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A Multiple Regression Technique of Estimating Mean Monthly Temperature Using Sea-Level Pressure

by

BRYAN ELAM LILIUS

A thesis submitted in partial fulfillment of the requirements for the degree of

MASTER OF SCIENCE
(Meteorology)

at the

UNIVERSITY OF WISCONSIN-MADISON

1979

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The Graduate School

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A Multiple Regression Technique of Estimating Mean Monthly Temperature Using Sea-Level Pressure

Eberhard W Wahl
John E Kutzbach

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ABSTRACT

A simple point to point stepwise linear regression model which predicts mean monthly temperature using mean monthly sea-level pressure data is shown to be comparable in skill to a model which uses the coefficients of the principal components of the sea-level pressure as predictors. Regression equations are formed using as dependent data the pressure records from individual grid points in an area centered over North America for the period 1899 to 1960. Forecasts are then made from the equations for an independent record from 1961 to 1977. These predictions are shown to be less accurate than the forecasts made using the coefficients of the principal components. However, they display identical skill in forecasting above or below the long term monthly mean. Limited skill is demonstrated in predicting mean monthly temperature for January based on an actual long range prediction.

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CHAPTER I

INTRODUCTION

It is well established that temperature and precipitation patterns are closely related to atmospheric circulation patterns. It has also long been recognized that long term departures from seasonal normals are intimately related to mean circulation features. Teisserenc de Bort (1881) used hemispheric monthly sea-level pressure maps and showed that temperature and rainfall anomalies were a result of anomalous sea-level pressure distributions. Namias (1953) stated that since most of the current meteorological work is directed toward forecasting the future pressure distribution, studies relating the sensible weather to circulation are important. He further stated: "Such work will and must be undertaken eternally." It is a premise of this study that Namias' words continue to be true.

Since Namias made that statement, most of the research correlating weather with circulation has been done by relating daily weather to daily circulation features. The Model Output Statistics of the National Weather Service are an excellent example of the way such studies can be applied in a practical operational manner. Petterssen (1956) showed that as much as 87% of the variance in the daily mean temperature at Indianapolis could be explained using a "perfect prog" of the sea-level pressure field.

There has also been an extensive period of active research into long range (30 day) forecasting. The main thrust of this effort has been toward predicting the mean 700 mb field over North America. Consequently most of the attempts to predict the temperature field used the 700 mb heights as predictors. Namias (1953) summarized this work well. A strong relationship between monthly temperature and the mean 700 mb circulation was demonstrated.

Klein (1965) has done what is perhaps the most extensive investigation of this kind. In his studies he related surface temperature anomalies to 700 mb height, 1000-700 mb thickness, and sea-level pressure. He actually produced a practical model which was used in the Extended Forecast Division of the US Weather Bureau which produced predictions of 5-day mean temperature using 5-day mean 700 mb heights centered two days prior to the forecast period. However, most of Klein's work investigated the specification of temperature from the concurrent circulation.

Recently some researchers have been demonstrating at least partial success in the long range prediction of the sea-level pressure field. For example, Wahl (1977) was able to show:

> "...that there is in the sea-level pressure some weak but potentially useful interrelationships 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 a meaningful long range forecast of a variety of long range circulation features."

In subsequent yet unpublished work he has shown definite skill in predicting five-year monthly mean sea-level pressure maps of the northern hemisphere based upon a physical model prediction of the mean northern hemisphere temperature developed by Bryson and Dittberner (1976). Also, Bryson and Starr (1977) have predicted long range sea-level pressure fields based upon the expected influences of the Chandler Tide upon the atmosphere. The sea-level pressure is used by these researchers and others because it is the only circulation parameter which has a sufficiently long record for the kind of statistical relationships they use in their forecast methods.

As a result of this recent research in the long range forecasting of the sea-level pressure field, there is renewed interest in finding an optimum method of relating the sea-level pressure pattern to temperature and precipitation. Parker (1977) related these variables using the coefficients of the principal components of the sea-level pressure field as predictors. His technique showed moderate skill in forecasting temperature. He showed less skill in his precipitation forecasts.

It is the purpose of this study to compare a point to point multiple regression scheme to Parker's method of using principal components. Rather than using the coefficients of the principal components, the actual observed pressures at specified grid points are used as predictors. Because of the poor success shown by Parker in his precipitation forecasts and because of the spatial inhomogeneity of the precipitation data, particularly in the summer, this study is restricted to temperature.

Part of the motivation for this study is to determine if a less costly method of estimating the mean monthly temperature field is comparable to using the coefficients of the principal components of the pressure field as predictors. It is recognized that the principal components method might perform better when a less than perfect prognosis is used as predictor, even though the simple regression scheme might compare well using a perfect prognosis. This would certainly be true if the prognosis contained the overall features of the actual pattern.

A description of the data used in this study and the method of performing the regression analysis are contained in Chapter II. Analysis and discussion of the results may be found in Chapter III. Chapter IV includes a description of the results of the method in an actual test case using a forecast sea-level pressure field. Conclusions are presented in Chapter V.

CHAPTER II

DATA AND METHOD

The data used in this study were the monthly mean temperature and pressure from 1899 through 1977. Temperature data through 1960 were taken from the *World Weather Records*. After 1960, the temperature data were from the National Weather Service records as consolidated at the National Center for Atmospheric Research. The sea-level pressure data came from the NCAR data set based for the first 40 years on the so-called Historical Series, extended into the late 1940's by several groups (MIT, US Navy) and then taken from the USWB/NWS analyses. All these data are available on magnetic tape at the Meteorology Department of the University of Wisconsin.

The temperature data for selected stations of the United States were the same as those used by Parker (1977) in order to facilitate comparison between the two methods. These stations are listed in Table 1. Some data were missing for St. Cloud, MN, namely: Oct, Nov, Dec, 1903, and Jan 1904. The monthly mean was substituted for the missing data when the analysis was performed.

The mean monthly sea-level pressures were available for each of the grid points shown in Figure 1. This 72 point grid is somewhat smaller than the one used by Parker in his study, so there is less pressure information available for the regression model than for Parker's eigenvector analysis. The area included in Parker's study is also outlined in Figure 1.

Stepwise multiple linear regression was the method used to determine the optimum prediction equations for each station. The sea-level pressure at any of the 72 grid points could have been chosen as predictors in the analysis. Regression equations were computed for each of the 18 stations and for each of the 12 months giving a total of 216 equations. The equations were formed using as the dependent data set observations from the years 1899 to 1960. The predictions using these equations were then verified for the independent observations from the years 1961 to 1977.

The regression coefficients were computed using standard least-squares techniques. The prediction equations are of the form:

$$T' = b_0 + b_1P_1 + b_2P_2 + \ldots + b_nP_n + e \qquad (1)$$

where T' is the predicted mean monthly temperature for a given month and station, P_i is the mean monthly sea-level pressure for a specified grid point i, and e is the error of estimate or residual (T-T'). In matrix notation

TABLE 1

List of stations used in this analysis. Monthly mean temperatures were available for each location for the period Jan 1899 through Dec 1977 except St Cloud, MN which was missing Oct, Nov, Dec,1903 and Jan,1904.

NO.	Station	Abbrev.	LAT	LONG	WMO#
1	Jacksonville, FL	JAX	30 N	81 W	72206
2	Abilene, TX	ABI	32	99	72266
3	Phoenix, AZ	PHX	33	112	72278
4	San Diego, CA	SAN	32	117	72290
5	Cape Hatteras, NC	HAT	35	75	72304
6	St. Louis, MO	STL	38	90	72434
7	Columbus, OH	CMH	40	82	72428
8	Denver, CO	DEN	39	105	72469
9	Sacramento, CA	SAC	38	121	72483
10	Block Island, NY	BID	41	71	72505
11	Chicago, IL	CHI	41	87	72534
12	Des Moines, IA	DSM	41	93	72546
13	Omaha, NE	OMA	41	95	72553
14	Madison, WI	MSN	43	89	72641
15	St. Cloud, MN	STC	45	94	72655
16	Rapid City, SD	RAP	44	103	72662
17	Boise, ID	BOI	43	116	72681
18	Walla Walla, WA	ALW	46	118	72689

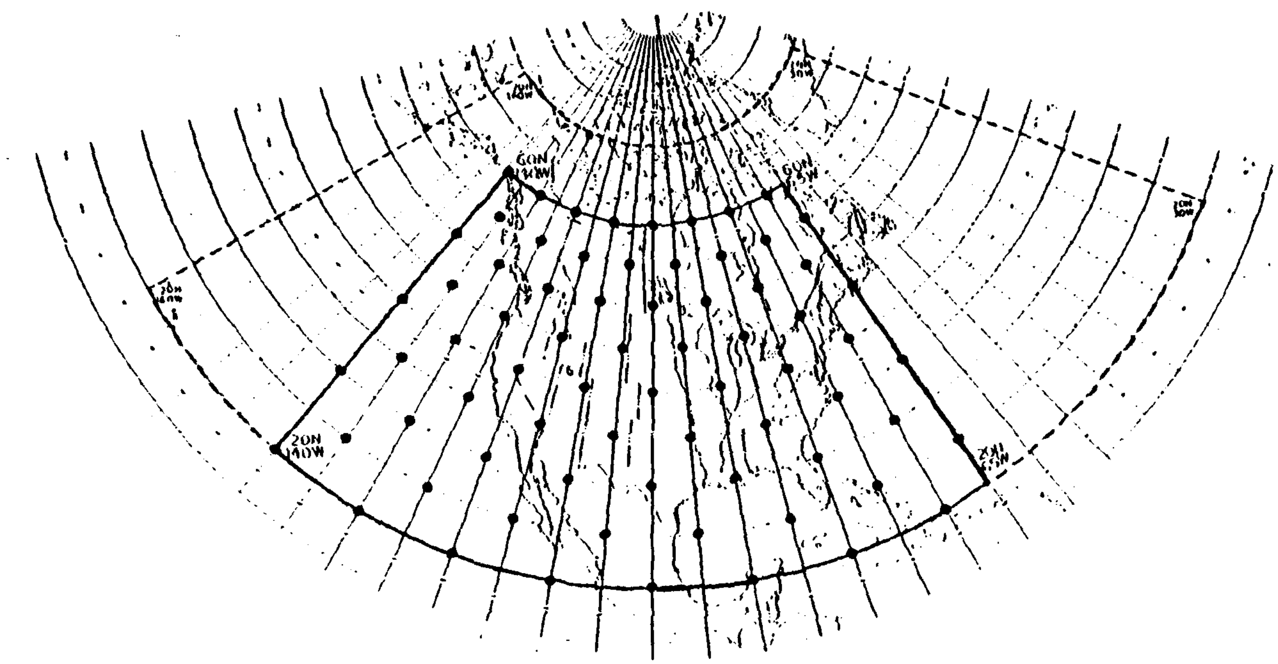


Figure 1. Points shown in area enclosed by solid lines used as predictors. Larger area enclosed by dashed lines shows grid used by Parker.

the equation is:

$$\underline{T}' = (P)\underline{b} + \underline{e} \tag{2}$$

Underlining the variables in this equation indicates a vector. $\underline{T}$ is k-dimensional where k is the number of years from which the equation set is formed. The regression coefficient vector, $\underline{b}$, is n-dimensional where n is the number of variables in the equation. The $\underline{e}$ vector is also k-dimensional while the (P) matrix is k by n. Then minimizing $\underline{e}$ by least squares, the coefficients are computed by:

$$\underline{b} = ((P^t)(P))^{-1}\underline{T} \tag{3}$$

where t denotes the transpose of the matrix and -1 the inverse. The (P) matrix contains the set of dependent observations (1899-1960) of the selected pressure records. It is the method by which these pressure records (predictor grid points) are selected which is of interest now. In the stepwise analysis used in this study, predictors are entered into the equation one at a time. The first predictor to enter the equation is the one with the highest correlation coefficient with the temperature record. The next variable to enter the equation is the one with the largest partial F value not already entered in the equation. This F value is defined:

$$F_i = \frac{q_i^2}{1 - q_i^2}(k - n) \tag{4}$$

where k is again the total number of observations and n is the number of independent variables in the equation. The q_i is the partial correlation coefficient between T and P_i with the linear relationship between T and the other pressure variables already in the equation removed. (Panofsky and Brier, 1968). In addition, before a variable may be entered in the equation it must pass a test for colinearity with the variables already in the equation. This test computes the determinant of the observation matrix with the newly chosen predictor included. If this determinant is less than a certain very small specified value (10^{-12}) then the predictor is excluded because it is approximately a linear combination of the observations already in the equation. This test is described more completely in Allen and Learn (1973).

The F value in equation 4 has a known distribution and it is possible to specify that a predictor be correlated at a certain significance level with the temperature record before it may enter the equation. It was decided to compare two regression models with Parker's results. Model I allowed 10 predictors to enter the equation irrespective of the significance of their correlation with the temperature record. This was done in order to spread the pressure information over as large an area as possible while at the same time attempting to keep the equations reasonably stable by limiting the number of terms in the equation to ten. Model II was formed using only those pressure records as predictors whose correlation with the temperature was significant at the 5% level. The number of predictors chosen in this model was highly variable and will be discussed further in Chapter III.

The program used to perform the stepwise analysis is a standard one available through the Madison Academic Computing Center (MACC) and is more completely described in the MACC publication STEPREG1 (Allen and Learn, 1973).

The verification statistics used to analyze the performance of these models are the same as those used by Parker. The first is a measure of how well the equations describe the dependent data from which they were formed. The reduction-in-variance, or explained variance is defined (Klein, 1965) as:

$$R^2 = 100\left(1 - \left(\frac{\Sigma(T_n - T_n')^2}{\Sigma(T_n - \bar{T})^2}\right)\right) \tag{5}$$

where the sums are taken over the number of dependent observations and the mean is for the dependent data only. A similar measure for the independent data is called the reduction-in-error (RE) which is computed as in 5 above, but the mean is again for the dependent data. Each forecast was also verified according to whether it correctly forecast above or below the mean of the dependent data.

This is called the sign test and a skill score computed for the sign test results is the standard Brier score (see for example Panofsky and Brier, 1968):

$$SS = \frac{O - E}{N - E} \tag{6}$$

where O is the observed number of forecasts with the correct sign, E is the expected number of correct forecasts if no skill were assumed (50%), and N is the total number of forecasts. These three statistics are the same as those used by Parker in his study.

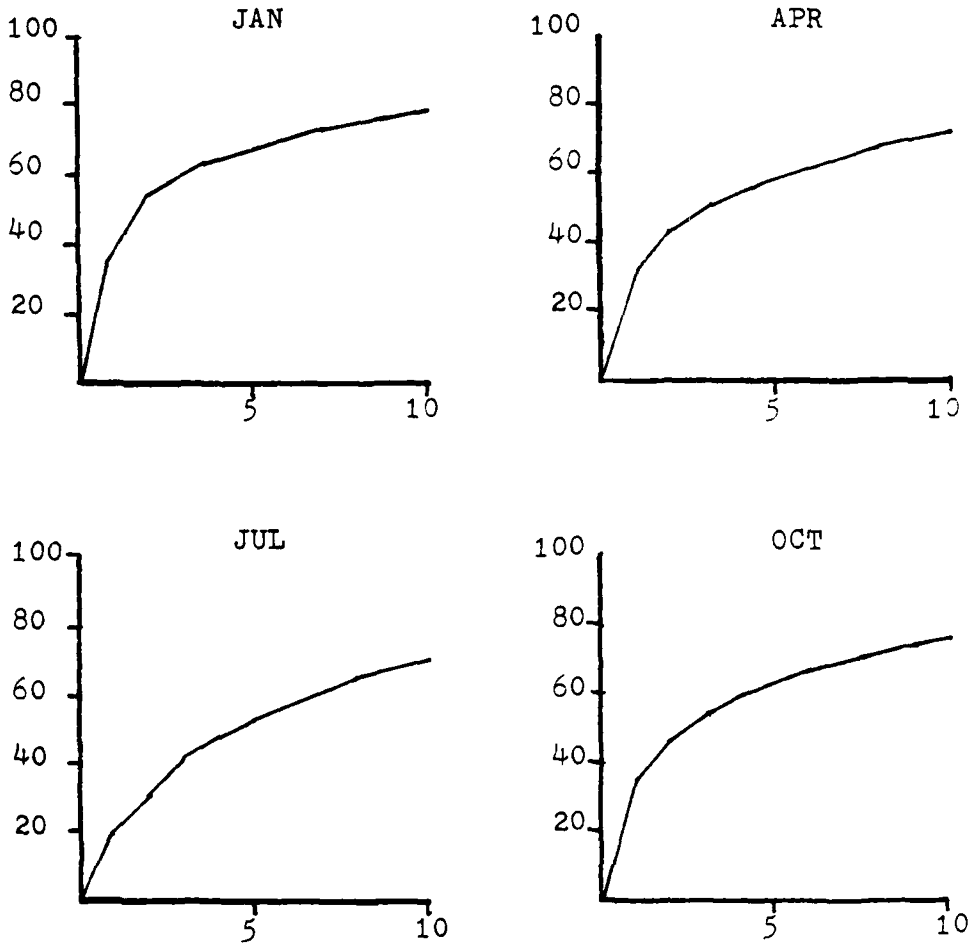
CHAPTER III

ANALYSIS OF RESULTS AND DISCUSSION

It was decided that both the temperature and pressure data would be normalized before beginning the regression analysis. This was done primarily because Parker also used normalized data and so the results were more easily comparable. Parker, after extensive comparison between normalized and non-normalized data had decided that his model performed better when the data were normalized. By normalizing the pressure data, the variance of the predictors is the same everywhere.

Figure 2 shows the average percent reduction-in-variance of the temperature record in the dependent data for all 18 stations as each predictor was added to the equations in Model I. Results are shown for the months January, April, July and October as representative of the four seasons. January showed the greatest overall reduction-in-variance (R^2) of 78%. Most interesting is the fact that the first three predictors chosen explain over half of the variance explained by the equations. Also the last several predictors chosen each add only two or three percent to the reduction-in-variance, indicating a

Figure 2. Cumulative average per cent reduction in variance vs. number of predictors in the equations. Four representative months. Model I. Average of results for 18 stations.



much weaker relationship with the temperature.

Ten predictors in Model I was more or less arbitrarily chosen as a limit to the number of predictors that might be selected. It was thought that any more than ten predictors would cause instabilities or inaccuracies in the predictions due to still existing colinearity between predictors. The results obtained from Model II confirm this expectation. Restricting the choice of predictors in Model II to those with which the interrelationships with the temperature record is significant at the 5% level reduces considerably the errors in the predictions, particularly during the summer when the overall relationship is the weakest.

As already noted, the equations in Model I explained a large percentage of the variance in the dependent data. Table 2a shows the reduction-in-variance for each month and station as well as station and monthly averages. The averages are shown for Parker's results also. Even thougn less pressure information was available for this model than Parker's, the simple point to point scheme explained considerably more variance in the dependent data, averaging 71.3% for all months and stations compared to 49.8% for Parker's model. Figure 3 shows this information graphically, averaged for all stations month by month. All three models (Model I, Model II, and Parker's Model) show

TABLE 2
Reduction-in-variance

a. Model I. PKR indicates results from Parker's model.

Station	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC	AVG	PKR
JAX	86	79	84	73	65	66	75	66	75	77	78	80	75	51
ABI	87	73	83	61	71	64	68	74	70	68	76	61	71	42
PHX	77	78	63	57	82	42	64	60	58	77	69	69	66	45
SAN	74	64	71	68	79	55	71	51	57	59	78	68	66	48
HAT	82	74	78	75	67	59	72	61	77	75	84	71	73	53
STL	80	69	62	73	84	78	66	60	72	68	73	73	72	48
CMH	75	46	79	78	79	70	68	55	71	76	76	70	70	54
DEN	76	74	74	67	77	74	81	71	54	75	82	73	73	50
SAC	67	64	78	82	80	69	68	45	48	75	54	54	65	48
BID	76	68	67	57	52	55	58	66	57	63	79	77	65	43
CHI	75	77	77	74	81	78	74	79	54	58	68	67	72	51
DSM	81	56	78	72	85	71	78	69	74	63	81	72	73	51
OMA	86	77	82	56	84	75	77	76	73	82	79	70	76	53
MSN	79	73	79	73	78	65	47	68	69	81	80	75	72	51
STC	77	74	72	74	83	72	69	74	65	84	75	75	74	47
RAP	89	62	80	72	79	71	76	66	63	82	87	56	74	56
BOI	72	71	66	74	78	71	71	70	57	78	83	67	72	52
ALW	85	66	64	78	75	72	75	76	70	78	82	62	74	52
AVG	79	69	74	70	77	67	70	66	65	73	77	69	71.3	
PKR	56	54	47	53	57	38	43	42	44	61	53	50		49.8

b. Model II

Station	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC	AVG
JAX	84	72	75	59	54	52	75	54	64	56	64	74	65
ABI	85	66	74	42	68	42	65	74	58	62	67	38	62
PHX	66	71	39	49	80	23	54	48	29	76	63	41	53
SAN	59	49	58	58	73	45	56	20	37	40	58	66	52
HAT	80	62	67	63	48	40	72	42	68	67	78	55	62
STL	73	53	47	54	84	68	56	41	66	58	56	52	59
CMH	68	21	70	68	68	66	68	29	63	68	63	63	60
DEN	74	62	58	65	66	71	81	59	21	69	82	62	64
SAC	45	47	52	78	75	69	58	15	11	73	32	18	48
BID	75	58	42	36	39	23	43	54	26	49	71	69	49
CHI	67	70	68	69	79	78	64	79	8	25	42	44	58
DSM	77	35	67	58	81	65	75	48	69	47	81	62	64
OMA	80	67	72	43	84	68	73	76	67	79	72	61	70
MSN	76	65	60	55	76	37	8	60	57	74	80	53	59
STC	69	74	65	65	80	72	69	56	60	81	69	63	69
RAP	86	48	74	60	77	65	76	56	43	75	87	26	64
BOI	48	60	58	71	75	62	60	57	38	76	77	62	62
ALW	75	54	50	64	73	59	61	73	53	78	82	39	63
AVG	72	57	61	59	71	56	62	52	47	64	68	53	60.2

Figure 3. Per cent reduction in variance in the dependent data. Averages of all 18 stations for each month.

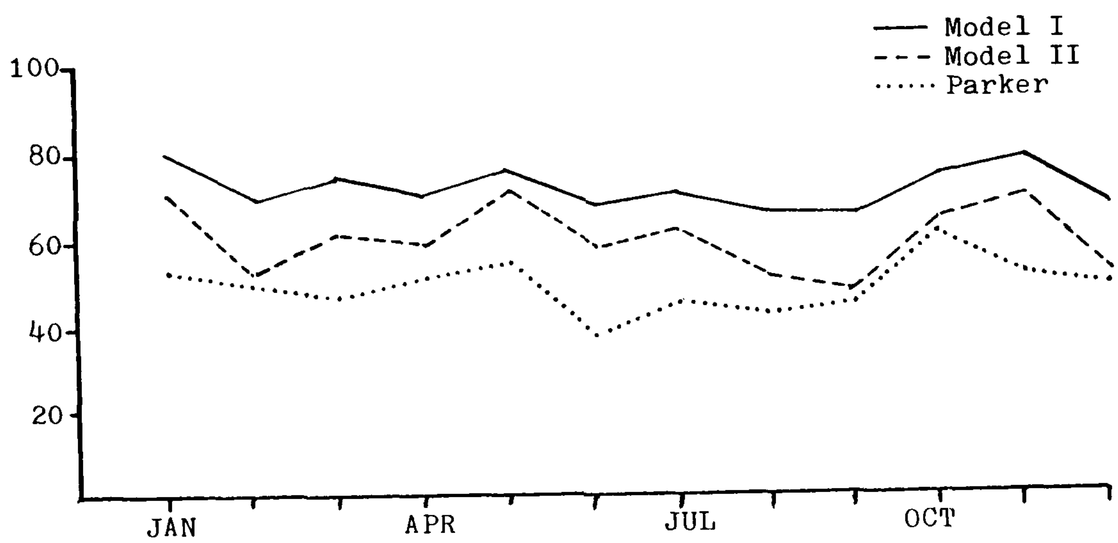


TABLE 3
Reduction-in-error

a. Model I. PKR indicates results from Parker's model.

Station	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC	AVG	PKR
JAX	54	2	40	-61	-92	36	-52	-61	-3	14	27	63	-3	10
ABI	38	15	62	19	-30	-111	-8	-35	34	-45	56	18	1	15
PHX	-15	45	28	8	29	-58	8	42	-1	-35	23	-47	2	16
SAN	17	46	-96	-125	-51	-25	-54	26	17	2	42	6	-16	1
HAT	46	23	51	-13	-97	-38	-102	-72	34	41	57	-35	-9	14
STL	65	-29	34	-45	27	-112	-163	-65	23	-1	22	41	-17	6
CMH	64	-29	72	-19	37	-90	-125	-103	22	-1	43	68	-5	10
DEN	36	18	40	-59	28	-36	-18	1	-25	13	-78	-54	-11	-1
SAC	-19	4	59	54	55	5	44	-139	-158	-42	-6	-16	-13	21
BID	43	0	27	9	32	15	36	5	13	-30	37	34	18	2
CHI	48	-26	59	45	74	13	48	-71	-55	-25	29	61	17	38
DSM	54	-47	27	-62	33	-103	-128	-54	-3	-73	-27	5	-32	5
OMA	-61	1	45	-51	27	-10	-177	-5	-3	39	-16	1	-18	18
MSN	55	-30	36	-46	46	-77	-1	-48	-34	37	-13	5	2	16
STC	15	11	54	-62	14	20	-19	-165	2	43	-58	53	-8	26
RAP	57	30	65	12	3	-112	-62	-3	-31	62	28	5	4	36
BOI	-19	40	14	72	32	22	-53	37	1	25	24	-39	13	32
ALW	43	18	-26	33	54	34	-85	18	-5	-30	-43	18	2	25
AVG	29	5	33	-16	12	-35	-51	-38	-10	0	8	10	-3.9	
PKR	44	-14	40	18	22	-37	4	31	33	17	11	25		16.2

b. Model II.

Station	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC	AVG
JAX	-10	6	38	-7	-128	34	-52	-47	23	21	28	67	-2
ABI	33	42	56	26	-52	-91	-16	-35	19	-52	63	30	2
PHX	2	48	14	45	12	-44	7	42	-6	-27	25	-34	7
SAN	10	57	-219	-71	-29	-16	38	21	42	11	19	0	-11
HAT	58	17	79	60	-7	-34	-102	-47	36	47	42	7	13
STL	21	37	68	49	27	-138	-108	-14	20	-5	24	42	2
CMH	47	-27	71	-5	54	-60	-125	-30	44	-23	62	51	5
DEN	27	1	47	-46	-17	-49	-18	-26	-20	-6	-78	-51	-20
SAC	-11	49	-7	56	57	5	49	14	8	-70	14	-5	13
BID	45	1	16	0	33	16	41	17	21	-2	14	28	19
CHI	67	-14	71	31	80	13	60	-71	-28	33	38	60	28
DSM	57	2	64	-7	34	-22	-102	-8	-22	-17	-27	37	-1
OMA	-5	8	60	29	27	-79	-162	-5	11	41	-17	11	-7
MSN	-70	-19	56	8	15	-1	40	-13	-3	27	-13	52	7
STC	35	11	48	-4	20	20	-19	-15	2	45	-18	50	15
RAP	62	49	67	3	-9	-28	-62	-5	9	69	28	47	19
BOI	18	46	10	80	25	7	-4	27	33	12	48	-57	20
ALW	50	24	-4	52	45	27	-93	18	16	-30	-43	21	7
AVG	24	19	30	17	10	-24	-35	-10	11	4	12	20	6.2

Figure 4. Per cent reduction-in-error in the independent data. Averages of all 18 stations for each month.

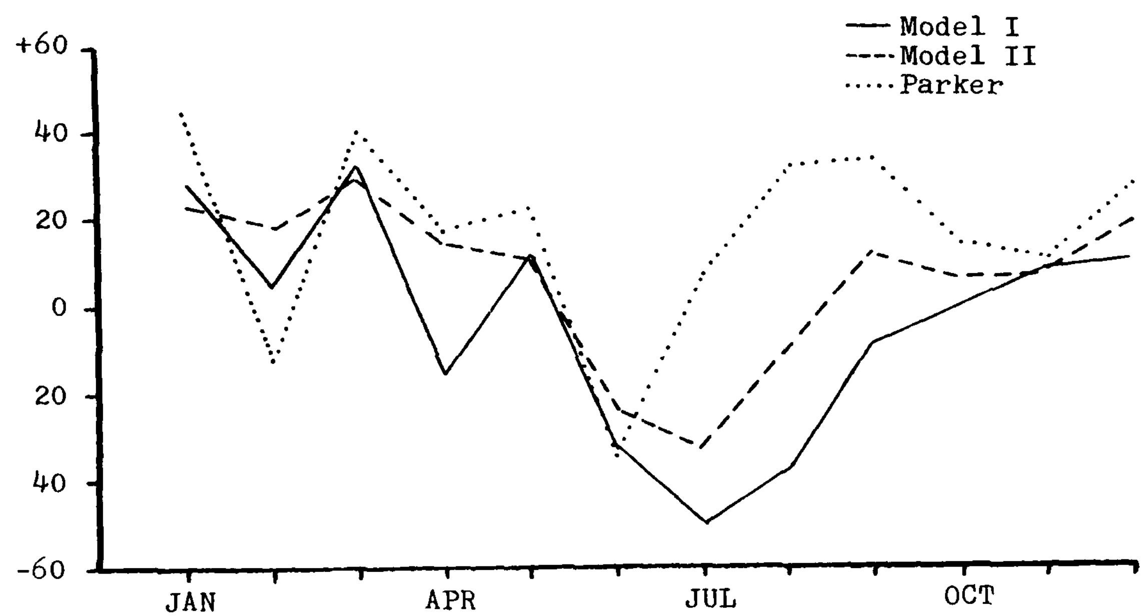


TABLE 4
Sign Test

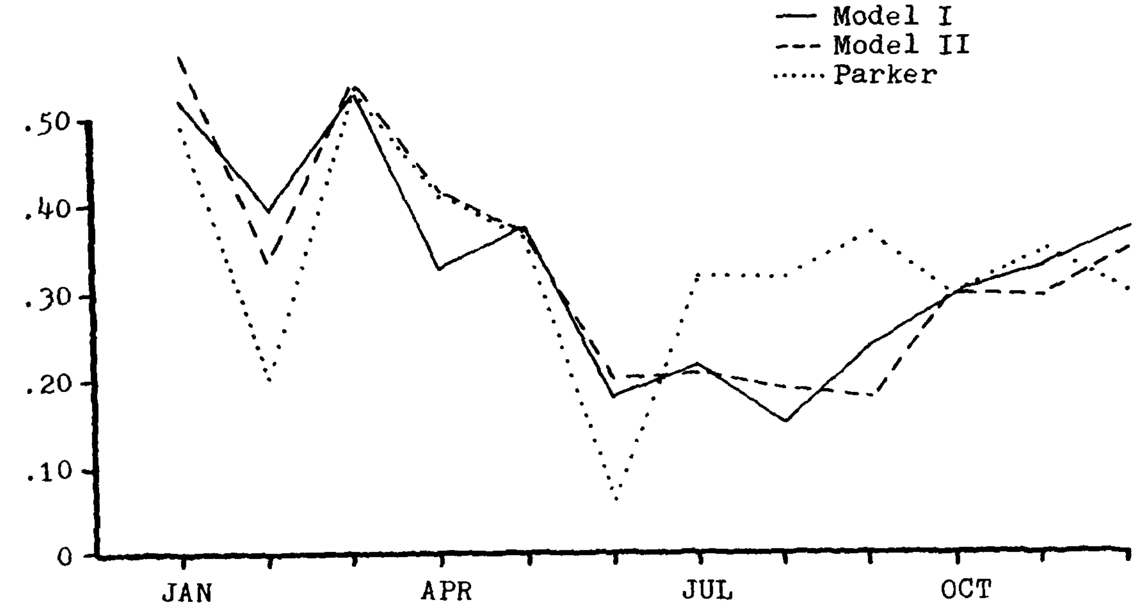
a. Model I. PKR [illegible]dicates results from Parker's model.

Station	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC	SS	PKR
JAX	13	12	14	10	9	13	10	10	11	13	13	13	.38	.20
ABI	13	14	15	12	13	10	11	11	10	9	14	11	.40	.32
PHX	10	13	12	11	12	5	11	13	11	9	13	9	.26	.27
SAN	10	13	9	8	12	11	10	11	12	9	10	12	.24	.36
HAT	15	11	12	11	9	9	8	8	13	14	11	11	.29	.36
STL	16	11	12	12	11	6	7	7	9	7	11	11	.18	.23
CMH	13	10	13	11	13	9	7	7	12	12	12	15	.31	.41
DEN	12	13	13	12	10	9	11	12	10	14	10	8	.31	.26
SAC	10	14	14	15	13	9	12	12	9	12	10	10	.37	.39
BID	13	10	10	14	12	11	13	10	11	10	13	15	.39	.31
CHI	13	11	15	14	12	12	14	9	9	11	12	14	.43	.40
DSM	16	11	10	9	11	10	8	11	9	9	9	13	.24	.28
OMA	13	11	14	12	11	16	8	11	12	12	11	10	.38	.38
MSN	16	12	16	11	14	7	11	6	6	10	7	11	.24	.23
STC	14	13	13	8	9	11	10	8	13	13	12	13	.34	.27
RAP	17	12	16	11	10	8	11	9	9	14	12	11	.37	.44
BOI	7	11	14	12	15	12	11	11	12	11	14	9	.36	.47
ALW	11	11	12	11	15	12	13	10	12	10	10	13	.37	.41
MODEL I	.52	.39	.53	.33	.38	.18	.22	.15	.24	.30	.33	.37	.33	
PKR	.49	.21	.52	.41	.36	.06	.32	.32	.37	.29	.35	.30		.33

b. Model II

Station	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC	AVG
JAX	10	11	14	9	9	13	10	10	11	12	11	14	.31
ABI	13	15	13	12	12	11	11	11	7	8	14	9	.33
PHX	12	13	11	12	12	6	10	13	7	9	12	11	.25
SAN	12	11	6	8	12	9	15	14	14	14	12	10	.32
HAT	16	9	14	14	8	9	8	6	12	15	13	12	.33
STL	14	10	14	12	11	6	5	7	8	8	8	10	.21
CMH	12	7	14	14	13	9	7	8	13	10	12	16	.32
DEN	12	11	13	13	9	8	7	13	6	14	10	9	.23
SAC	9	13	11	15	14	9	13	12	11	12	12	10	.38
BID	15	9	12	13	13	12	12	12	13	11	11	12	.42
CHI	14	13	13	12	15	12	11	9	7	14	12	12	.41
DSM	16	12	14	10	11	10	8	9	8	7	9	12	.24
OMA	13	11	16	11	11	13	8	11	11	13	10	11	.36
MSN	16	12	15	12	8	10	14	8	6	9	7	12	.26
STC	13	13	13	10	10	11	10	9	12	11	11	11	.31
RAP	17	11	16	13	11	13	11	11	12	14	12	14	.52
BOI	13	13	14	15	15	10	11	10	12	11	15	7	.43
ALW	13	10	12	12	15	12	13	9	11	10	10	12	.36
SS	.57	.33	.54	.42	.37	.20	.20	.19	.13	.31	.31	.35	.33

Figure 5. Skill scores for the sign test. Averages of all 18 stations for each month.



decreased reduction-in-variance during summer and early fall. Winter showed the greatest explained variance. It is well known that winter temperatures are determined by advection processes to a much greater extent than summer temperatures, so this result is as expected and reported by many researchers (e.g. Klein, 1965; Martin and Leight, 1949; and Friedman, 1955).

Even though the Model I equations explained a much greater amount of variance in the dependent data, the reduction-in-error data in Table 3a and Figure 4 show that it did not perform as well as Parker's for the independent data. Model I produced a negative RE for the months of April, and June through September. In those months a simple forecast of the mean would have performed better (i.e. RE would be zero). Parker's model did better for this statistic for all months except February and June, and the superiority of his model in this statistic is particularly noticable in summer and early fall. The reduction-in-error is a measure which is particularly sensitive to large errors in the predictions. These large errors are more common in the summer when the relationship between temperature and pressure is relatively weak. Nevertheless, Parker's model was certainly not as susceptible to these large errors as was Model I.

For verification of a simple forecast of above or below normal, the sign test is a good measure of success. Table 4a and Figure 5 show the results of the sign test. The entries in the table show the number of forecasts with the correct sign out of a possible 17. A binomial test in which the predictions were assumed to be independent and with $p = \frac{1}{2}$, showed that all monthly and station results were significant at the 1 % level, except for St. Louis which was significant at the 1.25 % level. The sign test results show the two techniques to be approximately equivalent with both showing an overall skill score of .33. Again, Parker's model did much better during July, August, and September, but Model I did considerably better during February and June.

Looking more closely at each individual month we see in Figures 6 through 11 the geographical distribution of these three statistics for Model I. The figures were drawn using the data from Tables 2a, 3a, and 4a. They are drawn as if the fields were continuous although it is recognized that there are many influences using a point to point regression scheme that make this a very weak assumption. Still the method is useful for showing the geographical distribution of these statistics. In each figure, a)shows the reduction-in-variance, b) is the reduction-in-error, and c) shows the number of correct sign forecasts of a possible 17.

The analysis for January shows the greatest reduction-in-variance over the north central and southwestern U.S., with more than 80% explained variance in that area. The reduction-in-error corresponds well except for an area of poor performance over Minnesota and Iowa. The worst results in the predictions were over the Rocky Mountains and the west coast. This is similar to Parker's results as well, which were about the same for January except that his model did not do as well in the southeast. January was the most successful month for both models, reflecting the fact that circulation is the dominant influence upon mean monthly temperature, particularly east of the Rockies.

The reduction-in-variance field in February is more complex, especially over the Midwest and the Ohio Valley, although there was greater than 70% explained variance over the entire southern half of the country. This southern region was where the best results were found for the predictions, which contrasted markedly to January. February was the second worst month for Parker's model, and Model I improves greatly over his February results, especially in the southeast and over the Rocky Mountains. It is difficult to specify a reason for the very different performance of both models in February compared to January.

Figure 6

Verification statistics for January and February for Model I. a) Per cent reduction-in-variance in the dependent data. b) Per cent reduction-in-error in the independent data. c) Sign test results indicating the number of correct forecasts of a possible 17.

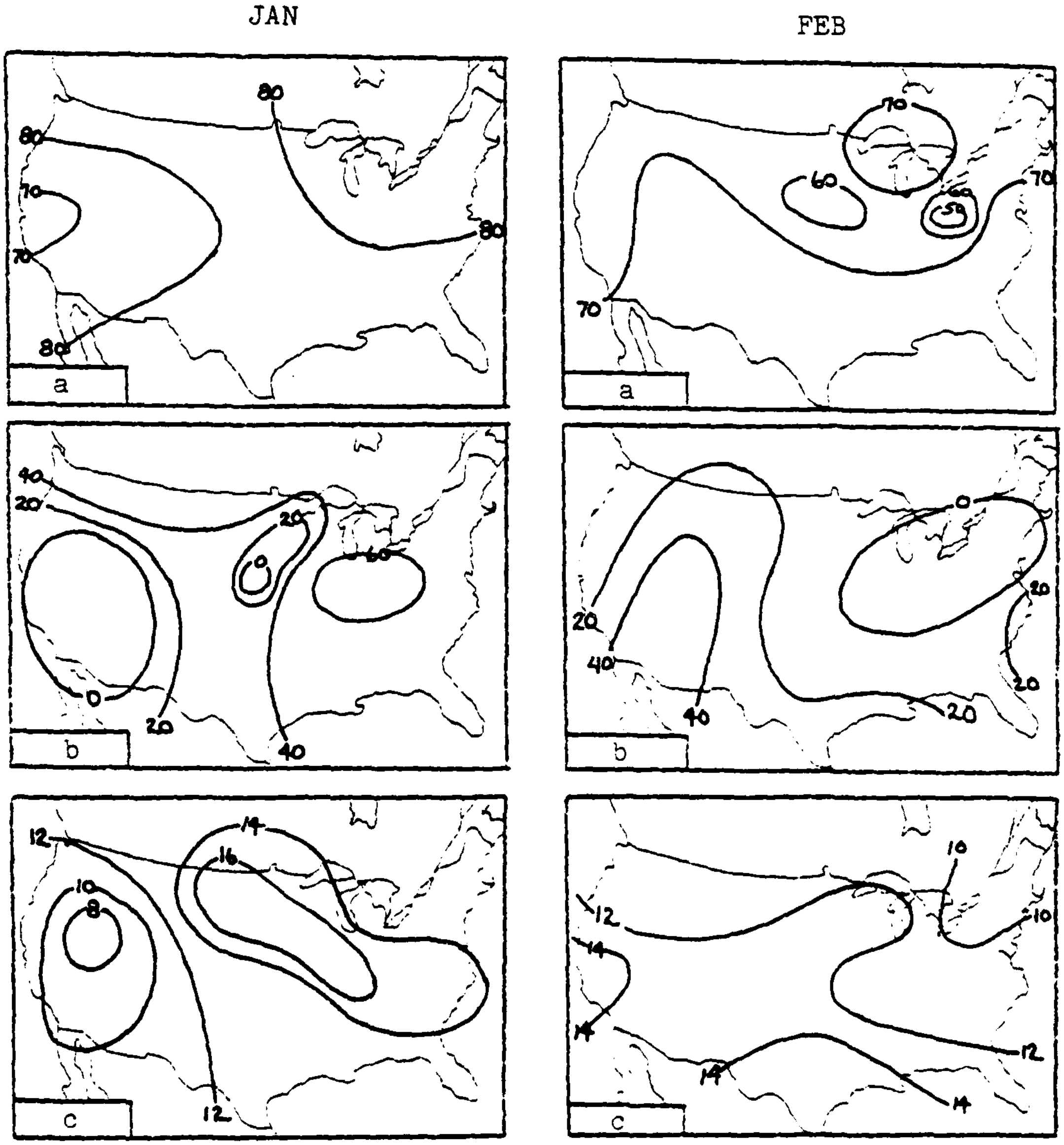


Figure 7

Verification statistics for March and April as in Figure 6. a) R^2. b) RE. c) Sign test.

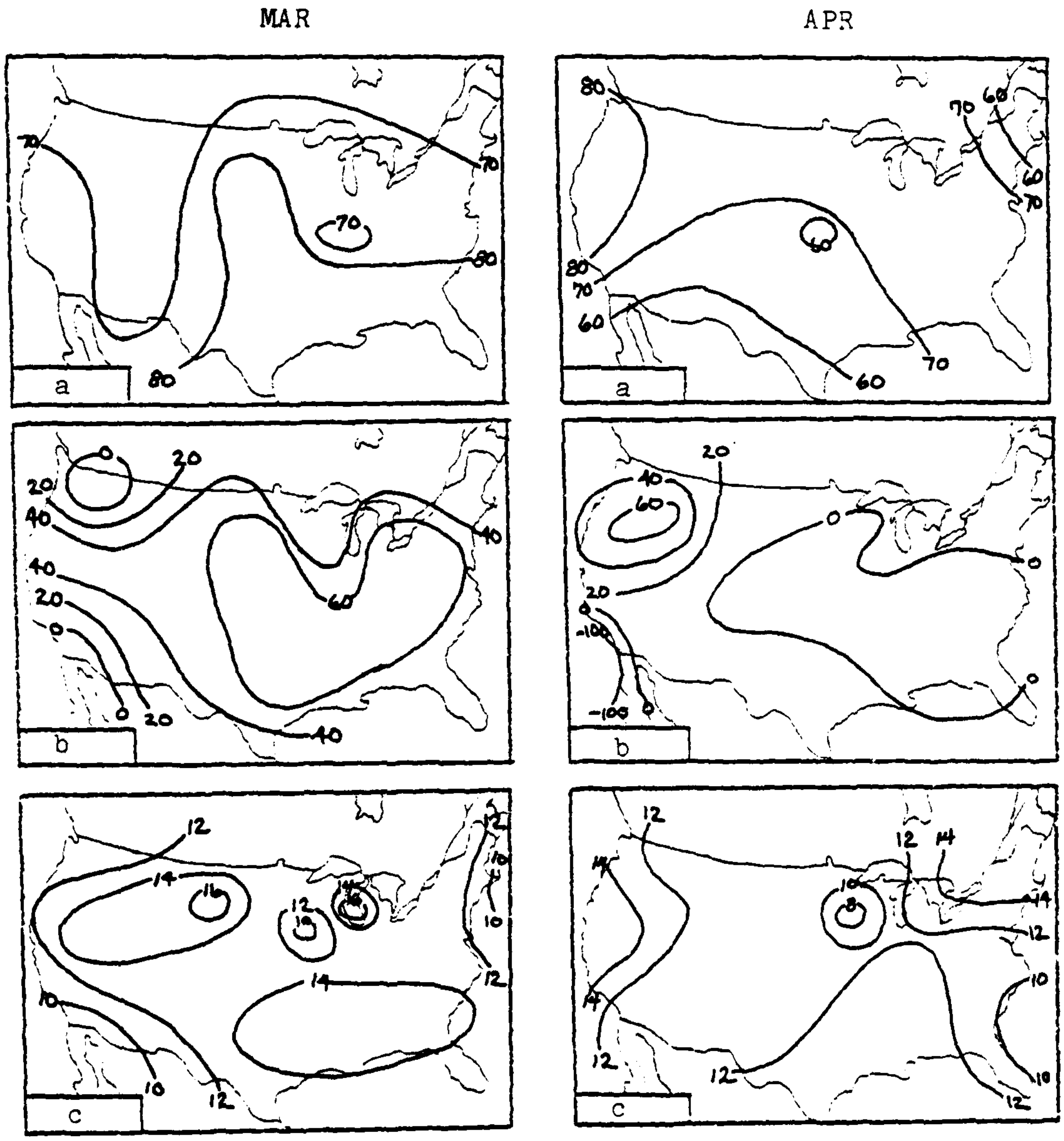


Figure 8

Verification statistics for May and June as in Figure 6. a) R^2. b) RE. c) Sign test.

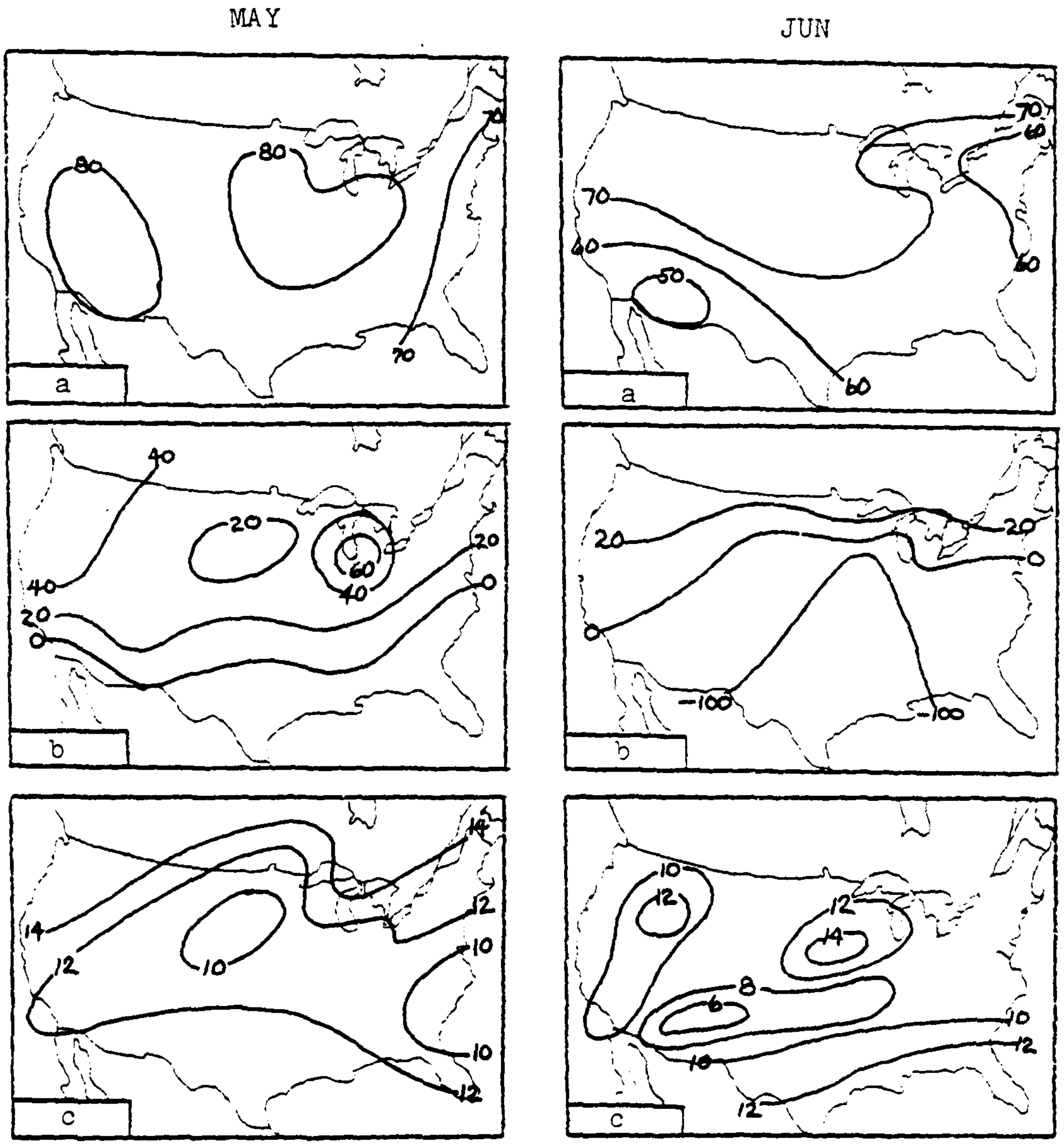


Figure 9

Verification statistics for July and August as in Figure 6. a) R^2. b) RE. c) Sign test.

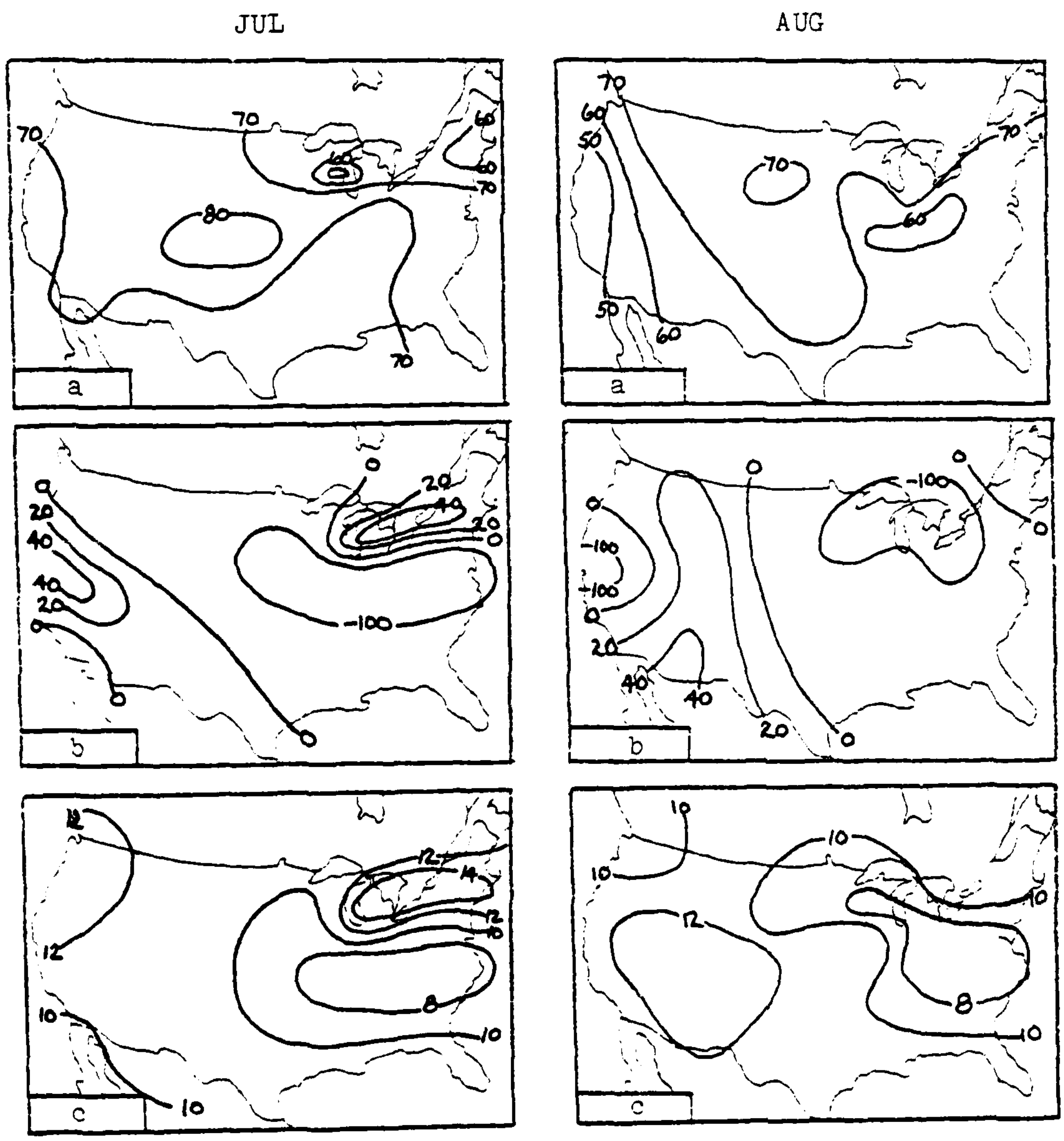


Figure 10

Verification statistics for September and October as in Figure 6. a) R^2. b) RE. c) Sign test.

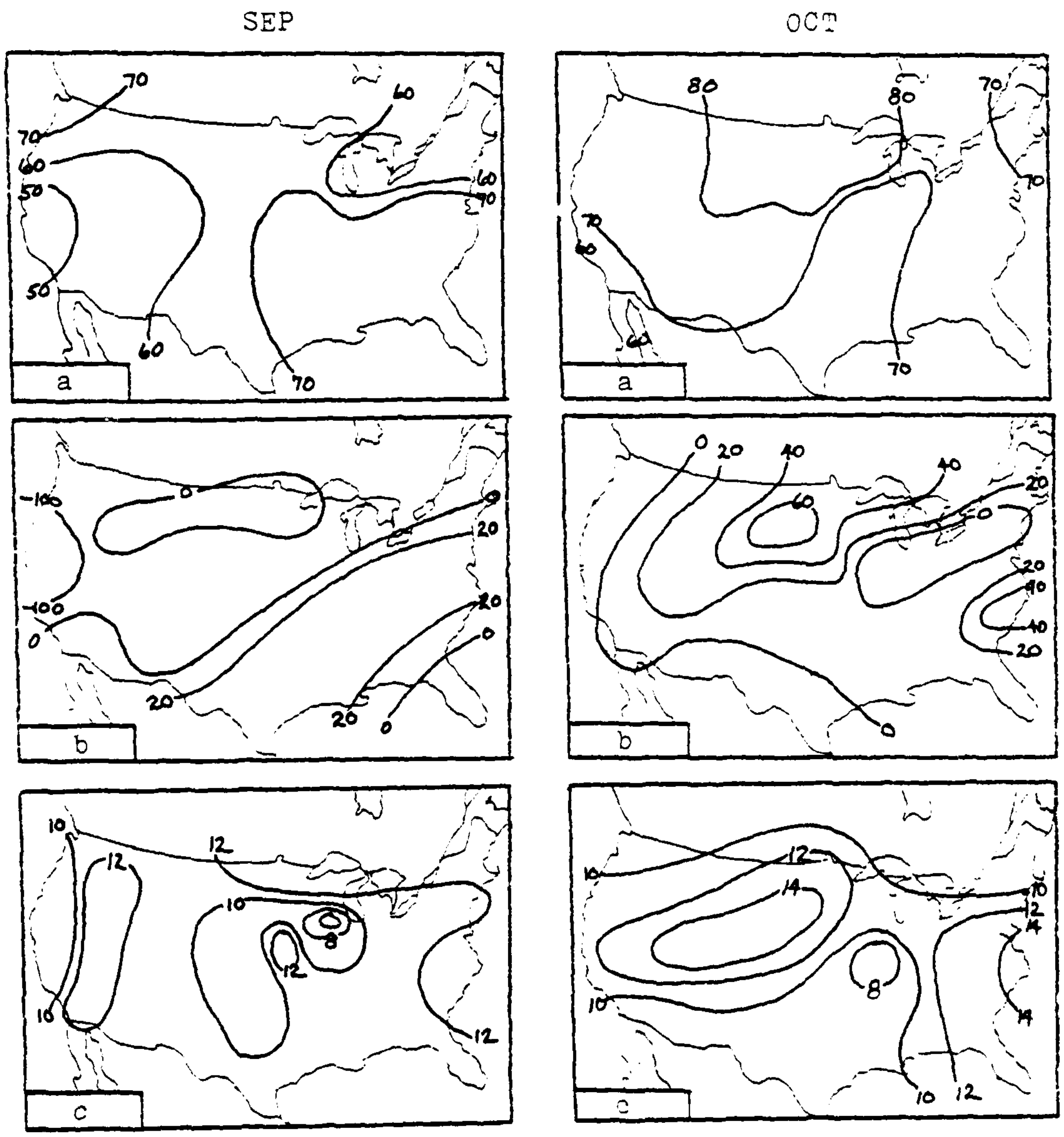
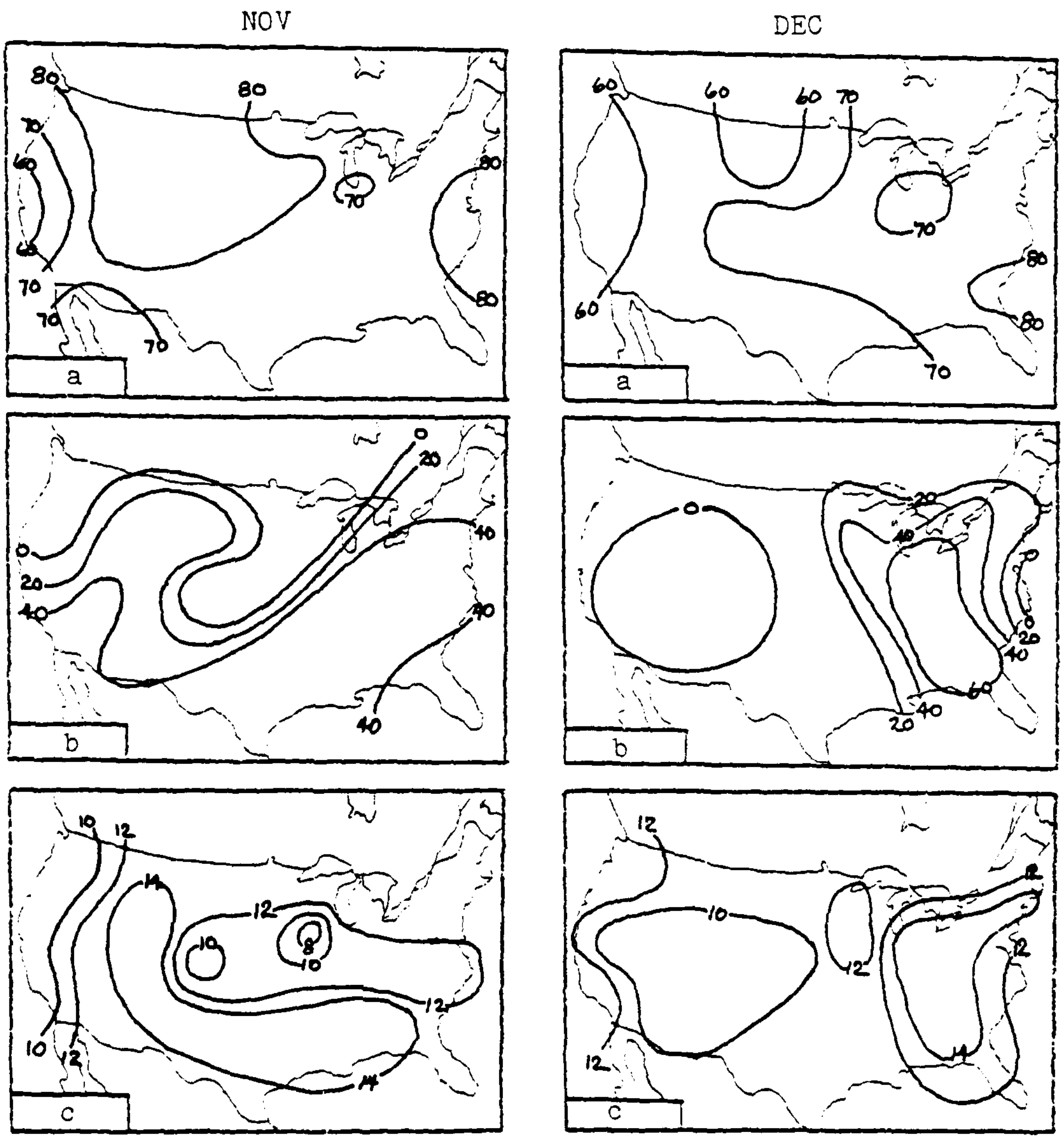


Figure 11

Verification statistics for November and December as in Figure 6. a) R^2. b) RE. c) Sign test.



March was the best month for both models. The sign test results were excellent for Model I except for the extreme east and west coastal areas and a small area over Iowa. Over 60% reduction-in-error is shown for a large area of the central U.S. Perhaps most noteworthy is the excellent performance of the equations over the southern U.S. At this winter-spring transition, advection is still the primary influence on the mean monthly temperature.

April shows an abrupt change from March. The area of poor results over the Pacific northwest in March becomes now the area of greatest reduction-in-error. The central U.S. which had over 60% reduction-in-error in March is now showing negative RE and the only good sign test results are for the Pacific coast and New England. April for Model I is distinctly different from Parker's results which showed good reduction-in-error and sign test results over a large area of the south central U.S. as well as the Pacific northwest, and very poor results for the northeast. Perhaps April provides a good warning against generalizing too much in relating the results of these statistical models to the known circulation since both models used to a large extent the same temperature and pressure information.

May shows good results from both models, except that the sign test performances over the north central U.S. are poor for both. Poor Model I results are found over the Mid-Atlantic states with Parker's model performing much better there.

Very poor results were obtained with Model I throughout the summer, including September. Only small pockets of good results were observable here and there. The overall negative reduction-in-error for Model I for these months has already been noted. Model I performed better in June than Parker's, most noticably in the corn belt and over the Rocky Mountains. For July, August, and September, Parker's model did much better. This would indicate that the principal component technique captured some large scale features of the circulation which had some influences on the summer temperatures which could not be discerned by the point to point regression technique.

October shows improvement with very good results over the Rockies and northern Great Plains, and also the south Atlantic coast. Parker's results are very similar, although his area of negative reduction-in-error is very large, encompassing almost the entire southern half of the country. However, the overall average reduction-in-error was greater for Parker's model.

Good performance for November was restricted to the eastern Rockies and the southern and mid-Atlantic states.

This month showed a good example of a phenomenon which was too common with Model I. Even though more than 80% of the variance in the dependent data was explained in the Pacific northwest, there was negative reduction-in-error and poor sign test results there in the independent data.

December was very different from November, but much like January with good results in all three statistics for the eastern half of the country and poor results in the mountains. This was different from Parker's model which showed the best performance in the northern Great Plains and the Pacific northwest.

Looking at the overall results for Model I, we can say that it performed a little better than Parker's model in winter, a little worse in summer, but that overall it provided comparable results. Generally the areas of good and poor results from the two models corresponded, although this was certainly not always true. The poor results in the reduction-in-error statistic prompted an investigation of the intercorrelation of the predictors. For January the average correlation coefficient between the 10 predictors for Abilene was .29, and in July it was .25. This average correlation was greater than the correlation: pressure to temperature, of some of the last predictors chosen. There was certainly enough intercorrelation to have caused some of the problems in the reduction-in-error results.

Model II was developed to see if a more stringent criteria for selection of predictors would improve the reduction-in-error performance of the equations. Table 5 shows the number of predictors which were chosen for each equation. In 20 equations, the entire 10 predictors were chosen as in Model I. Unexpectedly, 11 of these equations with all 10 predictors significant at the 5% level occur for the summer months when the model performs most poorly. The overall reduction-in-error was improved from -3.9% to +6.2% which is still not very good. Figure 4 shows the greatest improvement to be in the summer and early fall when Model I performed worst. The simple correlation coefficient between the number of predictors and the reduction-in-error was -.18, showing that the equations with fewer predictors tended to have slightly better reduction-in-error. However, Model II did not perform as well as Parker's model for reduction-in-error.

The sign test results shown in Table 4b for Model II show that overall performance was identical to Parker's model and to Model I. Figure 5 shows that the sign test results for Model I and Model II were essentially the same throughout the year, with Model II doing a little worse in February, July, September, November and December,

Table 5

Number of predictors in the Model II equations for each month and station.

Station	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC	AVG
JAX	6	4	5	4	4	4	10	4	5	3	3	6	4.8
ABI	8	6	5	4	8	3	9	10	5	7	6	2	6.1
PHX	5	7	3	6	8	3	6	5	2	9	7	4	5.4
SAN	2	5	4	6	7	4	4	2	2	4	4	9	4.4
HAT	7	4	3	4	4	3	10	4	5	5	6	5	5.0
STL	6	5	2	4	10	5	6	3	7	3	4	2	4.8
CMH	6	1	3	5	4	8	10	2	6	5	5	6	5.1
DEN	9	3	4	8	7	8	10	5	1	7	10	6	6.5
SAC	1	4	3	7	6	10	6	2	1	8	2	1	4.2
BID	9	4	3	3	4	2	5	5	1	4	6	6	4.3
CHI	5	5	4	6	8	10	5	10	1	2	2	2	5.0
DSM	6	2	4	4	8	6	8	4	7	3	10	3	5.4
OMA	6	4	5	5	10	6	7	9	7	6	6	3	6.2
MSN	6	6	4	4	8	3	1	6	5	5	10	4	5.2
STC	4	10	6	4	8	10	10	5	8	7	6	3	6.8
RAP	7	4	7	3	8	7	10	6	3	6	10	1	6.0
BOI	3	3	6	7	3	7	7	4	3	9	4	8	5.8
ALW	4	4	4	4	3	7	4	8	3	10	10	3	5.8
AVG	5.6	4.4	4.2	4.9	3.1	5.9	3.1	5.2	4.0	5.7	6.2	4.1	5.5

and a little better in January, April and August. The overall skill score for all three sets of equations is .33.

The geographical distribution of the verification statistics for Model II is shown in Figures 12 and 13, for the representative months of January, April, July, and October. The data for these maps is taken from Tables 2b, 3b, and 4b. January showed much improvement over Model I in both sign test results and reduction-in-error over the mountain states, with similar performance elsewhere. In April, Model II performed better in both the mountains and the central Great Plains. The area of poor sign test results was duplicated over Wisconsin and Minnesota. July results showed similar geographical distribution from both models as did October.

Model II showed the expected result that insuring a strong relationship between predictor and predictand will reduce the large errors in the predictions. The improvement in the reduction-in-error was not great, though, and this model did not do as well in explaining the variance in the dependent data. Perhaps the most interesting result was that both models in this study and Parker's model showed identical overall skill in predicting whether the temperature will be above or below the mean.

Figure 12

Verification statistics for Model II for January and April. a) Per cent reduction-in-variance in the dependent data. b) Per cent reduction-in-error in the independent data. c) Sign test results indicating the number of correct forecasts of a possible 17.

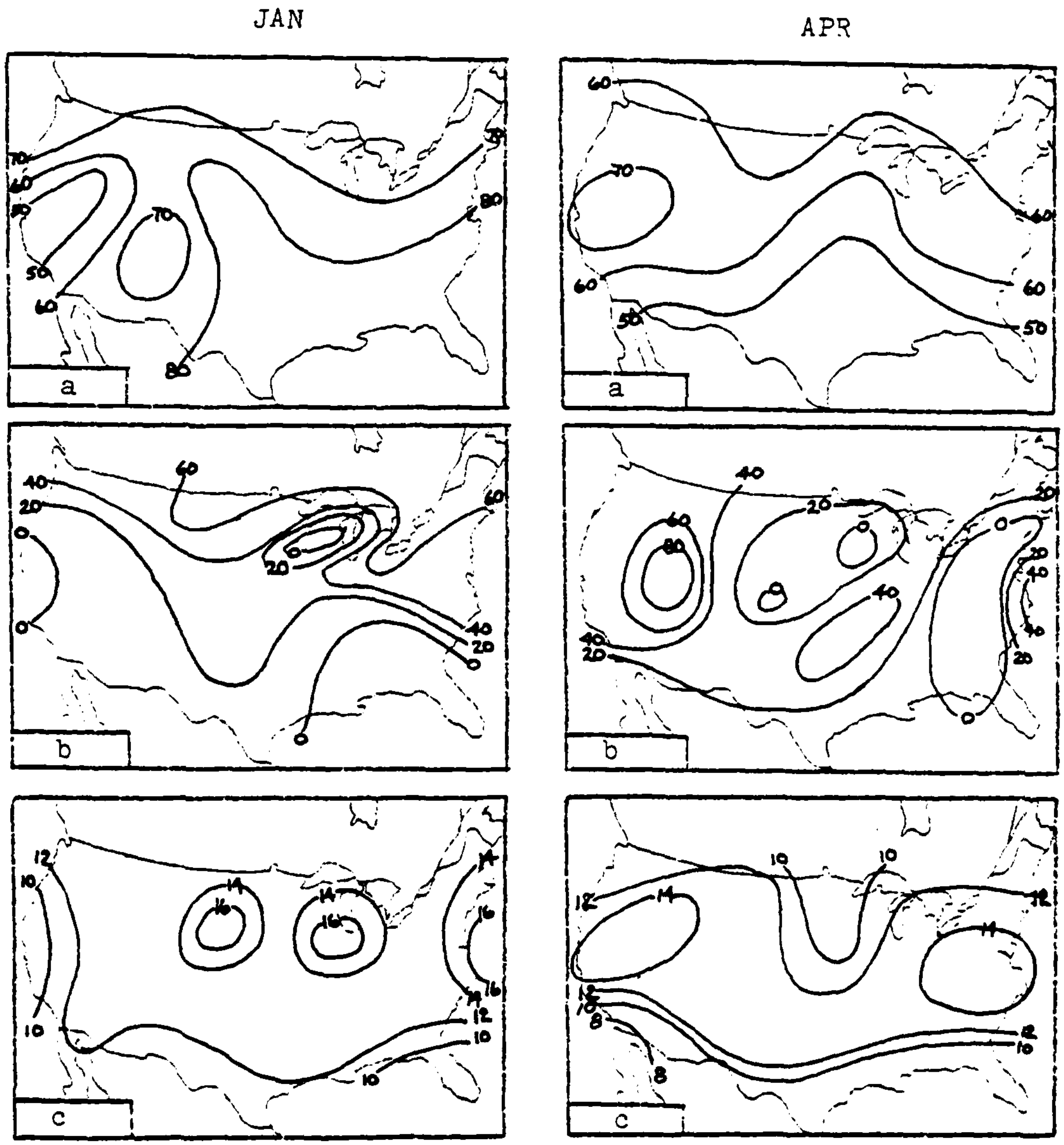
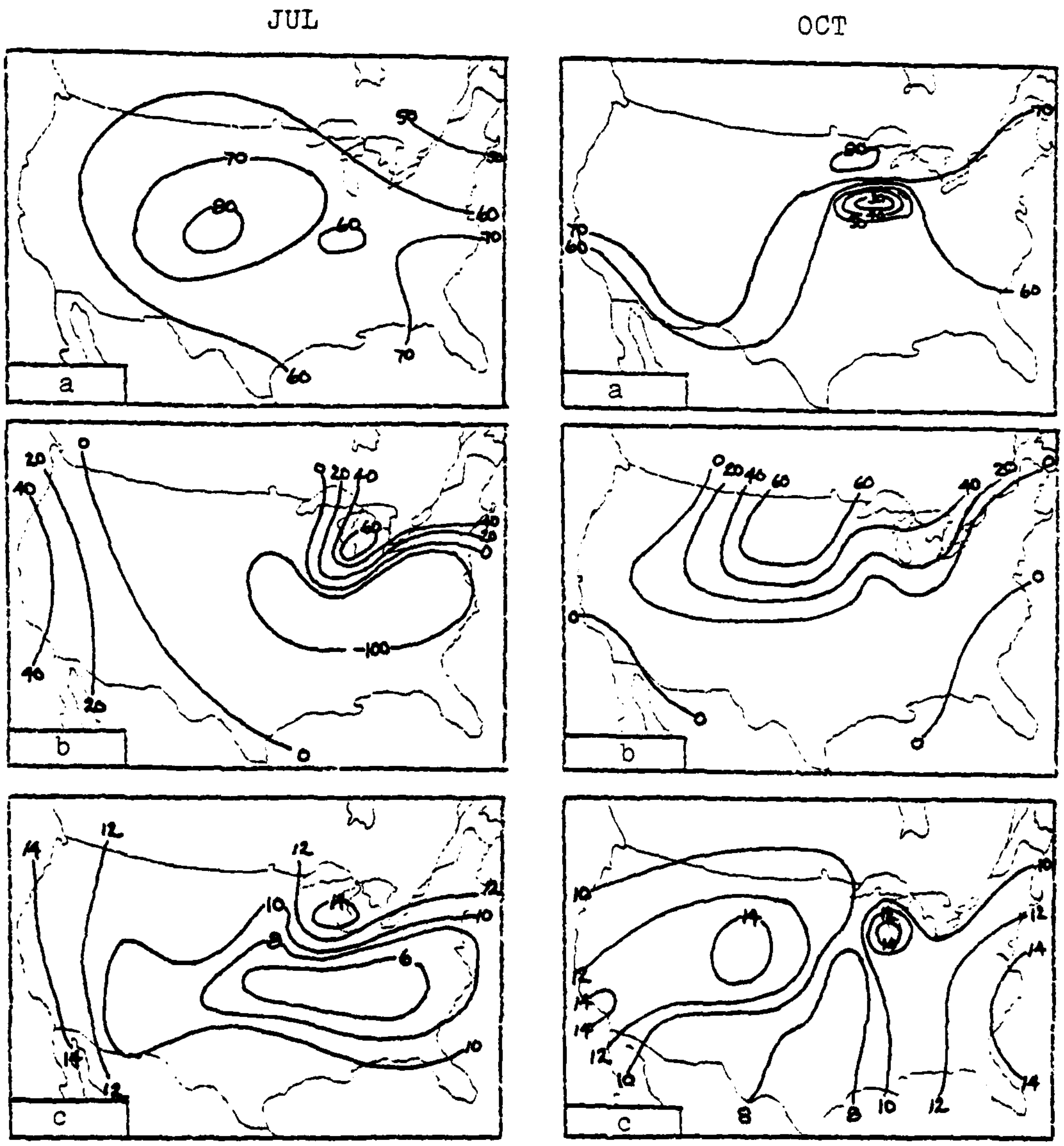


Figure 13

Verification statistics for Model II for July and October as in Figure 12. a) R^2. b) RE. c) Sign test.



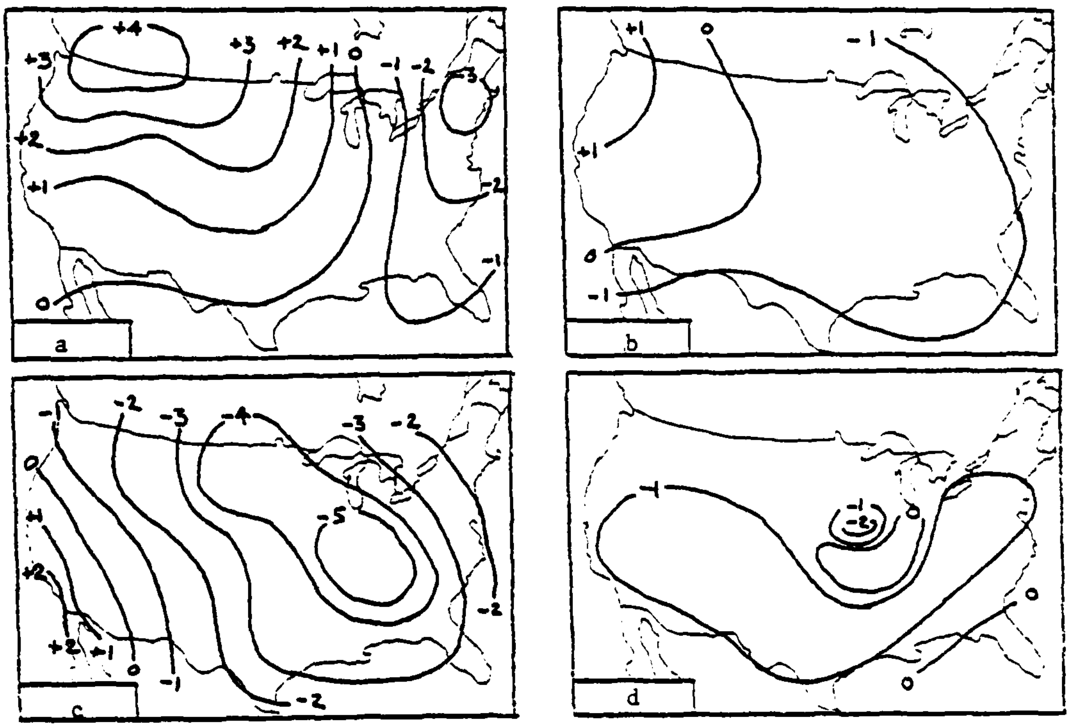
CHAPTER IV

ACTUAL PREDICTION EXPERIMENT

The underlying purpose of this study as well as Parker's was to establish an objective technique of specifying an expected mean monthly temperature field given a forecast mean monthly pressure field. E.W. Wahl (1979) (in work that has not yet been published) has in fact produced forecast mean sea-level pressure fields which show some skill. Using as predictors the five-year mean northern hemisphere temperature for five years ago and ten years ago as well as a forecast five-year mean temperature which was produced by a radiative model of Bryson and Dittberner (1976), he established regression equations for each of 180 northern hemisphere grid points. Figure 14a shows the observed sea-level pressure anomaly for the U.S. for the mean January from 1975 to 1979. Figure 14b shows the pressure forecast for this month and period. This forecast was made based on dependent data through December 1974. January was chosen because it was one of the best months forecast hemispheric-wide by Wahl's model as well as being a month for which this regression system forecasts best. This pressure anomaly

FIGURE 14

Results of actual prediction experiment. a) Observed mean pressure anomaly (mb) January 1975-79. b) Pressure anomaly forecast for January 1975-79 used in this experiment. c) Observed mean temperature degrees Celsius, January 1975-79. d) Forecast mean temperature anomaly, from Model I.



forecast showed an overall skill score of .22 for the area used in these regression equations, with 22 of the 36 points having the correct sign. The forecast was for a coarser grid than was used in this study, and the missing data was filled in by interpolating from a subjective analysis of the forecast pressures. Obviously this forecast is of limited skill, but it is perhaps typical of the type of forecast with which equations such as these might eventually be used.

The results of using this pressure anomaly forecast to produce a temperature forecast are shown in Figures 14c and 14d. Figure 14c shows the observed five-year mean temperature anomaly for January 1975 to 1979 and Figure 14d shows the forecast for this period derived from the Model I equations. Eleven of the eighteen forecast temperatures had the correct sign, and the forecasts showed a reduction-in-error of 7%, so there is perhaps some small skill in the equations. However it is disturbing to see the forecast warmer area in the heartland of the United States represented by Chicago, St. Louis, and Omaha, adjacent to the very cold forecasts of Des Moines, and Columbus. This certainly makes no sense meteorologically, and would be impossible to interpret in an actual forecast situation.

These results highlight what is a great advantage of the principal component technique, namely that the predictions show very high spatial correlation. The spatial correlation matrices for Columbus, St. Louis, Chicago, Des Moines, Omaha and Madison are shown for January, April, July, and October in Table 7. Also shown is the same information for the independent data predictions of Parker's model. The higher correlations are very evident in the principal component method. The average correlation between all stations for all months for Parker's model was .89 while for Model I it was .67. The actual observed correlation was between the two at .82. While this higher spatial correlation does not imply that the principal component method is more likely to produce correct forecasts, it does imply that it is more likely to produce consistent ones.

TABLE 6

Correlation coefficients between six central stations for the independent record. The first value is for the observed data, the second is for the Model I predictions and the third is for Parker's prediction. All values are multiplied by 100.

	CMH	STL	CHI	DSM	OMA	MSN
January						
CMH	1					
STL	89 90 89	1				
CHI	88 93 91	97 94 98	1			
DSM	67 84 73	85 96 95	89 90 95	1		
OMA	61 74 66	83 89 91	83 79 88	95 95 94	1	
MSN	82 91 85	92 96 97	97 97 97	93 92 95	86 83 97	1
April						
CMH	1					
STL	78 83 95	1				
CHI	84 82 91	71 76 95	1			
DSM	63 66 81	70 56 91	83 61 79	1		
OMA	64 47 76	86 65 88	78 71 69	89 22 79	1	
MSN	84 60 85	73 57 94	96 51 96	88 90 81	82 08 97	1
July						
CMH	1					
STL	72 54 93	1				
CHI	83 24 95	85 38 92	1			
DSM	72 68 92	81 97 99	78 44 75	1		
OMA	78 64 90	66 95 99	64 46 64	85 95 85	1	
MSN	67 26 94	60 40 98	76 72 77	76 44 72	57 50 97	1
October						
CMH	1					
STL	90 76 88	1				
CHI	94 65 94	95 52 97	1			
DSM	89 61 79	92 76 96	95 46 95	1		
OMA	79 80 68	86 90 92	87 53 84	95 56 94	1	
MSN	94 82 88	94 89 98	97 47 97	90 92 94	97 55 98	1

CHAPTER V

CONCLUSIONS

The purpose of this study has been to compare a simple point to point multiple regression method for using sea-level pressure to predict monthly mean temperature with a method which uses the principal components of the sea-level pressure field as predictors. Motivating this comparison has been the increased interest and slowly rising skill in recent years in the long range prediction of the sea-level pressure. Although the principal component method has some advantages, it has the disadvantage of requiring a larger amount of computer time than the simple regression method. Before a prediction can be made, the principal component coefficients of the observations have to be computed for the entire pressure field. The simpler technique used in this study requires only the pressure observations themselves.

Although the results of this point to point regression method varied greatly from month to month and station to station, the same skill as the principal component method was shown when forecasting the sign of the anomaly from the long term mean. It was also able to show some usefulness in forecasting temperature from a limited skill, long range forecast.

One of the drawbacks of this method was apparent in the reduction-in-error results. Intercorrelation between predictors led to larger errors which appeared as negative reduction-in-error in the predictions for many months and locations. Especially in summer, these reduction-in-error results cause the skill shown in the sign test to be suspect. The principal component method, with completely uncorrelated predictors, showed better results in the reduction-in-error, although it, too, occasionally produced large negative reduction-in-error results in its predictions.

Certainly no claim is made that the equations used in this study are the optimum possible. A great deal more work would be needed before a model such as this could be used in any kind of operational application. One possible way to improve this model would be to investigate whether a shorter more recent period used as the dependent data set would better represent the current and near future behavior of the atmosphere. Another suggestion would be that the statistical techniques used in the selection of predictors in this model be supplemented by meteorological reasoning, insuring that the choice of predictors made sense, based upon the known behavior of the atmosphere.

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