Contract
DOE-AC03-80ER30002

DOE/ER/30002--T1
1745-NS2

46039

JASON

DOE/ER/30002--T1

DE83 017430

Technical Report
JSR-80-05

August 1980

REGIONAL-SEASONAL WEATHER FORECASTING

DISCLAIMER

This report was prepared as an account of work sponsored by an agency of the United States Government. Neither the United States Government nor any agency thereof, nor any of their employees, makes any warranty, express or implied, or assumes any legal liability or responsibility for the accuracy, completeness, or usefulness of any information, apparatus, product, or process disclosed, or represents that its use would not infringe privately owned rights. Reference herein to any specific commercial product, process, or service by trade name, trademark, manufacturer, or otherwise does not necessarily constitute or imply its endorsement, recommendation, or favoring by the United States Government or any agency thereof. The views and opinions of authors expressed herein do not necessarily state or reflect those of the United States Government or any agency thereof.

By: H. Abarbanel
H. Foley
G. MacDonald
O. Rothaus
M. Rudermann
J. Vesecky

NOTICE

PORTIONS OF THIS REPORT ARE ILLEGIBLE.

It has been reproduced from the best available copy to permit the broadest possible availability.

SRI International
1611 North Kent Street
Arlington, Virginia 22209

MASTER

DISTRIBUTION OF THIS DOCUMENT IS UNLIMITED

RECEIVED BY HQ

SEP 12 1983

DISCLAIMER

This report was prepared as an account of work sponsored by an agency of the United States Government. Neither the United States Government nor any agency Thereof, nor any of their employees, makes any warranty, express or implied, or assumes any legal liability or responsibility for the accuracy, completeness, or usefulness of any information, apparatus, product, or process disclosed, or represents that its use would not infringe privately owned rights. Reference herein to any specific commercial product, process, or service by trade name, trademark, manufacturer, or otherwise does not necessarily constitute or imply its endorsement, recommendation, or favoring by the United States Government or any agency thereof. The views and opinions of authors expressed herein do not necessarily state or reflect those of the United States Government or any agency thereof.

DISCLAIMER

Portions of this document may be illegible in electronic image products. Images are produced from the best available original document.

TABLE OF CONTENTS

I.	SUGGESTIONS AND CONCLUSIONS.....	I-1
II.	INTRODUCTION	II-1
III.	POSSIBILITY FOR SEASONAL ANOMALY PREDICTIONS.....	III-1
	3.1 Introduction.....	III-1
	3.2 Present Methods for Forecasting Seasonal Anomalies.....	III-5
	REFERENCES.....	III-17

APPENDICES

A.1	Regional Weather Forecasting--The Next Step.....	A.1-1
	REFERENCES FOR A.1.....	A.1-7
A.2	Seasonal Weather Forecasts, Fuel Allocation, and Fuel Shortage: A Numerical Example.....	A.2-1
A.3	Weather Forecasting with Probabilistic Means.....	A.3-1
A.4	Viewing Seasonal Climate Forecasts in the Framework of Conditional Probability.....	A.4-1
	REFERENCES FOR A.4.....	A.4-7
A.5	A Possibility for Occasional Accurate Forecasts....	A.5-1
	REFERENCES FOR A.5.....	A.5-8
A.6	Partial Bibliography on Regional-Seasonal Forecasting.....	A.6-1

DISTRIBUTION LIST.....	D-1
------------------------	-----

LIST OF FIGURES

3.1a	Monthly Temperature Anomalies During the Three Winter Months of 1979-1980--December 1979.....	III-7a
3.1b	Monthly Temperature Anomalies During the Three Winter Months of 1979-1980--January 1980.....	III-7b
3.1c	Monthly Temperature Anomalies During the Three Winter Months of 1979-1980--February 1980.....	III-7c
3.2	Seasonally Averaged Temperature Anomalies for the Winter of 1979-80.....	III-8
3.3	Forecast of the Winter of 1979-80 by Gilman, Namias, Andrews, Douglas, Barnett, and Harnack.....	III-10
3.4	Skill Scores for Winter Forecast of Temperature for the Years 1958-1980.....	III-13
A.2.1	Fuel Shortage as a Function of Forecaster Skill.....	A.2-11
A.4.1	Observed and Forecast Temperature and Precipitation for Winter 1976-77.....	A.4-2
A.5.1	Correlation Coefficients Between 700 MB Geopotential Height at Gridpoints Poleward of 20° N.....	A.5-2
A.5.2	700 MB (L-H) SOI Composite Anomalies, LAG=0.....	A.5-5
A.5.3	700 MB (L-H) SOI Composite Anomalies, LAG=1.....	A.5-6
A.5.4	700 MB (L-H) SOI Composite Anomalies, LAG=2.....	A.5-7

LIST OF TABLES

3.1	Skill Scores for Various Predictions of Winter Temperatures.....	III-11
A.2.1	Fuel Shortage Vs Skill.....	A.2-10
A.4.1	Conditional Probabilities $p(0 F)$ for Forecasts and Observations Shown in Figure 1 for Winter 1976-77.....	A.4-3
A.5.1	Composites of Selected Surface Data for the Period 1910-1945 Based on Fanning Season Precipitations.....	A.5-3

REGIONAL-SEASONAL WEATHER FORECASTING

Prediction is very hard, particularly of the future.

Niels Bohr, 1926

I. SUGGESTIONS AND CONCLUSIONS

(1) Seasonal forecasting is a research problem that is only now beginning to draw the attention of the meteorological community.

(2) The present skill displayed in seasonal forecasting is insufficient to justify use of these forecasts in operational fuel allocation. In particular, the skill appears to be low in the highly populated and industrial parts of the United States.

(3) There appears to be a dichotomy in the meteorological community with respect to generating and improving seasonal forecasts. On the one hand there is the National Weather Service group, which is responsible for making forecasts. But this group has insufficient time and resources to do the extensive research which might lead to improved analogue models or eventually even GCM models. On the other hand, there are the academic and research institute-based groups for whom the possible improvement of seasonal forecasts is generally not a subject in which there is much enthusiastic effort. An arrangement for selected sabbaticals to

permit some full time professionals to spend an occasional semester or year in one of the related academic groups and vice versa could well be fruitful in marshalling more informed effort in this aspect of the forecasting problem.

(4) Seasonal predictions may be more usefully applied if they are always accompanied by some estimate of probability (see Appendices A.1, A.2, A.3). Perhaps several patterns could be published with relative probabilities (including one that reflects the probability that all of the above predictions would be incorrect).

(5) Relatively more effort should be devoted to improving and grading predictions for the large, rarer seasonal anomalies of great economic impact (the severe New England winter, the summer midwestern drought, etc.) as opposed to better forecasting of the sign and extent of anomalies. How well and with what confidence these can be predicted and how often they are missed is probably the single most important factor in measuring the "skill" of a forecaster or technique.

(6) Pure analogue forecasting is limited by its restricted data base for comparisons, but even so, it appears that more work may lead to important improvements. What variables are most important in determining the closest past analogue? Since this is unclear, the measure of a closest analogue state is probably not yet optimal. Perhaps simplest and most important is concentrating only on the seasonal anomalies of maximum economic impact. Can a computerized analogue forecasting technique be

developed which is an improvement over that of present experts for this special subset of states? Again, although there does not yet seem to be an answer, one should at least be able to determine if the present limited data base is sufficient to explore this question and how much earlier meteorological data might be useful for extending the comparison states for this special group.

(7) The correlation of sea surface temperatures with continental weather has highlighted patterns that are in turn correlated with regions in which forecasters have a high skill score. There are other surface features that have a high heat capacity and change on a relatively long time scale; for example, soil moisture. Correlation of these features with weather patterns appears to us a fruitful field of research.

II. INTRODUCTION

Meteorologists and others have, over the years, proposed and implemented various programs to obtain long range forecasts. Though attempts have been made to provide longer forecasts, we are concerned only with seasonal, three month, forecasts of seasonally averaged temperature and precipitation. Several categorizations are in use. In one, the prediction is whether the variable of interest will be above or below the mean for a given region. A three bin system uses the categories "above, normal, or below average." The British Meteorological Office employs the categories "above, normal, below and much below." This particular categorization is of interest since, as will be discussed, large variations from the mean are important.

Interest in long range forecasts is motivated in large part by the anticipated economic benefits. Many groups and institutions in society must allocate resources well in advance of their actual use. Natural gas and middle distillates are the sources of energy most often used for space heating, and their demand is most affected by weather conditions. Suppliers of fuel oil and natural gas would benefit from forecasts since they provide an energy demand indicator. The Department of Energy, under normal circumstances, does not take part in the distribution of fuel, this being the responsibility of the energy commodity suppliers. If a shortage of natural gas should occur, the Federal Energy Regulatory Commission (FERC) may require natural gas suppliers to implement curtailment plans

filed with FERC. Priority users of natural gas may be further protected if an emergency is declared under the Natural Gas Policy Act. But the redistribution of gas throughout the country requires only a few days; thus, the three month forecasts are of little use in natural gas allocation.

The situation with respect to allocation of middle distillate fuels differs. If a shortage of fuel oil develops, the State energy offices can allocate the four percent of such fuels set aside by regulation for such circumstances. The Department of Energy has standby authority to further allocate middle distillates. But, since the Department would likely become involved in the fuel distribution process only after the shortfall had occurred, the three month forecast would be of little use to the Department.

Farmers are often cited as being in need of good seasonal forecasts. However, a review of the literature on the subject reveals that forecasts that would be of use to the agricultural interest may not be feasible, at least in the foreseeable future. In order to aid the farmer, the forecast must be specific with respect to dates and areas. Since the timing, location, duration and intensity of precipitation is highly variable from place to place, even a perfect seasonal-regional forecast of the kind considered in this report would be of questionable value. Perhaps the greatest beneficiary of reliable seasonal-regional forecasts would be the general public in planning their activities, particularly their vacation prospects. The snowless December, January and most of February in

the Northeast in the winter of 1979-80 and the great heat wave of the summer of 1980 in the central and southeastern United States are two striking examples of how reliable forecasts would have been of assistance to the public. Manufacturers of such diverse items as galoshes, snow tires, raincoats, sun tan lotion, etc., would also benefit from good seasonal forecasts. Finally, the longer term forecast can assist the short period, 24 hour to five day, forecaster by alerting him to the possibility of large excursions from the mean for such events as hurricanes and other severe storms.

A number of methodologies for making seasonal forecast are currently under investigation. In the analogue method a computer stores a file of seasonal averages of various meteorological variables and the computer searches past history to find the "closest" match to the current season; the computer then forecasts the following season as the weather of the season following the historical match. Global circulation models use numerical solutions of the governing equations to explore seasonal weather. An increasing number of investigators are examining "teleconnections" which are persistent correlations over large distances of various parameters of meteorological significance. Several investigators use their long experience combined with one or more of the above methods. These approaches are discussed in greater detail in Section III.

We were impressed by the need to provide a forecast in the language of probability in order to give the user some feeling for the reliability of the forecast. In Appendix A.1 we explore how forecasts can

be put in the form of actuarial statements, to be followed by an assessment of the incremental value one can achieve with improvements in the forecasts. In Appendix A.2 we describe a numerical experiment which illustrates the point that forecasting skills must improve substantially if they are to be of any use in fuel allocation. The probabilistic approach is further considered in Appendix A.3, and Appendix A.4 provides a numerical example of how such probabilistic statements might be made. In Appendix A.5 we consider how teleconnection might be used for an occasional highly accurate forecast. Appendix A.6 provides a guide to the current literature on regional-seasonal weather forecasting.

As discussed in Section I, we are of the opinion that none of the methods used so far have sufficient skill to warrant the operational use of such forecasts for fuel allocation. The use of climatological averages is recommended particularly because of the low level of skill shown by forecasters in the populous Northeast and the Great Lakes states (see Figure 3.3). A numerical experiment described in Appendix A.2 suggests that skill levels three times those currently attained would have only a minor impact on reducing fuel shortages. We consider seasonal forecasting an important research problem that up until recently had been largely neglected by university meteorologists. The Department of Energy should monitor progress in the field but should not attempt to use forecast operationally.

III. POSSIBILITY FOR SEASONAL ANOMALY PREDICTIONS

3.1 Introduction

Can there be important improvements in seasonal weather prediction beyond that achieved with a naive use of seasonal means and fluctuation statistics from past records? The answer to this fundamental question depends upon how much of the fluctuation is uncorrelated "noise." If almost all is, no great improvement is possible. Weather patterns generally survive for an order of a week or so and detailed weather prediction may never be possible over periods longer than two weeks, or perhaps only several days. If fluctuations in seasonal averages were simply a result of adding entirely uncorrelated random weekly fluctuations, important improvements in seasonal forecasting will not be obtainable. But there is some reason for optimism that a judicious use of past data and present measurements can improve seasonal predictions in a very significant way. This view is based upon the following kinds of evidence:

3.1.1 Ocean Thermal Inertia

The sea surface temperature (SST) affects the temperature of the air in contact with the oceans, and the transport of this air over the continents is a crucial ingredient in the determination of land climate and weather. But the thermal inertia of the oceans' upper mixed layers is sufficiently large that the SST does not rapidly adjust to that of the atmosphere above it. The heat flow from ocean currents and the present SSTs depend upon the past weather above the oceans (temperatures, winds,

storm frequencies, mixed layer depths caused by storms, etc., during the past year or two) and long time scale features of the ocean climate (cold water upwelling, polar cold water, seasonal sinks, etc.).* Thus past climate anomalies may correlate with future anomalies both because the former, through the oceans, may influence the latter, or because they are both sensitive to the same slowly varying ocean variables even if they themselves do not perturb these variables in an important way. Possibly for this reason there is more persistence in Continental U.S. temperatures over six month periods than would otherwise be expected except for the seasonal transitions October to November and March to April.¹

In recent years, the correlation between sea surface temperatures and climate anomalies has been analyzed in some detail. Other features of the Earth's surface have large thermal inertia and a long time scale. The removal of soil moisture during a drought reduces the effective heat capacity of the ground, a feature that may persist through several seasons. The albedo of the surface can be changed in response to drought² and through anomalous snow cover which can also persist. There may be other changes with similar time scales that could affect weather.

*Pacific SSTs off California and Peru can play a crucial role in predicting North American land air temperatures many months later, especially in the winter when the oceans are a major source of atmospheric heating. These SSTs themselves seem correlated with Pacific winds of order a year earlier. (See Appendix A.5)

3.1.2 Empirical Evidence for Long Time Scale and Cyclic Non-Seasonal Components in Some Climate Variables

Some long time scale or quasi-periodic behavior may be attributed solely to the internal dynamics of the atmosphere (and oceans) while others may be driven by externally varying parameters. Among the former with a persistence beyond two weeks may be some relatively short time scale variations³ such as

- an approximate three week component in the energy of upper level zonal winds at temperate latitudes;
- one to three week variations in polar stratospheric heat flow;
- six to seven week pulsations in tropical pressures and zonal winds;
- "blocking" patterns of up to three weeks;
- nine week variations in polar region pressures;
- four week pulses in temperature and winds above North Atlantic (as observed on weather ships).

Possible longer time scale "spontaneous" fluctuations include:

- the strong 2.1-year "quasi-biennial" oscillation of tropical stratospheric winds;
- the large "Southern Oscillation," a back-and-forth movement of great masses of tropical Pacific air over intervals of two to seven years.

3.1.3 External Parameters

Variations in external parameters which may affect climate include:

- cooling of several tenths °C in the year or two following large atmospheric dust insertion by volcanoes;
- a significant 11.6-month oscillation in Northern Hemisphere temperature latitude zonal wind (Westerlies) strengths which has been attributed to effects of periodic maximum mutual reinforcement of tides from lunar and solar gravitational attraction. This reinforcement has also been suggested as the driving impetus for a 13 1/2-year period component in a 300-year record of central England air temperatures. These explanations are unlikely to be correct since the nonlinear reinforcement can always be expressed as some indifferent frequency multiplied by integers;
- possible solar cycle effects on weather from the 11-year oscillation in solar activity, for UV, and low energy cosmic ray fluxes, and from consequences of the 22-year cycle in the solar dipole field. The former could, for example, alter stratospheric ozone and, through it, surface temperatures in various ways. But evidence for this in the climate-weather records is a point of considerable contention. A 22-year period has been claimed for droughts in a 300-year record for U.S. western plains rainfall, but with poorly determined phase and locations.

Although no single one of all of the above may be compelling, the collection gives considerable support for the view that some climate variation may be correlated over sufficiently large time intervals to

encourage hope that significantly useful seasonal anomaly forecasting may be achievable.*

3.2 Present Methods for Forecasting Seasonal Anomalies

If past records of relevant climate variables (temperature, pressure, wind velocity, precipitation, etc.,) were sufficiently long and complete, maximally effective prediction of anomalies from seasonal means would be achieved by identifying past atmosphere-ocean states arbitrarily close to present ones and seeing what seasonal anomalies followed. But because even very closely identified initial states of the atmosphere will generally develop into very different states after one week, the prediction of seasonal anomalies would have to be given in terms of relative probabilities for a finite ensemble of anomalies. But records of meteorological variables may be insufficient to support such a program since the length of adequate records for the three dimensional hemispheric atmosphere and SST does not exceed three decades. A variety of techniques has been used in preparing actual seasonal forecasts and others have been suggested. These fall into three categories depending upon the roles of computer model atmospheres, human judgment, and historical records.

3.2.1 Expert Subjective Forecasting

Expert subjective forecasting in which human judgment is based upon a synoptic view of an existing anomaly pattern can be used to predict anomaly patterns for the following season.

*Many much longer time scale phenomena which affect terrestrial climate may exist but these would probably have little influence on climate anomaly prediction over the next few decades.

Thus the Climate Analysis Center (G) of the National Weather Service emphasizes anomalies in the height distribution of the 700 mb layer (a measure of low altitude atmospheric temperature). Continental U.S. forecasts for temperature and precipitation are decided by a committee of three which consolidates differing opinions. Namias (N) emphasizes Pacific SST anomalies and some in Atlantic Ocean circulation in predicting continental climate (teleconnections). SSTs are also essential inputs into semi-subjective analyses of Harnack (H) and Douglas (D). Andrews (A) of the Medium Range Forecasting Group of the National Weather Service uses the presumed persistence of key 500 mb height anomalies. In general, all available meteorological data and altitudes are not used in making forecasts, in part because of the human difficulty in realizing a synoptic view with many variables in three dimensions.

There are, of course, no compelling unique criteria to decide on the "success" of forecasts of seasonal anomalies (predicting rare extreme conditions is probably more useful than better predictions of small deviations) and the "success" of a forecast can also depend sensitively upon the precise interval. For example, Figure 3.1 gives the monthly temperature anomalies during the three winter months of 1979-80. While most of the West and Southwest were consistently warmer than the 30-year climate mean, the anomalies changed sign during this winter season in most of the other regions of the U.S. The seasonally averaged temperature anomalies for the entire winter are shown in Figure 3.2. Temperatures are designated as normal, high, and low according to the criterion that statistically during the past 30 years the temperature at any point is high

December Weather Summary

Figure 3.1.a MONTHLY TEMPERATURE ANOMALIES DURING THE THREE WINTER MONTHS OF 1979-1980

January Weather Summary

Figure 3.1.b MONTHLY TEMPERATURE ANOMALIES DURING THE THREE WINTER MONTHS OF 1979-1980

February Weather Summary

Figure 3.1.c MONTHLY TEMPERATURE ANOMALIES DURING THE THREE WINTER MONTHS OF 1979-1980

Figure 3.2 SEASONALLY AVERAGED TEMPERATURE ANOMALIES FOR THE WINTER OF 1979-1980

one-third of the time, normal one-third, and low one-third. The seasonal prediction for that winter by the five expert forecasters is given below in Figure 3.3.

The significance and variation of the subjective element in these forecasts is manifest in the variation among the predictions. And even a perfect seasonal forecast would have been very poor in at least one winter month in most regions.

One comparison⁴ of temperature anomaly predictions (High, Normal, Low) for the Continental U.S. with seasonal measurement is given in Table 3.1. Data and predictions are confronted at the N grid points of Figure 3.1. With no forecasting skill at all $N/3$ successful predictions are expected. If "skill" (S) is defined in terms of the number of successful predictions (N_s) at the N grid points by

$$S \equiv \frac{3}{2} \left(\frac{N_s - N/3}{N} \right),$$

then S can vary from 1 for perfect "skill," to zero for random predictions, to $-1/2$ for no successful predictions at all. Table 3.1 gives S for the five expert forecasters mentioned above, for an analogue-based computer forecast (B), discussed below, and for P^* , a fictitious forecaster who makes his prediction the day before the season begins and has enough skill to infer the subsequent dynamics of the known weather patterns correctly for the next six days and zero skill in predicting beyond that.

Figure 3.3 FORECAST OF THE WINTER OF 1979-1980 BY GILMAN, NAMIAS, ANDREWS, DOUGLAS, BARNETT AND HARNACK

TABLE 3.1

SKILL SCORES FOR VARIOUS PREDICTIONS OF WINTER TEMPERATURES

Winter	G	N	A	D	H	B	P*
1979-80	+.03	-.10	+.03	+.12	+.03	+.21	+.07
1978-79	+.03	+.03			+.03	-.06	+.07
1976-77		+.39					+.07

For this special criterion of "skill," large improvements over chance are not consistent for the forecasters as a group for any one winter or for any individual forecaster over several winters. It appears that, although skilled seasonal forecasters do, indeed, have significant skill, and occasionally do remarkably well, it is not yet clear when a seasonal anomaly prediction is apt to be especially reliable. Different criteria for success which may, for example, give more credit for the successful prediction of a large anomaly (drought, very severe winter, etc.,) and more penalty for missing one would, of course, yield a quantitatively different skill score.

Winter season forecasts may be more successfully managed in certain regions of the U.S. than is reflected in skill scores for the entire country. With a simple dichotomy for temperature prediction (hotter

or colder than the seasonal climate mean) and a corresponding skill score defined by

$$S = 2 \left(\frac{N_s - N/2}{N} \right) \times 100 ,$$

the average S for the past 22 winter season forecasts at the Climate Analysis Center is given in Figure 3.4 (supplied by Gilman). For the South, $N_s \sim 2/3N$ and $S \sim 1/3$; but most of New England seasonal forecasting for those 22 winters was somewhat poorer than that from pure guesswork. The results shown in Figure 3.4 are important in assessing the use of seasonal forecast in fuel allocation. The skill scores tend to be low in the highly populated Northeast and in the Chicago to Pittsburgh industrial belt. The high skill scores are found in the Southeast and the Northwest where fuel allocation is not as significant a problem as in the Midwest and Northeast.

The high skill scores in the Northwest and Southeast may be related to the "teleconnections" between the Pacific and North America noted by Namias, Dickinson and others in connection with operational long range forecasts.⁵ This pattern involves negative correlations between mid-tropospheric geopotential height anomalies over western Canada and i) a region near 45° N in the Central Pacific and ii) the southeastern United States and positive correlations between i) and ii). The apparent correlation of skill scores and teleconnection deserves further attention.

FIGURE 3.4 Skill Scores for Winter Forecast of Temperature
for the Years 1958-1980

3.2.2 Pure Analogue Forecasting

This method is based upon an objective computer search of past records for the closest analogue to a present pattern of meteorological anomalies; the prediction of subsequent seasonal anomalies is based solely upon the historical evolution which had followed the earlier analogue state. A forecasting program of this type has been initiated by Barnett and Preisendorfer.⁶ Sufficiently complete meteorological data for such comparisons extended over only 24 years; such data consists of temperature, precipitation, 700 mb height, 1000-700 mb thickness, SSTs, etc., over about 2000 grid points in the Northern Hemisphere. Strong correlations among measurements at different locations support the notion that only half a dozen or so anomaly patterns are typical for each variable but with considerable superimposed climate noise. The climate anomalies are described by a time dependent superposition of this finite set of repeating patterns and represented by the position of a point in a multidimensional space whose coordinates are the amplitudes of the characteristic anomaly patterns (Empirical Orthogonal Functions, EOF). The motion of the "climate anomaly point" in the EOF vector space is presumed ergodic but not random. Prediction of anomalies is based upon the trajectory of the "nearest" climate anomaly point in the 24-year data bank. "Nearness" is measured by the Euclidean distance between points in the multidimensional space, or in a phase space where both point position and point velocity are specified, or in position space again but with positions at two nearby times in the present compared to a pair of analogue states in the data bank with the same temporal separation. When the computer's "skill" (B) is compared with that of the other forecasters in Table 3.1, the prospects for

the development of this method are somewhat encouraging. Even with the small data base available and the naive separation measure which does not weight the many coordinate separations according to which are most significant for optimal forecasting, the computed "skill" is already at the same level of the group of human forecasters. However, it appears that "skill" is not particularly increased at present by using more than the SST and 700 mb level data, and that recent analogues work better for forecasting than do the distant past ones. The ability of the computer to use much more data and much longer records in considering analogues than does the more subjective human expert with his synoptic analyses may not make as great a difference as might be hoped.

3.2.3 General Circulation Models

General circulation models (GCMs) have been used to forecast seasonal weather from known initial conditions. GCMs (i.e., computer models for the full dynamics of the three dimensional atmosphere) have not played a significant role in attempts to make seasonal forecasts for several reasons. First, they are expensive to use. For the Princeton GFDL model to predict a full 90-day seasonal record would appear to require hundreds of hours of computer time at a thousand dollars per hour. Second, and more important, it is not yet at all clear that existing GCMs, which are tuned to describe seasonal climate means, also give reliable descriptions of the fluctuations about those means. GCMs do not yet include realistic ocean responses, much less full ocean climates, even though these appear to be important in correlating atmospheric temperature anomalies at different times through SSTs. There is not yet evidence that

they have in them the known long time scale anomaly correlations which are thought to be internally generated--the strong 2.1-year quasi-biennial oscillations, the large Southern Oscillation, or the various multiweek variations discussed earlier. Just how well GCMs will be able ultimately to establish a data base for seasonal anomalies equivalent to that being developed from observations remains to be explored.

REFERENCES FOR SECTION III

1. Namias, J. Persistence of U.S. seasonal temperatures up to one year. Mon. Wea. Rev., 1978, 106: 1557.
2. Henderson-Sellers, A. Albedo changes--surface surveillance from satellites. Climatic Change, 1980, 2: 275-281.
3. Gilman, D. "The Nature of Climate Variability." Unpublished draft dated June 12, 1980.
4. Chervin, R. Personal communication, June, 1980.
5. Wallace, J. M., and D. Gutzler. "Teleconnections in the Geopotential Height Field during the Northern Hemisphere Winter." Draft manuscript, 1980.
6. Barnett, T. P., and R. W. Preisendorfer. Multifield analog prediction of short term climate fluctuations using a climate state vector. J. Atm. Sci., 1978, 35, 1771-1787.

APPENDIX A.1

A.1 REGIONAL WEATHER FORECASTING - THE NEXT STEP

In considering the question of regional weather forecasting, it is natural to inquire how such forecasts might be used. The following is a possible, though highly simplified, setting.

We suppose the country divided up into a number of regions, r_1 , r_2 , r_3 , in each of which there is an efficient fuel distribution service. The total fuel storage capacity in the i^{th} region is s_i . If the oncoming winter is cold, the i^{th} region will require K_i units of fuel, if normal, L_i units of fuel, while if warm, M_i units of fuel will be needed. Before the start of the heating season, an allocation of a_i units of fuel is made to the i^{th} region from a total national store of a units.

We must have, of course, $a_i < s_i$, as well as $a_1 + a_2 + \dots + a_n < a$.

How are we to make an intelligent allocation? It is quite clear we do not have yet enough information to do so. Suppose then we are given a regional weather forecast for the oncoming winter, informing us that region 1 will be cold, region 2 will be normal, etc. We are still in a quandry as to how to proceed, because the forecast is not a statement made with certainty.

If, on the other hand, the forecast came in the form of probabilistic assertions of the sort the i^{th} region will be cold with probability C_i , normal with probability N_i , and warm with probability W_i , $C_i + N_i + W_i = 1$, we could proceed as follows.

If an allocation of a_i units of fuel is made to r_i , then there will be a well determined shortfall of fuel if the region has a cold, normal, or warm winter respectively. In the interests of simplicity, we will say the winter discomfort in the region equals the shortfall. With the probabilistic weather forecasts in hand, we can now compute, for any admissible overall allocation of fuel, the expected total discomfort of the country. A reasonably rational procedure might be that choice of allocation minimizing the expected total discomfort.*

The problem is now not quite one of linear programming, since the objective function to be minimized is not linear, but with a small number of regions it should be readily solvable by trial and error on a general purpose computer.

If the total discomfort is not additive, one could modify the procedure by weighting the discomfort for each region before adding them up.

*It is worth pointing out that the expected total discomfort for a given allocation does not depend on any probabilistic dependencies between the forecasts for different regions.

It might be quite interesting to experiment a few times with this simple model in order to see how much improvement in expected shortfall can be achieved by modest improvements in forecasting skill over random forecasting.*

An altogether different decision procedure would be that choice of allocation minimizing the probability of a shortfall anywhere. This procedure does depend on knowing the joint probability distributions for the collection of regions.

The point we wish to make is that with actuarial forecasts of weather variables available, it is possible to make rational decisions based on objective criteria. But a forecast without a measure of reliability is virtually worthless. Our conclusion is that one important next step in regional weather forecasting is to get the forecast in the form of actuarial statements, to be followed by an assessment of the incremental gains, economic or otherwise, one can achieve with improvements in actuarial forecasting. Nearly everyone will agree with the desirability of these goals, but how are they to be attained?

One method, basically the one we employ in our everyday affairs, is the use of subjective probabilities. If the track record of an individual forecaster is known, it is easy enough to assemble his

*We have been assuming all along, and will continue to do so, that over the long term each region is cold, normal, or warm in winter--each with probability one-third. Appendix A.2 describes a numerical experiment.

collection of forecasts to get probabilities that he predicts warm when it will be normal, etc., and then the probabilities that it will be warm when he predicts normal, etc., (see Appendix A.4). If we have a collection of forecasters who it is believed are forecasting independently, then by use of Bayes' Theorem we can assemble their individual forecasts of an event, provided we know their individual track records, to obtain probabilities of each of the possible outcomes. Since we have seen evidence that consensus forecasting is poorer than individual performance, there is some reason to believe independence of forecasters in applying Bayes' Theorem. If independence of forecasters is seriously in doubt, then the joint track records of all the forecasters must be used to obtain actuarial forecasts.

Another method to obtain actuarial forecasts is the employ of any of the extant methods of linear prediction or objective analogue forecasting.^{1,2,3,4,7} The procedure is very much the same as that described for subjective probabilities, and will require very little modification, if any, of extant programs. Suppose we have, for example, a linear predictor, of any sort whatsoever, for the winter temperature in the New England region. Using the known data base by means of which the linear predictor was constructed, or better still some independent data, one can obtain the track record of the predictor for tercile temperature prediction, by means of which we can readily obtain the probabilities we require for the fuel allocation problem.

The most powerful probabilistic procedure for forecasting would depend on the existence of an enormous data base, from which one could

determine accurately the conditional probabilities distribution of any weather variable, given as long a period of evolution of the weather as the data base permits. It might be possible, given some of the longer time series of weather variables we have available, to make a start on collecting such statistics. There are both naive and sophisticated means to remove monthly and/or seasonal phase variations in these time series in order to render them stationary and enlarge the sample size available. The problem of doing so has already received some attention and probably needs much more.^{1,5,6}

The method just described, requiring a large data base, is probably optimal. The method described earlier, of assembling track records to get actuarial forecasts, while relatively easy to carry out, suffers from some serious methodological defects. The use of track records lumps together all of a forecaster's predictions, independently of the prior evolution of the weather, even though the prior evolution significantly conditioned the prediction. It would be desirable to turn directly any objective method of forecasting into an actuarial forecast.

Once actuarial tercile forecasting becomes the practice, the question arises of skill scoring. If we adopt a Bayesian point of view, it is possible to devise a straightforward scoring procedure which appears reasonably acceptable. Suppose, for example, the forecaster's prediction is probabilities C_1 , N_1 , and W_1 of cold, normal and warm respectively in a given region. Let H be the hypothesis that these are the true probabilities given the past, and H_0 the null hypothesis that the correct

probabilities are one-third each. Given the observed temperature θ , the a-posteriori odds in favor of H over H_0 are

$$\frac{p(H|\theta)}{p(H_0|\theta)}, \text{ which equals by Bayes' Theorem,}$$

$$\frac{p(\theta|H)}{p(\theta|H_0)} \times \frac{p(H)}{p(H_0)} . \quad \frac{p(\theta|H)}{p(\theta|H_0)} \text{ is the "Bayes factor"}$$

by which the a priori odds, $\frac{p(H)}{p(H_0)}$, differ from the a-posteriori ones.

It is not too unreasonable to assume that $p(H)$ is approximately constant over all choices for H in the middle range of forecasts we would tend to see, but this consideration is not too important in our skill score, which we take simply as

$$\log \text{ Bayes Factor} = \log \frac{p(\theta|H)}{p(\theta|H_0)} = \log 3 p(\theta|H) .$$

The logarithm is taken so that the skill scores for several experiments are added up. An obvious defect of the scoring is the heavy penalty exacted of a forecaster who predicts, say, probability zero of normal temperature, and then normal temperature occurs.

REFERENCES FOR APPENDIX A.1

1. Barnett, T. "Application of Seasonably Nonstationery Linear Prediction Models." WMO Symposium on Probability and Statistical Methods in Weather Forecasting, Nice, France, Sept. 1980.
2. Barnett, T. P., and K. Hasselmann. Techniques of linear prediction, with application to oceanic and atmospheric fields in the tropical Pacific. Reviews of Geophysics and Space Physics, 1979, 17(5): 949-968.
3. Barnett, T. P., and R. W. Preisendorfer. Short-term prediction of global climate using multi-dimensional analog methods. Preprint Volume, Fifth Conf. on Probability and Statistics in Atmospheric Sciences, Las Vegas, Nev., Nov. 15-18, 1977. Published by Am. Met. Soc., Boston, Mass., 11-15, 1977
4. Barnett, T. P., and R. W. Preisendorfer. Multifield analog prediction of short-term climate fluctuations using a climate state vector. Jour. Atmos. Sci., 1978, 35(10): 1771-87.
5. Hasselmann, K., and T. P. Barnett. Seasonal cycle effects in linear prediction models, (in manuscript), 1980
6. Lorenz, E. N. Empirical orthogonal functions and statistical weather prediction. Rep. I, Statist. Forecasting Proj., Mass. Inst. of Technol., Cambridge, 1956, 49 pp.
7. Preisendorfer, R. W. Model skill and model significance in linear regression hindcasts. SIO Ref. Series #79-12. Scripps Institution of Oceanography, A-024, La Jolla, Ca., 92093, 1980.

APPENDIX A.2

A.2 SEASONAL WEATHER FORECASTS, FUEL ALLOCATION, AND FUEL SHORTAGE: A NUMERICAL EXAMPLE

Following the theoretical discussion of Appendix A.1 we present here an analysis of the relation between forecasting "skill" and the resulting hypothetical regional fuel allocations, and the consequent fuel "shortages." The model employed is crude, and numerous simplifying but explicit assumptions are made. The principle result will be that what is presumably the present level of skill does not differ in the practical results from a completely random prediction, more precisely, from those of allocations made on the basis of long term climate averages. Indeed, the level of skill required to yield a significant improvement over random forecasting may be unattainable for this almost "undetermined" physical system.

A really complete analysis would include the effects not only of spatial (regional) allocations, but also of allocations in time, i.e., the use of "savings" from efficient forecasting of milder seasons carried forward to alleviate shortages in succeeding years. This possibility is discussed but is not carried through in this Appendix for reasons given below.

A.2.1 The Model

We consider a "nation" of three regions, in each of which a seasonal forecast will be made. For fuel consumption purposes we employ a tercile division of seasonal average temperatures, as Cold, Normal, Warm, or C, N, W, respectively. Thus CCN represents a possible seasonal weather state for the nation. Obviously, there are 27 such states for the nation. We arrange the division of the temperature distribution such that in each geographical region the three states C, N, W, are equally populated over a long time interval. (The three regions may have different average climates, i.e., $N_1 \neq N_2 \neq N_3$ without any difficulty, as it is only the effect of differences in seasonal temperatures, i.e., $N_2 - C_2$, that will matter). In the following, we will discuss weather states as if all regions were identical.

The forecaster, or forecasting system, will produce a tercile forecast for the next season for each region. We denote the forecasted weather by greek letters $\kappa \nu \omega$; the actual weather by latin C, N, W. We imagine that the "track record" of the forecaster is known from long experience. Thus, for each forecaster, a conditional probability matrix is known, of the form

$$\begin{array}{c} \kappa \quad \nu \quad \omega \\ \begin{array}{c} C \\ N \\ W \end{array} \begin{pmatrix} P_{11} & P_{12} & P_{13} \\ P_{21} & P_{22} & P_{23} \\ P_{31} & P_{32} & P_{33} \end{pmatrix} \end{array}$$

where $p_{11} = P(C|\kappa)$, etc. A typical element is written $p_{i\sigma}$. As defined the column sums are unity. The "skill" is defined as the average of the principal diagonal values.

We also require that this matrix be symmetrical for the following reason. It is assumed that the distribution in forecasted values is the same, statistically, as the distribution in observed weather states, one may say as a result of the forecaster's training and experience. The forecaster, in short, may be of low competence, but he is not biased. Since we have already assumed that the actual weather states populate the tercile division C, N, W, uniformly, we now assume that the forecasts populate $\kappa \vee \omega$ uniformly.

We assume, further, that the overall forecast for the nation is compounded from the probability matrix elements $p_{i\sigma}$ for the three separate regions as simple products; thus regional correlation effects are neglected. This is a more serious approximation than those assumed above. It is very likely that regional correlations do exist and that future developments in forecasting will learn to make better use of them. It is not clear at present that they have any predictive value. In any case no such coherent system seems to exist which could be analyzed on the lines used in this paper. For us, then, the conditional probability for the seasonal weather state $i j k$ is $\pi_{ijk}^{p\sigma\omega} = p_{i\rho} p_{j\sigma} p_{k\mu}$, a 27×27 matrix easily obtained from the individual $p_{i\rho}$ matrices. We note that these weather distribution matrices are taken to be the same in all three regions.

A.2.2 Fuel Allocation

Some limitation on fuel supply must be assumed; otherwise no problem exists. We assume in what follows that annual production is adequate to supply the requirements for a uniformly "normal" winter season, NNN. Thus, in a colder winter as CCN, there will be necessarily some shortage of fuel. The forecaster's task is to predict this situation sufficiently well to alleviate the potential shortage. Conversely, it may be expected that prediction of milder winters should result in reduced "waste," or with efficient procedures, even some "savings" that could be carried over to reduce shortages in succeeding years. This latter possibility of seeking savings as well as reducing shortages by the most rational allocation system was examined in some detail but was abandoned for the following reasons:

- (1) At mediocre levels of predictive skill there would be frequent instances of withholding fuel at the central supply in the face of severe and "unnecessary" shortages, in the interest of future years, all because of erroneous forecasts. One may well doubt that this situation would be politically and socially acceptable.
- (2) We have not found a simple algorithm for the calculation of the long term effects of the carried-over savings. The direct method would seem to be a Monte Carlo type calculation, tracking through all possible succeeding seasonal weather states to evaluate the long term value of

this allocation procedure. This tedious calculation did not seem worthwhile in view of argument (1).

What in fact we have done, explained in detail below, is to evaluate the short term policy of allocating fuel so as to minimize shortages in the season immediately ahead, at the cost of some "waste," in terms of fuel sent to regions where it will be an excess supply. This is done by "renormalizing" the rational allocation referred to above to distribute all of the fuel to appropriate regions in each season. There are then no savings and no carry-over to the next season. It is in terms of this short term procedure that the evaluation of forecasting skill is made.

A.2.3 The Calculation

The relation between forecast skill, fuel allocation, and resultant shortages is examined for the six skill levels displayed below:

Case	r(andom)	a	b	c	d	p(erfect)
	<div> <div>.33 .33 .33</div> <div>.33 .33 .33</div> <div>.33 .33 .33</div> </div>	<div> <div>.4 .3 .3</div> <div>.3 .4 .3</div> <div>.3 .3 .4</div> </div>	<div> <div>.5 .3 .2</div> <div>.3 .4 .3</div> <div>.2 .3 .5</div> </div>	<div> <div>.6 .25 .15</div> <div>.25 .5 .25</div> <div>.15 .25 .6</div> </div>	<div> <div>.7 .2 .1</div> <div>.2 .6 .2</div> <div>.1 .2 .7</div> </div>	<div> <div>1 0 0</div> <div>0 1 0</div> <div>0 0 1</div> </div>
Skill	0.33	0.40	0.47	0.57	0.67	1.00

For any chosen such Case we may calculate directly the 27×27 matrix of conditional probabilities.

Fuel Unit: We assume that in any region the difference in fuel requirement between C and N equals that between N and W, and is the same in all regions. This quantity is taken to be the unit amount of fuel. Since only differences in fuel consumption are relevant here, it is convenient to take the fuel requirements in any region to be 0, 1, 2, for W, N, C, respectively. For a completely normal winter, NNN, the national fuel requirement is 3 units, and from our earlier assumption this is just the annual supply. On this scale, for example, a CCC winter would "require" 6 units (not available), but a NWW winter just 1 unit of fuel.

Allocation: It is to be understood that allocations are made from a central supply for the season, and once made, are irrevocable. The first step is to establish what allocations are to be made, with the restricted supply, for the various weather states. Where more than 3 units are "required" the 3 available units are distributed fractionally. Thus a CCN season would receive an allocation 1.2, 1.2, 0.6, while CWW would get 2, 0, 0. The allocations for an ijk season are designated $a_i a_j a_k$. These elementary allocations are independent of the forecasted weather and of "skill." They are what would presumably be allocated by a "perfect" forecaster (Case p). For an actual forecaster we proceed as follows.

For the selected skill level (r, a, b, c, d, p) we consider successively the particular predicted weather states, as $\rho\sigma\mu$. From the probability table for the various actual weather states $i j k$ and the elementary allocations a_i, a_j, a_k we form the products $a_i \pi_{ijk}^{\rho\sigma\mu}$, $a_j \pi_{ijk}^{\rho\sigma\mu}$, $a_k \pi_{ijk}^{\rho\sigma\mu}$ and sum them over the 27 weather states to form the rational allocation

$$A_{Rp} = \sum_{i=1}^{27} a_i \pi_{ijk}^{\rho\sigma\mu}, \text{ similarly for } A_{R\sigma}, A_{R\mu}.$$

This triple set gives the efficient allocation which minimizes waste, permits savings, and over a long time gives minimum shortage. ("Waste" here is an allocation to a region in excess of its actual needs in a given year). We note that $A_{Rp} + A_{R\sigma} + A_{R\mu} < 3$ for imperfect forecasters.

Shortage for any state $i j k$ is defined as the difference between need in that state and the allocation defined above. If N_i, N_j, N_k , are the needs of the three regions in the $i j k$ state then the average shortage in the first region, for example, is $\sum_{i=1}^{27} (N_i - A_{Rp}) \pi_{ijk}^{\rho\sigma\mu}$ for a $\rho\sigma\mu$ forecast. The shortages for the three regions are then added to obtain the total shortage for the given forecasted state. We note that negative regional shortages are not counted as favorable, but as waste. The average of the shortage defined above over the 27 possible forecasts gives the net shortage characteristic of this level of skill.

Savings: is defined simply as the difference between the available supply, 3 units, and the total allocation $A_{R\phi} + A_{R\sigma} + A_{R\mu}$ in any forecast. This represents fuel withheld at central supply, not available in the current season, available to increase the disposable supply in the following seasons.

Following the procedure outlined above for the Rational Allocation, the perfect forecaster finds an average shortage of 0.56 units, which is exactly balanced by his savings (since he never mis-allocates fuel). This savings, carried forward, will statistically balance out future shortages, so that over a long period of time the average shortage will be zero. The random forecaster, on the other hand, on the above prescription, will make an allocation of 0.815, 0.815, 0.815 in every case, resulting in a net shortage of 1.37 units, savings of 0.56, the latter largely mis-allocated in subsequent years. It is obvious that with our restricted supply one cannot do better with the random forecaster than an allocation 1, 1, 1, which leads to an average shortage of 1.00 and, of course, no savings.

Short Term Allocation: For the reasons given previously we abandoned the long term allocation outlined above in favor of a short term allocation designed to minimize shortages in the current season at the cost of some excess allocation and no carry over. In this procedure we simply renormalize the above rational allocations $A_{R\phi}$, $A_{R\sigma}$, $A_{R\mu}$ in the three regions for a forecasted state $\rho\sigma\mu$ into a net set normalized to 3.

$$\text{Thus } A_p = \frac{3 A_{Rp}}{A_{Rp} + A_{R\sigma} + A_{R\mu}} \quad \text{similarly for } A_\sigma \text{ and } A_\mu .$$

All the fuel is now used up in each season.

This calculation has been made for each of the six skill levels. The resulting net shortages are shown in Table A.2.1 for each type of weather state, and the average over all 27 weather states is given in the last column. (The 27 states divide into 10 classes, from the "permutation degeneracy" of the three regions.) These net average shortages, the principal results of this study, are plotted in Figure A.2.1.

A.2.4 Discussion

The range of the magnitude of possible shortages is from 1.00 (random) to 0.56 (perfect) in our units. (This presentation is unfair to the very skillful forecaster, as his savings balance out his shortages, if carry-over is allowed, yielding a long term shortage of zero). It is evident that, for this simple model, the results for the present level of skill ($\approx .4$) are indistinguishable from those of random forecasting (which is the same as average climate forecasting). This suggests that there is no reason at present to attempt to employ such seasonal forecasts in a national fuel allocation program. Indeed, an improvement to a skill level of 0.57, which is, in a sense, three times as accurate as the present 0.40 (in terms of the difference from random) would reduce the average national shortage by only .02/3 of the difference between the requirements of a uniformly normal winter and a uniformly cold winter. This level of

skill may not be achievable for such a nearly random quantity as weather. In any case inspection of the variation in shortages for skill level 0.57 over the weather states (Table A.2.1) will indicate that even this small improvement will not be visible for many years.

TABLE A.2.1

FUEL SHORTAGE VS SKILL

Case	Skill	CCC	CCN	CNN	CCW	CNW	NNN	NNW	CWW	NWW	WWW	AV
r	.33											1.00
a	.40	1.20				1.02	.90				.90	1.00
b	.47	1.50	1.28	1.09	1.19	1.00	.90	.83	.90	.72	.60	1.00
c	.57	1.80	1.58	1.17	1.26	.90	.75	.71	.74	.62	.45	.98
d	.67	2.10	1.64	1.14	1.21	.74	.60	.50	.52	.48	.30	.89
p	1.00	3	2	1	1	0	0	0	0	0	0	.56
Weighting factor		1	3	3	3	6	1	3	3	3	1

Figure A.2.1 FUEL SHORTAGE AS A FUNCTION OF FORECASTER SKILL

One may suggest, finally, that a practical policy may be to make allocations on the average climate basis, and at the same time attempt to conserve and carry forward the residual mis-allocated fuel in each region. This will require adequate local storage facilities--enough to save up several years' supply during extended mild periods, and social discipline, in the form of public authority or market prices.

APPENDIX A.3

WEATHER FORECASTING WITH PROBABILISTIC MEANS

The record of weather or climate variables shows certain regular or organized behavior along with significant "noise." The regular patterns include a diurnal and seasonal cycle as well as other identifiable weather modes which have been outlined in Section 2. Suppose we have a long record of a set of important climate variables such as sea surface temperature, 700 mb-1000 mb thickness, etc., and suppose the identifiable regular behavior has been removed. We now want to assume that the remaining variation in our data is random. How can we learn in a reasonably efficient and reliable manner how to make probability predictions from the random data?

Call the record we now have a vector $\tilde{w}_j$ where j stands for a time label $j=1,2,\dots$. N = total number of time periods (days, months, seasons) over which the variables $\tilde{w}_j$ have been measured at each geographical station. We wish to predict the probability for $\tilde{w}_j$ at some time j given certain information at times earlier than j . What we need then is the joint probability distribution of the $\tilde{w}$ variables. Let us take the information we have at each geographical station for each variable and create N_B bins into which we cast the results of each observation. The probabilities we seek will be in terms of the frequency with which the variables lie in each bin.

For sake of illustration let us focus on one variable measured at one station; call it ξ_j . First we calculate its mean value

$$\bar{\xi} = \frac{1}{N} \sum_{j=1}^N \xi_j.$$

Now we take 3 bins ($N_B = 3$) defined by

Bin 1	$\xi_j < \bar{\xi} - \Delta\xi$	"Below Normal"
Bin 2	$\bar{\xi} - \Delta\xi < \xi_j < \bar{\xi} + \Delta\xi$	"Normal"
Bin 3	$\xi_j > \bar{\xi} + \Delta\xi$	"Above Normal"

where $\Delta\xi$ is some range about the mean; say, 1°C for temperature.

Now we define the bin occupation probability by

$$P(a) = \frac{1}{N} \sum_{j=1}^N (\# \text{ of times } \xi_j \text{ is in Bin } a)$$

with $a=1, 2, 3$. We will also be interested in the probability that ξ_j is in Bin a and ξ_{j+m} is in Bin a^1 ; that is, after m time steps the weather has gone from state a to state a^1 . This is given by

$$P_m(a^1, a) \equiv \frac{1}{N-m} \sum_{j=1}^{N-m} (\# \text{ of times } \xi_j \text{ is in Bin } a \text{ and } \xi_{j+m} \text{ is in Bin } a^1).$$

How well do we know quantities like $P(a)$ or $P_m(a^1, a)$? If the number of bins is N_B and the number of observations is N , then a totally uncorrelated random distribution would have about N/N_B points in any bin for $P(a)$ and N/N_B^2 for $P_m(a, a^1)$. The expected statistical error in $P(a)$ will be of order $(N/N_B)^{1/2}$, and in $P_m(a, a^1)$ of order $(N_B^2/N)^{1/2}$. Let us take as a useful criterion that the error from statistics alone be 10%. Then to determine $P(a)$ we need $N > 100 N_B$ observations; for $P_m(a, a^1)$, $N > 100 N_B^2$. For $N_B = 3$ and seasonal time periods we need 300 seasons or 75 years to learn $P(a)$. For monthly time periods we need 5 years of data for $P(a)$ and 75 years for $P_m(a, a^1)$. If we lower our demands on accuracy to 20% then $N > 25 N_B$ for $P(a)$ and $N > 25 N_B^2$ for $P_m(a, a^1)$. For monthly time periods we need about 6 years of data for $P(a)$ and 30 years for $P_m(a, a^1)$.

With $P(a)$ and $P_m(a, a^1)$ what questions shall we ask? The foremost is to know when bins a and a^1 are independent of each other, since then information about one is totally uncorrelated with the other. To learn that, we propose to study the correlation function

$$C_m(a, a^1) \equiv \frac{P_m(a, a^1)}{P(a)P(a^1)} - 1$$

as a function of m and a and a^1 . There are nine pieces of information (for $N_B = 3$) at each m . When $C_m(a, a^1)$ is zero (within

statistical errors), information at any time step is totally independent of information m steps away. Prediction is not possible under that circumstance. We expect that each element of the matrix $C_m(a, a^1)$ will decrease with m and after, say, $m > m_I$ will be "zero." One will invent some criterion for zeroness such as

$$\frac{C_{m_I}(a, a^1)}{C_1(a, a^1)} < \frac{1}{10} \text{ for all } a \text{ and } a^1.$$

After this independence time, m_I , prediction will be impossible.

Next one wants to know the answer to the following: given the state of the weather at some time—that is, which bin it is in—what is the probability to be in another bin m steps later? So we wish the transition probability $P_m(a|a^1)$ defined by

$$P_m(a|a^1) \equiv P_m(a, a^1) / P(a^1).$$

For $m < m_I$ this question has content. For $m > m_I$ it is simply $P(a)$ itself and has no new information. ◇

How do we use this lore? Returning to our weather variables, $W_{\sim j}(\alpha)$ with a station label $\alpha = 1 \dots S = \#$ of stations introduced, we will compute $P(\tilde{a}(\alpha))$ and $P_m(\tilde{a}(\alpha), \tilde{a}^1(\beta))$. We then observe the binning of the weather in April, say, for monthly time steps; this gives us the occupations of the bins $\tilde{a}^1(\beta)$ for the vector of variables at each station β . Our prediction is in terms of

$$P_m(\tilde{a}(\alpha) | \tilde{a}^1(\beta)) \equiv P_m(\tilde{a}(\alpha), \tilde{a}^1(\beta)) / P(\tilde{a}^1(\beta))^1$$

which tells us the probability to find the weather variables at stations α in bins $\tilde{a}$ given $\tilde{a}^1(\beta)$ m months earlier in April. If M_I is 3 months, for example, we can reliably give the weather in June knowing the weather in April; more precisely, we can give the probabilities for the weather in June to be in certain bins given knowledge of the weather in April.

Now a key ingredient is the length of the record. Clearly the record must be long enough to have explored a wide swath in the many dimensional weather fluctuation spaces for us to believe our results. As the record grows, so will our faith in the method. Even today's records are long enough to begin experimentation with the technique.

The statistical technique began with the assumption that we knew which variables to use in the weather vector $\tilde{w}$. The method contains a straightforward way to learn if the variables chosen are in fact important in prediction. In the correlation tensor

$$C_m(\tilde{a}(\alpha), \tilde{a}^1(\beta)) \equiv \frac{P_m(\tilde{a}(\alpha), \tilde{a}^1(\beta))}{P(\tilde{a}(\alpha)) P(\tilde{a}^1(\beta))} - 1 ,$$

we may find elements that are consistently zero. Since this is a correlation function, we will have learned that those variables involved are uncorrelated. Thus we might learn that sea surface temperature in the North Pacific is independent of rainfall in Western Kansas. If we wish to use the method to predict the latter, we can say we have learned to ignore the former.

APPENDIX A.4

A.4 VIEWING SEASONAL CLIMATE FORECASTS IN THE FRAMEWORK OF CONDITIONAL PROBABILITY

Let us adopt the viewpoint of a user of seasonal climate forecasts, such as the distributor of oil stocks (see Appendix A.1). What is presently available to such a person is a set of several tercile (above average, average, or below average) forecasts made by different forecasters for a particular time period, geographical location, etc. Suggested here is a framework in which to view these forecasts so as to assess the skill of the forecaster in some detail and to convert the simple tercile forecasts into probabilistic forecasts along the lines discussed in Appendix A.2. Conditional probability is the suggested framework.

To begin we will estimate the required conditional probabilities using a specific example and discuss applications thereafter. Conditional probability refers to the probability $p(O|F)$ that a particular climatic state (O) is observed given that a state (F) was forecast. As our illustrative example, we take the temperature and precipitation forecasts of Namias¹ for the winter of 1976-77 shown in Figure A.4.1 and the corresponding observations. A grid of 158 equally spaced sample points was used to compute a histogram having 9 bins for temperature and 9 for precipitation as indicated in Table A.4.1. The histogram results were used to estimate the conditional probabilities in Table A.4.1. Each row of the 3 X 3 tables corresponds to a conditional probability density distribution

**PRECIPITATION PREDICTED FOR WINTER
(DECEMBER, JANUARY, FEBRUARY 1976-77**

**OBSERVED FOR WINTER (DECEMBER,
JANUARY, FEBRUARY) 1976-77**

**CANCELED DECEMBER 1, 1976 FROM 0010
ENDING NOVEMBER 23, 1976**

Figure A.4.1 OBSERVED AND FORECAST TEMPERATURE AND PRECIPITATION FOR WINTER, 1976-77. THE LETTERS A, N & B REFER TO CLIMATE STATES HAVING TEMPERATURES ABOVE NORMAL, NORMAL AND BELOW NORMAL. THE LETTERS L, M & H REFER TO CLIMATIC STATES HAVING PRECIPITATION LOWER THAN THE MEAN, MEAN AND HIGHER THAN THE MEAN RESPECTIVELY (AFTER NAMIAS¹).

TABLE A.4.1 Conditional Probabilities $p(O|F)$ for Forecasts and Observations Shown in Figure A.4.1 for Winter 1976-77.

<u>TEMPERATURE</u>				<u>PRECIPITATION</u>					
F O R E C A S T	A*	0.10	0.61	0.29	F O R E C A S T	H*	0.42	0.40	0.18
	N	0.26	0.53	0.21		M	0.66	0.29	0.05
	B	0.73	0.25	0.02		L	0.81	0.14	0.05
		B	N	A			L	M	H
OBSERVED					OBSERVED				

*The definitions of A, N, B, etc., are given in Figure A.4.1.

over the three states--one density function for each forecast. Thus given an above average temperature forecast (A) we find that the estimated conditional probabilities for A, N and B temperature states to be $p(B|A) = 0.10$, $p(N|A) = 0.61$ and $p(A|A) = 0.29$. Obviously the estimates of $p(O|F)$ given in Table A.4.1 are taken over much too small a sample population to be representative in any real sense. Nevertheless, they serve as a convenient example for illustration.

Since different climatic situations allow forecasts of varying accuracy,² one would presumably want to stratify the sample population and thus estimate $p(O|F)$ for various geographical regions, seasons,

forecasters, etc. For example, summer forecasts are notoriously difficult compared to winter.

Clearly a sufficiently large sample population is required to obtain accurate estimates of $p(O|F)$. As discussed in Appendix A.3, the total number of seasonal sample points required to obtain 10% statistical accuracy in a table such as Table A.4.1 is roughly $100 N_B^2$ where $N_B = 3$ for our tercile forecasts. For a single geographical point this works out to about 900 seasons. Averaging over a geographical area reduces the length of time required to collect the appropriate samples. Elaborate stratifications on the other hand increase the time required to accumulate the required number of samples.

Having obtained useful estimates of $p(O|F)$ several important applications exist. First, the quantities in Table A.4.1 give one a quantitative feel for the forecast. Not only can one evaluate the general skill of the forecast in terms of right vs wrong, but one can also see more subtle characteristics such as the ability to forecast extreme conditions, the chances of a forecast being badly wrong, e.g., $p(A|B)$, and so forth.

A second application can be made in terms of the fuel allocations scheme discussed in Appendix A.1. In this scheme one wants a probabilistic forecast, whereas only tercile forecasts are presently available. Using $p(O|F)$ values, such as illustrated in Table A.4.1, one can convert a tercile forecast into a probabilistic one. For example, using the middle row of the temperature table, a tercile forecast of N would be

interpreted as the probabilistic forecast $p(B) = 0.26$; $p(N) = 0.53$ and $p(A) = 0.21$. As discussed in Appendix A.1, one would like the forecaster himself to make a probabilistic forecast in the first place. The point here is that a user can produce the required probabilistic forecast using the forecaster's track record as embodied in $p(O|F)$ data. The forecaster himself might also use this method to aid in issuing a probabilistic forecast. Once forecasts are converted to probabilistic form, they can be used to combine the forecasts of different forecasters. In such a combination scheme, the conditional probabilities weight the individual forecasts in terms of such features as conservatism, ability to predict extreme conditions and so forth, as judged from the forecaster's track record.

As is pointed out in Appendix A.1, the logarithm of the Bayes factor can be used to measure the skill level of a forecaster.³ For application here we use the logarithm of the ratio $[p(x|x)/(1/3)]$ where x is given climate state (A, N, B, etc.) and the $1/3$ represents an equiprobable forecast. A positive Bayes skill implies a better than equiprobable forecaster while a negative implies worse. For the example of Table A.4.1 the Bayes skill of temperature forecasts is $\log [p(x|x)/(1/3)] = -0.1 \pm 0.3$, 0.5 ± 0.3 and 0.8 ± 0.1 for A , N and B forecasts respectively. The uncertainties quoted reflect the number of geographical samples used to estimate $p(O|F)$ in each case. For precipitation the Bayes skills are $-.06 \pm 0.3$, -0.1 ± 0.3 and 0.9 ± 0.1 for H, M and K states respectively. Based on this one season forecast one would conclude that considerable skill is evident in forecasting below average temperature

and precipitation but little elsewhere. One seasonal forecast is clearly insufficient for establishing a track record and the above calculations are merely illustrative of the method. It is nevertheless clear that the "Bayes skill" provides a versatile method for exploring forecasting. Further it is clear, even from this example, that forecasting skill can vary, depending on the forecast made.

REFERENCES FOR APPENDIX A.4

1. Namias, T. Multiple causes of the North American abnormal winter of 1976-77. Mon. Wea. Rev., 1978, 106: 279-295.
2. Barnett, T. P. and R. W. Preisendorfer. Multifield Analogue Prediction of Short-Term Climate Fluctuations Using a Climate State Vector. J. Atm. Sci., 1978, 35: 1771-1787.
3. Sturrock, D. A. "A Theory of Theories." SUIPR Rpt. #324, Inst. for Plasma Research, Stanford University, Stanford, CA 94305, 1969.

APPENDIX A.5

A.5 A POSSIBILITY FOR OCCASIONAL ACCURATE FORECASTS

One of the more interesting possibilities for occasional accurate forecasting was presented to our study by J. M. Wallace.^{1,2} He reported strong evidence for significant correlations among the following variables: sea surface temperature in the equatorial Pacific, 200 mb height at several tropical stations, the difference between normalized sea-level pressure anomalies at Darwin and Tahiti, the mean temperature of the tropical troposphere, precipitation at numerous Pacific islands, and the Northern Hemisphere 700 mb height field. Some of these correlations are shown in Figure A.5.1.

What appears to occur is that whatever sets up warm sea-surface temperatures in the equatorial eastern Pacific and accompanying weak Pacific tradewinds starts a meteorological chain of events which results in a relatively stable pattern in all the other variables listed above. A most interesting feature of the pattern for North American weather forecasting is the below normal 700 mb heights in the North Pacific (the Aleutian low) and the southeastern U.S. and above normal 700 mb height over Western Canada (see Section 2.2 and Figure 2.4). This is expected to lead to lowered sea-surface temperatures in the North Pacific and the Southeastern U.S. and higher than normal temperatures in Western Canada. Table A.5.1 indicates the existence of this correlation.

Figure A.5.1 CORRELATION COEFFICIENTS BETWEEN 700 mb GEOPOTENTIAL HEIGHT AT GRIDPOINTS POLEWARD OF 20°N AND: (a) THE TROPICAL 200 mb INDEX, (b) THE SEA-SURFACE TEMPERATURE INDEX, (c) OUR SOUTHERN OSCILLATION INDEX, AND (d) DECEMBER-FEBRUARY RAINFALL AT FANNING. CONTOUR INTERVAL, 0.2 THE LOCATIONS OF THE CENTERS OF ACTION OF THE PACIFIC/NORTH AMERICAN AND WEST PACIFIC PATTERNS ARE DENOTED, RESPECTIVELY, BY DOTS AND OPEN CIRCLES.

Table A.5.1 Composites of selected surface data for the period 1910-1945 based on Fanning seasonal precipitation. Values of Honolulu seasonal rainfall, Dutch Harbor sea level pressure, Edmonton temperature, and Jacksonville temperature for each of the 12 wettest Northern Hemisphere winter seasons at Fanning are shown, together with the mean and standard deviation for the entire 46-year period, the mean for the 12 wettest years at Fanning, and the mean for the other 34 years.

YEAR	Fanning season precip. (cm)	Honolulu season precip. (cm)	Dutch Harbor sea level pressure (mb)	Edmonton temperature (°C)	Jacksonville temperature (°C)
1912	215.9	16.8	-9.0	12.8	
1914	139.2	13.4	-10.7	13.5	
1915	136.9	14.1	-11.3	12.8	
1919	137.7	17.1	-8.9	13.9	
1920	88.4	14.0	-11.0	13.2	
1924	76.0	24.3	1000.0	-9.1	13.8
1926	146.6	9.0	992.4	-6.6	13.0
1928	113.0	49.0	996.6	11.2	12.8
1931	132.3	4.7	988.1	-3.0	12.1
1940	146.8	10.9	994.2	-10.5	11.2
1941	145.3	3.4	991.8	-12.1	13.3
1942	71.6	11.2	989.5	-9.0	12.8
46 winter mean	59.1	26.1	999.1	-11.8	14.0
Mean for 12 wettest winters at Fanning	129.1	15.8	993.3	-9.4	12.9
Mean for other 34 winters	22.6	31.2	1002.0	-13.0	14.5
46 winter standard deviation	56.4	16.8	6.2	3.2	1.6

If we knew a signal which would tell us in advance that the equatorial eastern Pacific sea-surface temperature would be warmer, we could predict what appears to be one standard deviation change in surface temperature over Western Canada and the southeastern U.S. We may not yet know the mechanism, but the correlation is present.

An analysis by E. M. Rasmussen of the NMC Climate Analysis Center of the lagged correlation between the "Southern Oscillation Index" (SOI) defined to be $(\Delta \text{ Pressure in Darwin}) - (\Delta \text{ Pressure in Tahiti})$ and the December-January-February 700 mb height anomalies in the Northern Hemisphere (see Figures A.5.2, A.5.3, A.5.4) has shown a remarkably strong correlation for a lag of two seasons. This has the very suggestive implication that a measurement of the SOI in June-July-August will give a prediction of unusual 700 mb heights in the winter Northern Hemisphere. More precisely, when the SOI rises by about one standard deviation in summer we can expect the pattern described above for the Northern Hemisphere winter. One also expects significant equatorial Pacific rainfall, lowered Northern Pacific sea-surface temperatures, etc.

This is clearly a source for an occasional accurate forecast. We are presently unable to predict when the SOI index will rise; however, when it does, we can say with some confidence the remaining pattern will follow.

FIGURE A.5.2 700 MB (L-H) SOI Composite Anomalies, LAG = 0

FIGURE A.5.3 700 MB (L-H) SOI Composite Anomalies, LAG = 1

FIGURE A.5.4 700 MB (L-H) SOI Composite Anomalies, LAG = 2

REFERENCES FOR APPENDIX A.5

1. Wallace, J. M. and D. Gutzler. Teleconnection in the Geopotential Height Field in the Northern Hemisphere Winter. Draft Manuscript, June, 1980.
2. Hortel, J. and J. M. Wallace. Planetary Scale Atmospheric Phenomena Associated with Interannual Variability of Sea-Surface Temperature in the Equatorial Pacific. Draft Manuscript, June, 1980.

APPENDIX A.6

A.6 PARTIAL BIBLIOGRAPHY ON REGIONAL-SEASONAL FORECAST

- Adamec, D., R.L. Elsberry, R.W. Garwood, Jr., R.L. Haney, A coupled mixed layer-ocean circulation model for the study of ocean dynamics; Naval Postgraduate School, Monterey, CA., 1980.
- Barnes, J.A.; H.H. Sargent, III, P.V. Tryon; Sunspot cycle simulation using a narrowband Gaussian Process: A stochastic model based on a simple physical principle simulates the features of sunspot cycles; Submitted to Science, 1980.
- Barnett, T. P.; An attempt to verify some theories of El Niño . J. Phys. Oceanogr.; 7, 633-647, 1977a.
- Barnett, T. P.; The principal time and space scales of the Pacific Trade Wind Field; J. Atmos. Sci., 34, 221-235, 1977b.
- Barnett, T. P.: Predictability of ocean/atmosphere fluctuations in the tropical Pacific; , submitted to J. Phys. Oceanogr, 1980.
- Bendat, J. S. and A. G. Piersol; Random Data: Analysis and Measurement Procedures, Wiley-Interscience, New York, N.Y., 297 pp, 1971
- Bjerknes, J.; The possible response of the atmospheric Hadley circulation to equatorial anomalies of ocean temperature;. Tellus, 4, 820-829, 1966
- Bjerknes, J.; Atmospheric teleconnections from the equatorial Pacific. Mon. Wea. Rev., 97, 163-172, 1969
- Chervin, R. M.; On the comparison of observed and GCM Stimulated Climate Ensembles; NCAR June, 1980.
- Chervin, R. M., J. E. Kutzbach, D. D. Houghton, and R. G. Gallimore: Response of the NCAR General Circulation Model to prescribed changes in ocean surface temperature. Part II: Midlatitude and subtropical changes;. J. Atmos. Sci., 37, 308-332, 1980
- Chervin, R. M., W. M. Washington and S. H. Schneider; Testing the statistical significance of the response of the NCAR General Circulation Model to North Pacific Ocean surface temperature anomalies. J. Atmos. Sci., 33, 413-423, 1976

- Davis, R. E.; Predictability of sea-surface temperature and sea-level pressure anomalies over the North Pacific Ocean; J. Phys. Oceanogr., 6, 249-266, 1976
- Davis, R. E.; Techniques for statistical analysis and prediction of geophysical fluid systems. Geophys. Astrophys. Fluid Dyn., 8, 245-277, 1977
- Davis, R. E.; Predictability of sea level pressure anomalies over the North Pacific. J. Phys. Oceanogr., 8, 233-246, 1978
- Diaz, Henry F., Quayle, Robert G.; An analysis of the recent extreme winters in the contiguous United States; Mon. Wea. Rev., 108, 687-699, June, 1980.
- Dickson, Robert R., J. Namias; North American influences on the circulation and climate of the North Atlantic sector; Mon. Wea. Rev., 104, 1255-1265, 1976.
- Elsberry, Russell L., R.W. Garwood, Jr.; Sea-surface temperature anomaly generation in relation to atmospheric storms; Bull. Amer. Meteor. Soc., 59, 786-789, 1978.
- Enfield, D.B., J.S. Allen; On the structure and dynamics of monthly mean sea level anomalies along the Pacific Coast of North and South America; J. Phys. Oceanogr., 10, 557-578 1980
- Gilman, Donald; Sea-surface temperatures, and short-term Colorado climate prediction; Proceedings of the Eighth technical exchange conference; General Circulation Models, 1978.
- Gilman, Donald L.; The nature of climatic variability; NOAA, National Weather Service, June, 1980.
- Glantz, M.H.; Saskatchewan Spring Wheat Production, 1974: A preliminary assessment of a reliable long-range forecast; Climatological Studies No. 33, 1979.
- Glantz, Michael H.; Science, politics & economics of the Peruvian anchoveta fishery; Marine Policy, 201-210, July 1979.
- Glantz, Michael; The value of a long-range weather forecast for the West African Sahel; Bull. Amer. Meteor. Soc., 58, 150-158, 1977.
- Haney, Robert L., W.S. Shiver, K.H. Hunt; A dynamical-numerical study of the formation and evolution of large-scale ocean anomalies; J. Phys. Oceanogr., 8, 952-969, 1978.
- Haney, Robert L.; A numerical case study of the development of large-scale thermal anomalies in the Central North Pacific Ocean; Naval Postgraduate School, Monterey, CA., 1980.

- Haney, Robert L.; Numerical models of ocean circulation and climate interaction; Rev. Geophys. Space Phys., 17, 1494-1506, 1979.
- Harnack, R. P. and A. J. Broccoli: Associations between sea surface temperature gradient and overlying mid-tropospheric circulation in the North Pacific region; J. Phys. Oceanogr., 9, 1232-42, 1979
- Harnack, R. P. and H. E. La: Winter season temperature outlooks by objective methods; J. Geophys. Res., 83, 3601-16, 1978
- Hastenrath, S.: Interhemispheric sea temperature coupling and Ecuador, Peru El Niño . Revista Italiana Di Gofisica E. Scienze Affini, 3, 255-256, 1976.
- Hastenrath, S. and L. Heller: Dynamics of climatic hazards in northeast Brazil; Quart. J. Roy. Met. Soc., 103, 773-792, 1977.
- Henderson-Sellers, A.; Albedo Changes-Surface surveillance from satellites; Climatic Change, 2, 275-281, 1980.
- Henderson-Sellers, A., A.J. Meadows; The zonal and global albedoes of the earth; Tellus, 31, 170-173, 1979.
- Hendrickson, G. C.; An attempt to project winter temperature departures for the eastern United States; National Weather Digest, 4, 27-35, 1979.
- Hindman, Edward E., II, and James Spear; An evaluation of some ultra-long-range weather predictions; Bull. Amer. Meteor. Soc., 61, 321-328, 1980.
- Horel, John D., J.M. Wallace; Planetary scale atmospheric phenomena associated with the interannual variability of sea-surface temperature in the equatorial Pacific; University of Washington, Seattle, 1980.
- Houghton, D. D., J. E. Kutzbach, M. McClintock and D. Suchman: Response of a General Circulation Model to a sea temperature perturbation. J. Atmos. Sci., 31, 857-868, 1974.
- Jenkins, G. M. and D. G. Watts; Spectral Analysis and its Application, Holden-Day, 525 pp., 1968.
- Jenne, R. L.; Data sets for meteorological research. NCAR Tech. Note, NCAR-TN/1A-111, pp. 194, 1975.
- Julian, P. R. and R. M. Chervin; A study of the southern oscillation and Walker Circulation phenomenon; Mon. Wea. Rev., 106, 1433-1451, 1978.
- Krishnamurti, T. N.; Tropical east-west circulations during the Northern summer; J. Atmos. Sci., 28, 1342-1347, 1971.
- Krishnamurti, T. N.: The subtropical jet stream of winter, J. Met., 18, 172-191, 1961.

- Krueger, A. F. and T. I. Gray, Jr.; Long-term variations in equatorial circulations and rainfall; Mon. Wea. Rev., 97, 700-710, 1969.
- Krueger, A. F. and J. S. Winston; A comparison of the flow over the tropics during two contrasting circulation regimes; J. Atmos. Sci., 31, 358-370, 1974.
- Krueger, A. F. and J. S. Winston; Large scale circulation anomalies over the tropics during 1971-72; Mon. Wea. Rev., 103, 465-473, 1975.
- Kukla, G.J., J.K. Angell, J. Korshover, H. Dronia, M. Hoshiai, J. Namias, M. Rodewald, R. Yamamoto, and T. Iwashima; New data on climatic trends; Nature, 270, 573-580, 1977.
- Kutzbach, J. E., R. M. Chervin and D. D. Houghton: Response of the NCAR General Circulation Model to prescribed changes in the ocean surface temperature, Part I: Midlatitude changes. J. Atmos. Sci., 34, 1200-13, 1977.
- Madden, Roland A.; An attempt to separate changes due to statistical sampling from real climate change; NCAR, 1979.
- Madden, Roland A.; A simple approximation for the variance of meteorological time averages; J. App. Meteor., 18, 703-706, 1979.
- Madden, Roland A.; Estimates of the natural variability of time-averaged sea-level pressure; Mon. Wea. Rev., 104, 1695-1703, 1976.
- Madden, R. A. and D. J. Shea; Estimates of the natural variability to time averaged temperatures over the United States; Mon. Wea. Rev., 106, 1695-1703, 1978.
- McCreary, J.; Eastern tropical ocean response to changing wind systems with application to El Niño . J. Phys.Oceanogr., 6, 635-645, 1976.
- McIntosh, Patrick S.; Annotated Atlas of Ha Synoptic Charts for Solar Cycle 20;(1964)1974) Report UAG-70, World Data Center A for Solar-Terrestrial Physics; NOAA, 1979.
- Namias, J. and P. F. Clapp; Confluence theory of the high tropospheric jet stream. J. Met., 6, 330-336, 1949.
- Namias, Jerome; Suggestions for research leading to long-range precipitation forecasting for tropics; Preprint Vol. (Part I) Int'l Tropical Meteorology Mtg, Jan 31-Feb. 7, 1974, Nairobi, Kenya, Published by American Meteorological Society.
- Namias, J.; Short Period Climatic Variations, Collected Works of J. Namias 1934 through 1974 (2 vols.). Univ. Calif. San Diego, 905 pp, 1975.

- Namias, Jerome; Stabilization of atmospheric circulation patterns by sea surface temperatures; Sears Foundation; Journal of Marine Research, 33, 53-60, 1975.
- Namias, Jerome; Some statistical and synoptic characteristics associated with El Niño ; J. Phys. Oceano., 6, 130-138, 1976.
- Namias, Jerome; Seasonal forecasting experiments using North Pacific air/sea interactions; Preprint Vol. Sixth Conference on Weather Forecasting and Analysis, May 10-14, 1976, Albany, N.Y., Published by American Meteorological Society.
- Namias, Jerome; Forecasting Climatic Fluctuations: Winter of 76-77; Science, 196, 1386-87, 1977.
- Namias, Jerome; Multiple Causes of the North American Abnormal Winter 76-77; Mon. Wea. Rev., 106, 279-295, 1978.
- Namias, Jerome; Recent drought in California and Western Europe; Rev. Geophys. Space Phys., 16, 435-458, 1978.
- Namias, Jerome; Persistence of U.S. seasonal temperatures up to one year; Mon. Wea. Rev., 106, 1557-1567, 1978.
- Namias, Jerome; Long Range Weather and Climate Predictions; Studies in Geophysics: Geophysical Predictions, National Academy of Science, 1978.
- Namias, Jerome; The sea as a primary generator of short-term climatic anomalies; Proceedings of the WMO/IAMAP Symposium on Long-term Climatic Fluctuations.
- Namias, Jerome; Negative ocean air feedback systems over the North Pacific in Transition from warm to cold seasons; Mon. Wea. Rev., 104, 1976.
- Namias, Jerome; The enigma of drought-A challenge for terrestrial & extra terrestrial research; Solar-Terrestrial Influences on Weather and Climate, pp. 41-43, D. Reidel Publishing Co., Dordrecht, Holland, 1979.
- Namias, Jerome; Premonitory signs of the 1978 break in West Coast drought; Mon. Wea. Rev., 107, 1674-1681, 1979.
- Namias, Jerome; Severe drought and recent history; Interdisciplinary History, 697-712, 1980.
- Namias, Jerome; Some concomitant regional anomalies associated with hemispherically averaged temperature variations; J. Geophys. Res., 85, 1585-1590, 1980.
- Namias, Jerome; The Art and science of long-range forecasting; EOS, 61, 1980.

- Oort, A. H. and E. G. Rasmusson; Atmospheric circulation statistics, NOAA Professional Paper #5, U. S. Dept. of Commerce, National Ocean and Atmospheric Administration, 223 pp, 1971.
- Palmen, J. and C. W. Newton; Atmospheric Circulation Systems, Their Structure and Physical Interpretation. Academic Press, New York, N.Y., 595 pp, 1969.
- Preisendorfer, R. W.; Model skill and model significance in linear regression hindcasts; SIO Ref. Series #79-12, Scripps Institution of Oceanography, A-024, La Jolla, Ca., 92093, 1980.
- Quirk, William J., J.B. Knox; A Consensus of Several Forecasts for the winter of 1979-80; LLL (Lawrence Livermore Laboratory), UCID-18328; 1979.
- Reiter, E. R.; The interannual variability of the ocean-atmosphere system; J. Atmos. Sci., 35, 349-370, 1978a.
- Reiter, E. R.; Long-term wind variability in the tropical Pacific, its possible causes and effects; Mon. Wea. Rev., 106, 324-330, 1978b.
- Robinson, G.D.; Weather and climate forecasting as problems in hydrodynamics; Mon. Wea. Rev., 106, 448-457, 1978.
- Rowntree, P. R.; The influence of tropical eastern Pacific Ocean temperatures in the atmosphere; Quart. J. Roy. Met. Soc., 98, 290-321, 1972.
- Salmon, R. and M. C. Hendershott; Large-scale air-sea interactions with a simple general circulation model; Tellus, 28, 227-242, 1976.
- Spar, J.; Transequatorial affects of sea surface temperature anomalies in a Global General Circulation Model; Mon. Wea. Rev., 101, 554-563, 1973a.
- Spar, J.; Some affects of surface anomalies in a global general circulation model; Mon. Wea. Rev., 101, 91-100, 1973b.
- Van Loon, H. and R. L. Jenne; Estimates of seasonal mean temperature, using persistence between seasons; Mon. Wea. Rev., 103, 1121-28, 1975.
- Van Loon, H. and J. Williams; The association between temperature trend and variability; Mon. Wea. Rev., 106, 1012-17, 1978.
- Van Loon, H. and J. Williams; The connection between trends of mean temperature and circulation at the surface; Part I; Mon. Wea. Rev., 104, 365-380, 1976.
- Wallace, John M., D.S. Gutzler; Teleconnections in the Geopotential Height Field During the Northern Hemisphere Winter; University of Washington, Seattle, 1980.

- Weare, B.C., A.R. Navato and R.E. Newell; Empirical orthogonal analysis of Pacific sea-surface temperatures; J. Phys. Oceanogr., 6, 671-678, 1976.
- Webster, Peter J.; Response of the tropical atmosphere to local, steady forcing; Mon. Wea. Rev., 100, 518-541, 1972.
- White, Warren B., R.L. Haney; The dynamics of ocean climate variability; Oceanus, 21, 33-39, 1978.
- Williams, J. and H. Van Loon; Examination of the Northern Hemisphere sea level pressure data set; Mon. Wea. Rev., 104, 1354-61, 1976.
- Wyrtki, K.; El Niño , the dynamic response of the equatorial Pacific Ocean to atmospheric forcing; J. Phys. Oceanogr., 5, 572-584, 1975.