td>19.345</td>
<td>99.9</td>
</tr>
<tr>
<td>EV1-4</td>
<td>16.821</td>
<td>99.8</td>
</tr>
<tr>
<td>EV1-5</td>
<td>16.317</td>
<td>99.7</td>
</tr>
<tr>
<td>EV1-6</td>
<td>16.284</td>
<td>99.7</td>
</tr>
</tbody>
</table>

Table 5. Number of correct forecasts (out of 78) (a) using all predictors with lags 1–50, (b) using predictors with lags 7–50, (c) using predictors with lags 13–50.

<table>
<thead>
<tr>
<th></th>
<th>(a)</th>
<th>(b)</th>
<th>(c)</th>
</tr>
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<tbody>
<tr>
<td>1</td>
<td>40</td>
<td>36</td>
<td>38</td>
</tr>
<tr>
<td>2</td>
<td>35</td>
<td>36</td>
<td>34</td>
</tr>
<tr>
<td>3</td>
<td>35</td>
<td>31</td>
<td>28</td>
</tr>
</tbody>
</table>

total independence in the so-called independent test set as mentioned before. The basic eigenvector patterns for the six eigenvectors were originally obtained by using the total data record from 1899 to 1971; the individual coefficients for any given month depend on the basic pattern. The classification of the EV coefficients for the independent time period was, however, based on the class limits derived solely from the dependent set. It thus is not anticipated that major changes will occur either in the contingency tables derived from the dependent set or in the results of forecasts with truly independent data. However, it is planned to remedy this shortcoming, recalculate the whole system with both eigenvector patterns and coefficients derived from the dependent set 1899–1964 only and then obtain forecasts with truly independent data from 1965 on. By that time we also hope to be able to extend our data base to the end of 1976, giving us a larger independent sample of test forecasts with approximately 120 forecasts for each eigenvector. Work along these lines is currently underway. In spite of this, the preliminary results reported here are highly encouraging. It is not so much the fact that, apparently, the eigenvector coefficient class can be forecast with some skill for several months ahead. Much more important seems to be the fact that this result demonstrates that there are in the general circulation patterns of sea level pressure some weak but potentially useful inter-relationships over long time spans which lend some weight to the hope that by some kind of technique one might, in the future have a reasonable chance to make meaningful long-range forecasts of a variety of large-scale circulation features.

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REFERENCES


