Seasonal and Extraseasonal Predictions of Summer Monsoon Precipitation by Gcms①

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ABSTRACT

A semi-operational real time short-term climate prediction system has been developed in the Center of Climate and Environment Prediction Research (CCEPRE), Institute of Atmospheric Physics / Chinese Academy of Sciences. The system consists of the following components: the AGCM and OGCM and their coupling, initial conditions and initialization, practical schemes of anomaly prediction, ensemble prediction and its standard deviation, correction of GCM output, and verification of prediction. The experiences of semi-operational real-time prediction by using this system for six years (1989–1994) and of hindcasting for 1980–1989 are reported. It is shown that in most cases large positive and negative anomalies of summer precipitation resulting in disastrous climate events such as severe flood or drought over East Asia can be well predicted for two seasons in advance, although the quantitatively statistical skill scores are only satisfactory due to the difficulty in correctly predicting the signs of small anomalies. Some methods for removing the systematic errors and introducing corrections to the GCM output are suggested. The sensitivity of prediction to the initial conditions and the problem of ensemble prediction are also discussed in the paper.

Key words: Seasonal and Extraseasonal Predictions, General Circulation Model

I. INTRODUCTION

It is a great social demand to make long-range predictions such as monthly, seasonal, extra-seasonal (i. e. prediction for two seasons or more seasons ahead) and even annual predictions of climatic anomalies for planning the social activities and the economy of countries, especially, in the monsoon regions and Asian countries, where climatic variabilities are large and very much influence agriculture. Experiments in such climate predictions have been made even on a routine or subroutine basis a long time ago by China, India, Japan, and other countries. The methods adopted to issue the predictions were more or less empirical. Starting from the middle of the last decade, the great success of routine medium-range numerical weather prediction and the implementation of World Climate Research Programme (WCRP) stimulated scientists to try to apply GCMs to the predictions up to monthly and seasonal time scales, meanwhile advances in supercomputers and space techniques of observations provide the technical conditions for realizing these ideas, the experimental monthly, seasonal and extra-seasonal predictions by using GCMs have been developed very rapidly (Miyakoda and Sirutis, 1986; Zebeik and Cane, 1987; Zeng et al., 1990; Krishnamurti, 1991; Palmer et al.,

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1991; Shukla, 1991). There is no doubt that in the near future numerical seasonal and extraseasonal predictions of climate anomalies will become operational, although in the present there are still some problems to be solved.

In this paper we would like to report some experiments of seasonal and extraseasonal predictions of summer precipitation, carried out by the institute of Atmospheric Physics, Chinese Academy of Sciences, by using GCMs. Such predictions became semi-operational in 1989. The first successes in the predictions resulted in the setting up of the Center of Climate and Environment Prediction Research (CCEPRE) at IAP / CAS in 1991. Briefly speaking, a Real-Time Short-Term Climate Prediction System has been developed by CCEPRE. The system consists of AGCM-OGCM, initial conditions and initialization of oceanic dynamics, practical schemes of anomaly prediction, ensemble prediction and its standard deviation, correction of GCM prediction output, and verification of prediction. By using this system CCEPRE provides real-time predictions of monthly and seasonal mean anomalies of precipitation for spring and summer and other climatological elements in every March. The predictions are also made by the so-called assemble method which consists of statistical inferences, dynamical considerations (by using simplified models or sensitivity studies), recognition of pattern similarity and some empirical predictors (Huang et al. 1990). All the predictions including those by GCMs are then integrated to make a final decision of prediction. The result of experiments for the last six years is very encouraging.

II. BRIEF DESCRIPTION OF IAP GCMS

The GCMs adopted by CCEPRE in the real-time short-term climate prediction are developed by IAP (Zeng, 1983; Liang, 1986, 1990; Zeng et al., 1986, 1988; Zhang and Liang, 1989; Zeng et al., 1990, 1991; Zhang et al., 1992, 1994; Bi, 1993). These IAP GCMs are characterized by (a) the subtraction of a standard (reference) stratification both in the AGCM and OGCM for reduction of truncation errors, (b) the removing of the rigid-lid approximation in the OGCM, and (c) the compactness and convenience in mathematical formulation and numerical computation. Our long-term integrations in the simulation and prediction of climate have shown that these techniques are very helpful (see the references listed below).

The stratifications of both the atmosphere and ocean are complicated and difficult to be well represented by the present existing GCMs. In fact, the climatological mean vertical profile of atmospheric temperature $\tilde{T}(p)$ and those of oceanic temperature $\tilde{T}(z)$, density $\tilde{\rho}(z)$ and the Brunt-Vaisala frequency (which is proportional to the vertical gradient of density) are very complicated. The vertical gradient of atmospheric temperature $\partial\tilde{T} / \partial z$ undergoes an abrupt change in the vicinity of tropopause, and the Brunt-Vaisala frequency possesses a very sharp peak in the upper ocean, both they cannot be correctly represented by finite difference with low resolution due to the large truncation error. However, they are known from observation. It is convenient to decompose the vertical profiles of thermal variables such as temperature, density and geopotential heights into the climatological means and the departures from them, i.e. T', ρ', φ'. Therefore, taking the mean parts as known functions in the model, we need to predict only the departures. By so doing a better accuracy of their vertical gradient can be obtained due to removing the large truncation errors. Another advantage of this technique lies in the computation of the horizontal gradient of surface pressure ∇p_s over complicated topography. Since we need to predict only the departure $p'_s(\theta,\lambda;t)$ from the mean $\tilde{p}_s(\theta,\lambda)$, the large truncation error of $\nabla \tilde{p}_s$ is avoided.

The removing of the rigid-lid approximation in the OGCM avoids the distortion of energy dispersion relationship and the difficulty in solving the balance equation for determining the oceanic surface elevation and the barotropic component of the oceanic circulation. It is very convenient to apply the free surface OGCM to the 4-dimensional assimilation of observed altimeter data. The free surface OGCM even is more economical in computation and leads to a unique algorithm in solving the evolutionary equations for both the atmospheric and oceanic dynamics.

The IAP GCMs have been tested by long-term integrations and shown their capabilities in the simulation of large scale features of climate, especially, the monsoons and the abrupt seasonal transitions of atmospheric general circulation under the input of observed climatological SST in the AGCM, the oceanic ENSO events under the input of observed surface wind field and the surface air temperature in the OGCM, and strong enough interannual variabilities of both atmospheric and oceanographic circulations in the CGCM (Liang, 1986; Zeng et al., 1988, 1991; Yuan, 1990; Bi, 1993; Xue, 1993; Yang et al., 1993; Zhang and Endoh, 1994).

The models adopted in our subroutine climate prediction consist of a 2L (two levels) grid point AGCM and a 4L (4 levels) OGCM with grid sizes $4^{\circ}\times 5^{\circ}$, although a 9L (9 levels) AGCM and a 14L (14 levels) OGCM are also used occasionally in 1992–1994, and are applied to the climate prediction in semi-operational way starting from 1995.

III. PRACTICAL SCHEMES OF PREDICTION AND INITIAL CONDITIONS

Two practical schemes of prediction by using GCMs are simultaneously adopted in our subroutine prediction in CCEPRE (Zeng et al., 1990; CCEPRE Monograph No.1, 1994).

One scheme (S1) consists of a global AGCM and a prescribed SST in the boundary conditions. The SST is equal to the sum of a climatological mean SST (with seasonal cycle) and a known SSTA, which is either persistent and taken as the observed monthly mean for the initial month (S1.a), or predicted by other method (S1.b), say, by the statistical method (Zhang et al., 1993, 1994). This is uncoupled scheme but very convenient for making a prediction which is an ensemble mean of several predictions initiated from different data and for the study on the sensibility of prediction to the boundary conditions and the atmospheric initial conditions.

The second scheme (S2) consists of a global AGCM coupled with a global or the Pacific OGCM, but the SST outside the Pacific model region is given by the same method as in S1.

All schemes have been applied to climate prediction of summer precipitation since 1989. The predictions given by the two schemes are compared each other and also with other methods such as the Empirical Assemble Method (Huang et al., 1990).

The prediction of anomalies but not the meteorological elements themselves is more useful in practice because of the existence of systematic errors in the model's climate. At present, we have only prepared the simulated atmospheric climate given by an AGCM with observed climatological SST and the simulated oceanic climate given by an OGCM with the input of observed climatological wind stress and surface air temperature. Therefore, only such separated model's climates are adopted in our practical prediction scheme, although it is desirable to replace them by those obtained by the CGCM in the future. Note, that even in the predicted anomalies there are still some systematic errors resulting from the inconsistent model's climates and the errors of models themselves. Introduction of corrections to the GCM output is desirable (see Section 6).

It is required in China that the prediction of monthly mean and seasonal mean anomalies of precipitation and of other climatological elements would be issued by the end of March every year. In most cases of our real-time predictions by using S1 three or seven runs are made, the initial atmospheric conditions consist of the atmospheric observations on particular individual days, for example February 1 in the first run, February 15 in the second run, and February 28 in the third run (in the case of three runs). Finally, the predicted anomaly is taken as the ensemble mean of these results initiated from different days. Together with the ensemble prediction a map of standard deviation is also provided to the users. (Of cause it would be desirable to run the model initiated from every day in February and then to make an ensemble prediction. In most cases our choice of three or seven runs was only due to the limitation of computational facilities.)

The initial atmospheric conditions in S2 are usually taken from the observations on February 15. The initial oceanic conditions are obtained by the 4–dimensional data assimilation technique with injection of observed wind stress and SST into the OGCM for six months (Li et al., 1992). The ensemble prediction was also applied to the S2 only occasionally due to the limitation of our computer.

IV. EXAMPLES OF SEASONAL AND EXTRA–SEASONAL PREDICTIONS

In CCEPRE we have several sets of predicted maps, i.e. by S1, S2 and also by the Empirical Assemble Method. At present real–time prediction is decided by subjectively integrating of all these predictions, although an objective integration is desirable. In the first stage, it is important to verify every scheme or method separately.

Since the prediction of precipitation is most difficult, here we will focus our attention to the verification of prediction of precipitation anomaly, especially in China. Comparing the predicted maps issued by S1, S2 and the Empirical Assemble Method and the observed factual maps, the qualitative verification shows that in most cases the predictions issued by the three schemes are consistent, and that the seasonal prediction (for one season) and extra–seasonal (for two seasons) of precipitation anomalies are promising. Especially, disastrous drought and flood events during the summer monsoon in East Asia can be well predicted.

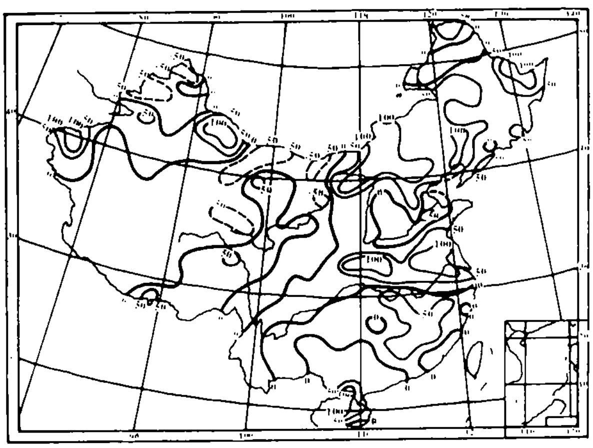

Fig. 1 Observed monthly mean precipitation anomaly (in percentage) for June, 1991. The contour interval is 50%.

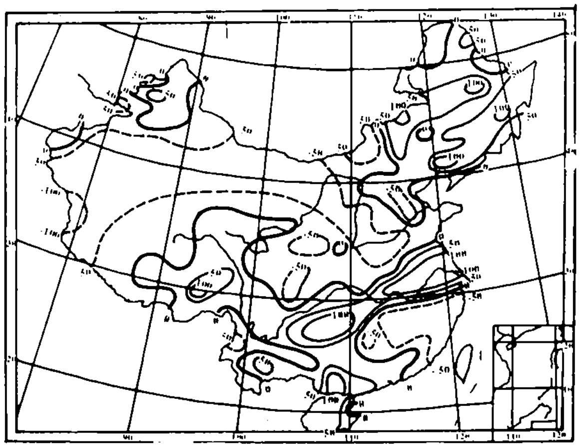

Fig. 2. The same as Fig. 1 but for July, 1991.

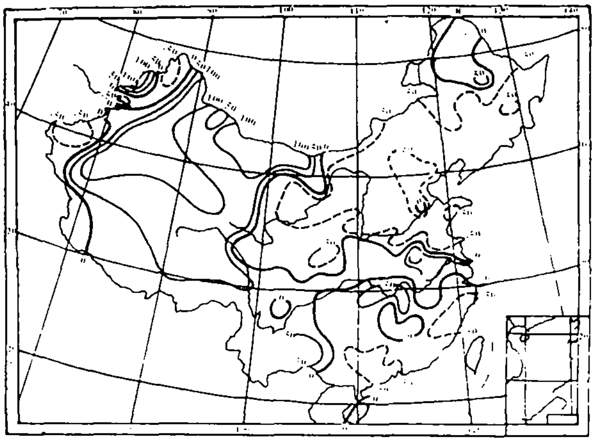

Fig. 3. The same as Fig.1 but for August, 1991.

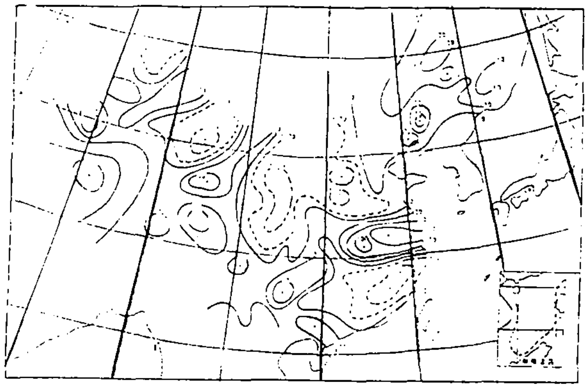

Fig. 4. Observed seasonal mean precipitation anomaly (in percentage) for summer season (JJA), 1991. The contour are 0, ± 20%, ± 50% and ± 100%.

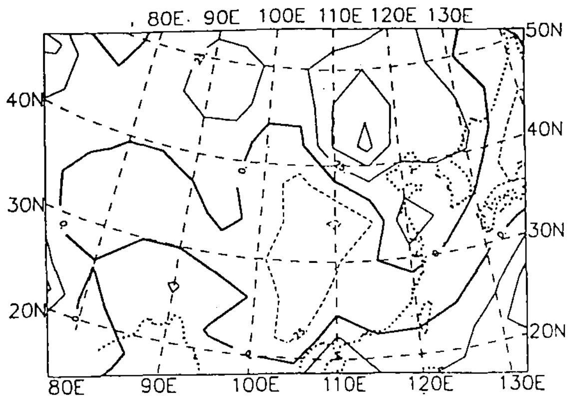

Fig. 5. The same as Fig.1 but predicted by S1.a with initial conditions on Feb.15, 1991. The correction by using (9) has been introduced to the prediction. The contour interval is 25%.

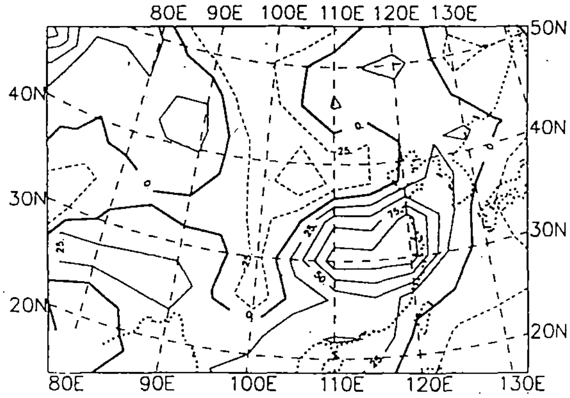

Fig. 6. The same as Fig. 5, but for July, 1991.

Figs. 1–4 show the observed precipitation anomalies (in percentage) for June, July, August and the summer season (JJA) 1991 respectively. Starting from June and lasting to August 1991, there were unusual severe flooding (precipitation anomaly is as large as 100%) in the Huaihe–River and Yangtze–River regions, but severe drought (negative precipitation anomaly even excesses −50%) in North China and South China, and severe– to moderate flood in Northeast China. Figs. 5–8 show the predicted anomalies by using S1a initiated from February 15, 1991 (It is the prediction given at first to the user). It can be seen that the very severe flood event in the Huaihe–River and Yangtze–River regions is very well predicted, except for June; the severe drought in North China is also correctly predicted, but the drought in South China is absent in the prediction. Besides, the predicted positive anomaly is as large as surpassing +50%, but is less than the observed one (>+100%), except for July. The predicted July anomaly does surpass +100%. Such large anomalies cannot be predicted by empirical

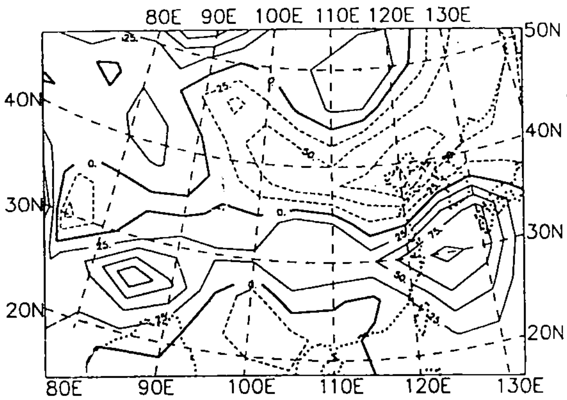

Fig. 7. The same as Fig. 5, but for August, 1991.

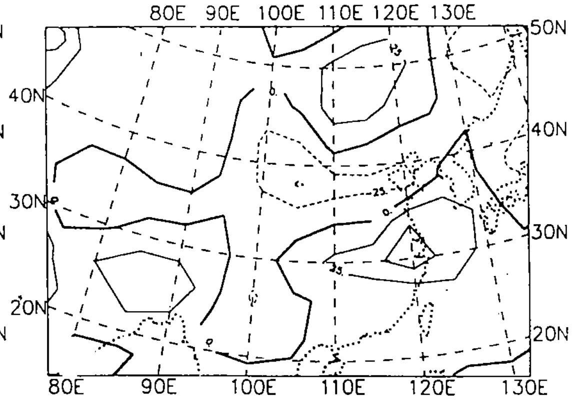

Fig. 8. The same as Fig. 5, but for the summer season (JJA), 1991.

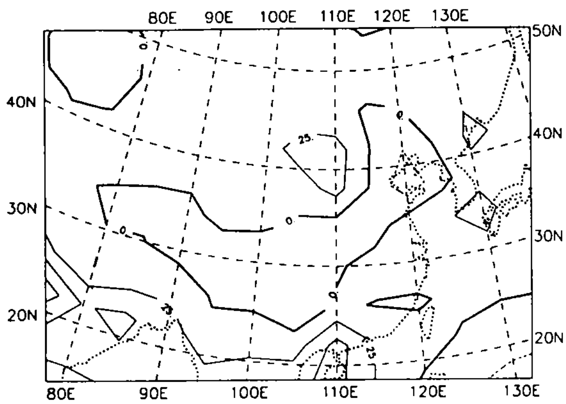

Fig. 9 The same as Fig. 5, but issued by S1.a and the ensemble mean of predictions initiated from Feb.1,5,10,15 and 20 respectively.

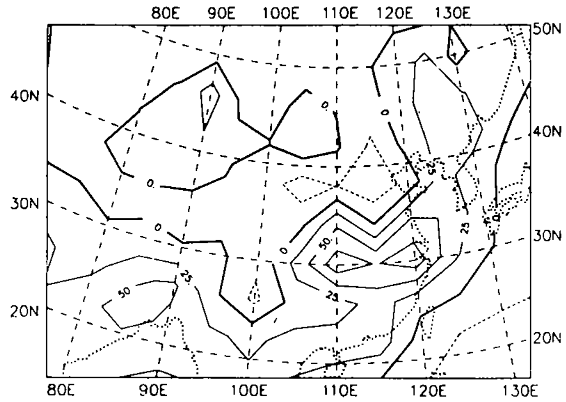

Fig. 10. The same as Fig.9, but for July 1991.

method. Figs. 9–12 show the ensemble means of predictions initiated from February 1,5,10,15 and 20, 1991. (The integration initiated from 25 and 28 February has not been made due to the limitation of our computational facility.) It can be seen that they are similar to but not better than the predictions initiated from an individual day (February 15, 1991). Fig. 13 shows the standard deviation of the ensemble prediction of precipitation anomalies for the summer season. The small standard deviation in the regions of large anomalies makes the prediction more confident.

The predictions issued by using S2 (both ensemble prediction and prediction initiated from February 15, 1991) resemble the same patterns as Figs. 5–8 but with less intensity of the anomalies and a better result in South China (figures not given here).

There was an El Nino event in 1991, the pattern of precipitation anomaly could also be correctly predicted by empirical method, but the unusual severe flood event was un–expected until the prediction was made by using GCMs.

The 1991 prediction by using S1 was very successful due to the fact that the variability of SSTA in the western Pacific Ocean was small during this El Nino period. Besides, the absence of drought in South China and the reduced intensity of anomalies in the prediction might be

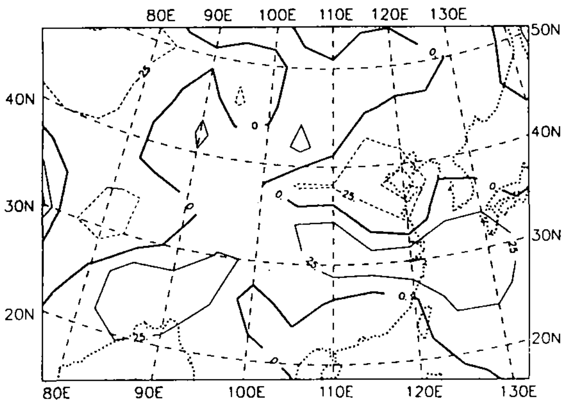

Fig. 11. The same as Fig. 9, but for August 1991.

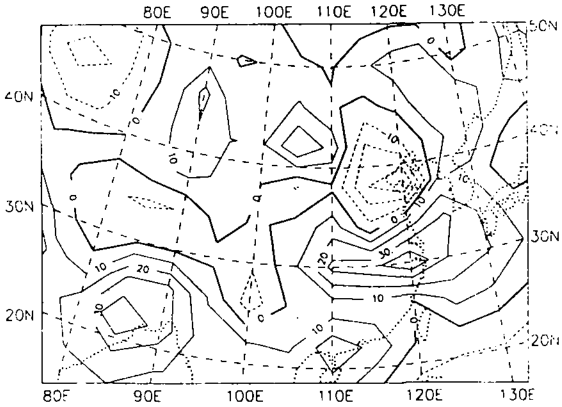

Fig. 12. The same as Fig. 9, but for the summer season (JJA) 1991, and the contour interval is 10%.

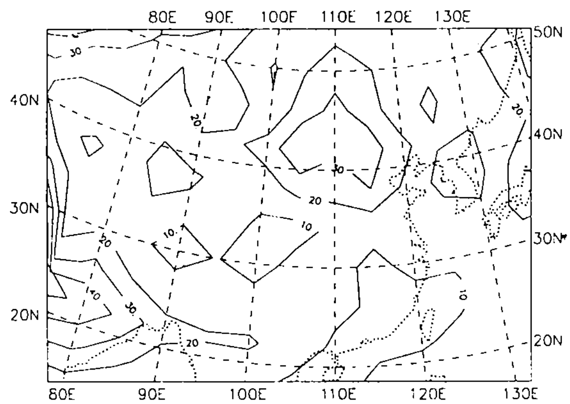

Fig. 13. The standard deviation of ensemble prediction of seasonal mean precipitation shown in Fig. 12. The contour interval is 10%.

due to the influence of the unexpected factors such as the eruption of Pinatubo volcano, and the "prediction" was improved as this effect was re–examined indeed (figures not given here).

Figs. 14–15 show the observed and predicted (by S2) summer season precipitation anomalies for 1992, respectively. Both observed and predicted patterns are very different from the 1991 case. Generally speaking, in the predictions the regions with positive and negative anomalies are almost elongated meridionally, namely along 110°E there is positive anomaly with maximum 50% located along 40°N, but east and west to this region there are two zones of negative anomaly. The structure and the intensity in the observation are almost the same. However, the observed large positive anomaly located in the southeast coastal region has not been well predicted. It was predicted with two centers, one shifted to the land, and the other to the ocean.

Figs. 16–18 show the observed SSTA for February (initial) and July 1992 and the July SSTA predicted by S2 respectively. The decaying of El Nino and the development of negative SSTA in middle latitudes of the northern Pacific and the western tropical Pacific were well predicted.

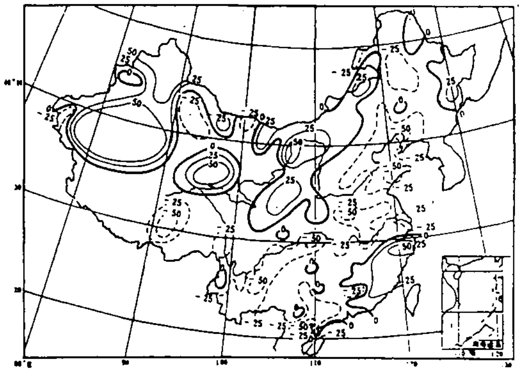

Fig. 14. Observed seasonal mean precipitation anomaly (in percentage) for summer season (JJA), 1992. The contour interval is 25%.

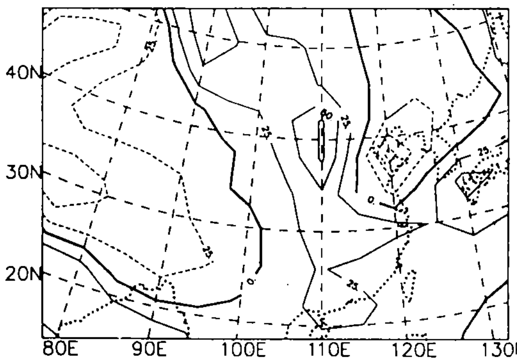

Fig. 15. The same as Fig.14 but predicted by S2 with initial conditions on Feb.15, 1992. The correction by using (9) has been introduced to the prediction.

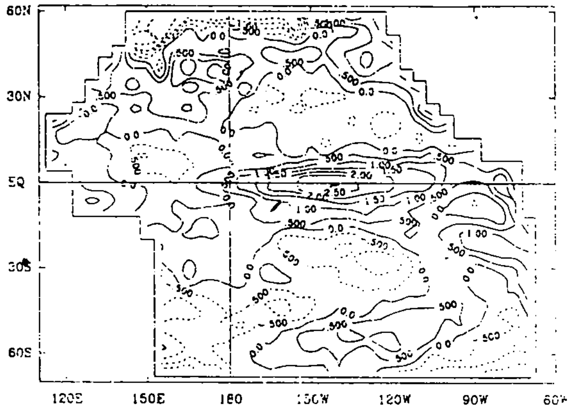

Fig. 16. Observed monthly mean SSTA in Pacific Ocean basin for Feb. 1992.

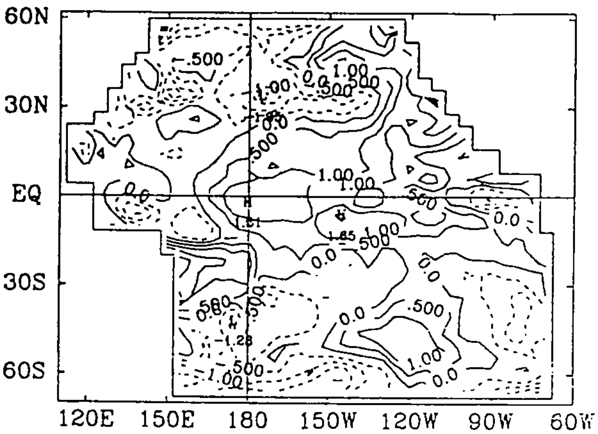

Fig. 17. The same as Fig.16, but for July, 1992.

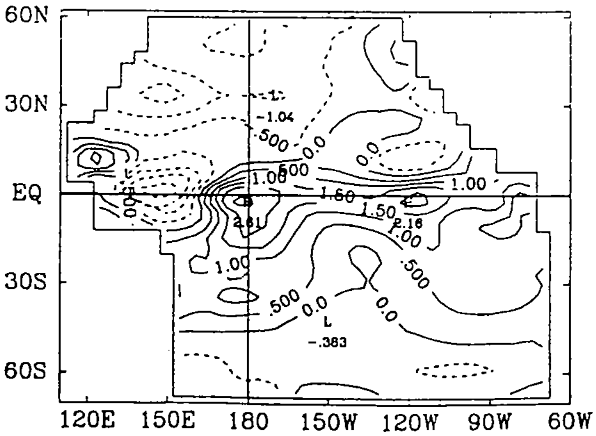

Fig. 18. The same as Fig.17, but predicted by S2 with initial conditions on Feb.15, 1992.

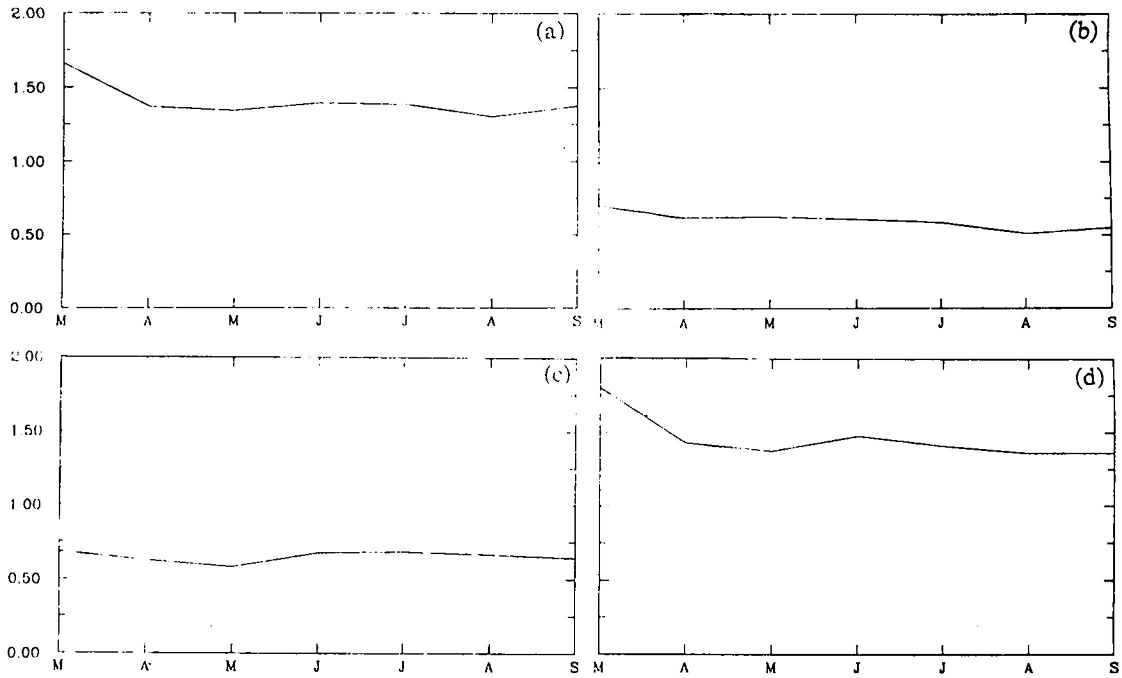

Fig. 19. Global mean of standard deviation of monthly mean anomaly predictions initiated from February 1,5,10,12,15,18,20,25,28,1995 and by S1.a. (a) height of 500 hPa, unit: 10 m; (b) precipitation, unit: mm / day; (c) surface air temperature, unit: °C; (d) sea level pressure, unit: hPa.

Note that the S2 prediction is better than the S1 prediction in 1992 due to the correct prediction of SST variation by S2, although the S1 prediction also represented the major features of observed precipitation anomalies.

The very severe drought in the Huaihe–River and Yangtze–River regions in 1994 was also correctly predicted by our S1 and S2 (figures not given here). In summary, the major large anomalies of precipitations for 1989–1994 were well predicted.

V. STATISTICALLY QUANTITATIVE VERIFICATION OF PREDICTION

It is desirable to have also statistically quantitative verification of climate prediction. According to the Chinese user's need we (Zeng et al., 1994) suggest to adopt the following two criteria: the weighted correlation coefficient r of the predicted and observed anomalies and the ratio of the weighted intensity μ of the two anomalies, defined as

$$r = (A,B)[\|A\| \cdot \|B\|]^{-1} , \tag{1}$$

$$\mu = \|A\| \cdot \|B\|^{-1} , \tag{2}$$

where A and B stand for the observed and predicted weighted anomalies respectively, $\|A\|^2 = (A,A)$, and (A,B) is inner product defined over the area for verification. Note that the mean squared weighted error σ is given by the known r and s by the formula

$$\sigma^2 = 1 - 2r\mu + \mu^2 . \tag{3}$$

Suppose. we have observed and predicted anomalies a and b respectively, and take the weighting function w, therefore

$$A = aw(a), \quad B = bw(b) \tag{4}$$

It is obvious that, r becomes the conventional one if $w \equiv 1$. However, in the climatological study the anomalies are also, and even always, divided into grades, and the correctness of predicted sign of anomaly is adopted as a good index. Therefore, it is better to adopt a proper weighting function. For example, taking

$$w(c) = |c| / c^2 \ , \tag{5}$$

from (1) we have the weighted correlation coefficient

$$r = \frac{S^+ - S^-}{S^+ + S^-} \ , \tag{6}$$

where S^+ and S^- are the areas of correctly and incorrectly predicted signs respectively, and the skill score of correctness of predicted sign ρ is given by

$$\rho = \frac{S^+}{S^+ + S^-} = (1 + r) / 2 \ . \tag{7}$$

So far the sample set of real-time climate prediction is too small, in order to examine the capability of AGCM in the climate prediction, we have first verified 10 years "prediction" (simulations) for 1980–1989 obtained by our AGCM with initial conditions on February 15 every year and a prescribed SSTA which is equal to the observed one during the whole prediction period. The 10–year mean skill scores of correctly predicted sign ρ and the index μ of 500–hPa geopotential height anomaly over the globe, the Northern Hemisphere and the Eastern Asia (70°E–140°E, 10°N–50°N) for spring (MAM) and summer (JJA), respectively, are given in Table 1.

Table 1. The Mean Skill Scores of Correctly Predicted Sign ρ and Index μ of 500 hPa Geopotential Height Anomaly for 1980–1989

Season	Global		N.Hemisphere		Eastern Asia	
	ρ	μ	ρ	μ	ρ	μ
Spring (MAM)	0.617	0.45	0.605	0.54	0.565	0.79
Summer (JJA)	0.600	0.40	0.607	0.35	0.684	0.53

This table tells us that on the average our model makes better prediction over East Asia than other regions, and the predicted intensity of anomalies is less than the observed one, even when no ensemble prediction was applied.

The "prediction" of precipitation anomaly for 1980–1989 has been verified only for East China and the vicinity (100°E–130°E, 20°N–50°N). The 10–year mean skill scores ρ are 0.598 and 0.544 for spring (MAM) and summer (JJA) respectively. The predicted intensity is also less than the observed one.

All these verifications indicate that the prediction by using our current model is only satisfactory, although its capability in predicting disastrous events is good. This is due to the fact that the signs of small anomalies (both the positive and negative) are difficult to be correctly predicted by our model, but they do occupy a large area, and that there is always a shift, although not large, of the location of predicted large anomalies from the observed one.

Note, that no any correction has been introduced to these ten–year hindcasting. The ρ and μ can be certainly improved if the systematic errors of predictions are removed by the method suggested in Section 6.

It should be pointed out that users always pay much attention to the large anomalies and even verify the prediction of grades of the anomalies. This can be made by proper choice of the weighting function W. For example, taking

$$W(c)=g_j|c|/c^2, \quad \text{as} \quad c_{j-1}\leqslant|c|\leqslant c_j \ , \tag{8}$$

where constant g_j is the grades, and $g_{j-1}<g_j$, $j=1,2,\cdots$, we have the correlation coefficient presented in grades. The formula is still simple, but more complicated than (6) due to $\|A\|\neq\|B\|$ (in general) if g_j defers from each other.

VI. CORRECTION OF GCM OUTPUT

As there are systematic errors in the climate simulations, and there is some inconsistence in our practical scheme, it is favourable to introduce correction to the GCM output (Li, 1992; Zeng et al., 1994).

First of all, a corrected prediction of anomaly a$'$ can be made by subtracting the ensemble mean error ε,

$$a'=a^*-\varepsilon \ , \tag{9}$$

where a^* can be equal to a or $a\mu^{-1}$ (intensity corrected), and ε the ensemble mean of a^*-b, i.e.

$$\varepsilon=\langle a^*-b\rangle_h \ , \tag{10}$$

where $\langle\ \cdot\ \rangle_h$ is calculated for a sample set of historical predictions, say the hindcasting for 1980–1989 in our practice. It should be pointed out that this sample set is too small.

Note that ε usually is not equal to zero due to the facts: (a) The reference "observed" climate $\langle f\rangle_r$ (from which we calculate the anomaly for the sample set of historical predictions and the real–time climate predictions) is the ensemble mean of other sample set, i.e. the sample set r is different from sample set h, hence $\langle f\rangle_r\neq\langle f\rangle_h$ because of decadal variabilities of SST and initial atmospheric conditions (or the initial atmospheric–oceanic initial conditions in a fully coupled model as S2). $\langle f\rangle_r$ is also different from $\langle f\rangle_v$ which is the observed climate of the sample set for which the real–time prediction is being made. (b) The reference model climate $\langle f\rangle_{rm}$ is also different from $\langle f\rangle_{hm}$, which is the simulation of $\langle f\rangle_h$ under the sample set $\{\mathrm{SST}\}_h$ and initial conditions set. Denoting the observation and prediction of f for i–th year as f_{oi} and f_{pi} respectively, we have

$$a_i=f_{pi}-\langle f\rangle_{rm}, \quad b_i=f_{oi}-\langle f\rangle_r \ .$$

Therefore, $\varepsilon=\langle a-b\rangle_h=(\langle f\rangle_{hm}-\langle f\rangle_{rm})-(\langle f\rangle_h-\langle f\rangle_r)$. Requiring $\langle a'-b\rangle_h=0$ leads to (10).

There are still other errors even (9) has been introduced. The further correction can be made by (a) introduction of coordinate transformation mapping (x,y) into $(\xi,\ \eta)$ and by requirement of maximum similarity of a' and b, i.e.

$$\langle r\rangle=\langle\iint_S a'(\xi,\eta)b(x,y)dS/\|a'\|\cdot\|b\|\rangle_h=\max. \ , \tag{11}$$

where $\langle\ \cdot\ \rangle_h$ denotes again the ensemble mean for sample h, or (b), by the optimum interpolation technique

$$a''=\iint_S a'(x',y')\ K(x,y;x'y',\{c\})dS \ , \tag{12}$$

where K is the kernel function, and the parameters $\{c\}$ are determined by the requirement of minimum difference

$$\|a''-b\|^2=\min. \ , \tag{13}$$

(see Zeng et al., 1994, in detail), or (c) by using EOFs. Suppose, that the normalized EOFs for prediction samples and the observed samples are $\{X_a\}$ and $\{X_b\}$ respectively, and we have

$$a' = \sum_K c_K X_{aK} \ , \tag{14}$$

it is better to have a corrected prediction a'' by taking

$$a'' = \sum_K c_K X_{bK} \ . \tag{15}$$

In our practice (9) has been introduced in the real-time prediction, and the corrected predictions are improved a lot. The other additional corrections are under examination in CCEPRE now.

VII. THE SENSITIVITY OF PREDICTION TO THE INITIAL CONDITIONS

The prediction is sensitive to initial and boundary conditions both. The sensitivity of the prediction to the boundary conditions is obvious if the prediction is made by using uncoupled AGCM. Our experiments show that the sensitivity of prediction to initial conditions is also not negligible if the prediction is for one or two seasons. In fact, the standard deviation of the ensemble prediction (see Fig.13 for example) is some demonstration of this sensitivity, and the standard deviation is not small in smoe cases and in some regions (they vary from one to another year, but along the Yangtze-River in the East China there is always a minimum. We have more confidence of prediction where the standard deviation of the ensemble prediction is small).

Figure 16 shows the global means of standard deviation of monthly mean 500 hPa height, precipitation, surface air temperature and see level pressure respectively based on 9 predictions by S1. a for 1995. It is clear that even for the global scale motion the standard deviation due to different initial atmospheric conditions (but under the same boundary conditions) is not negligibly small after three months. This means that the initial conditions are still important if the prediction is made for two seasons and that the climate anomalies are not simply determined by the so-called boundary forcing alone. Otherwise, the climate would be independent of initial atmospheric conditions if the SSTA is given.

Note that SSTA is also a variable to be predicted if a CGCM is adopted. In such case SSTA is not boundary condition, and one can make climate prediction by solving the initial value problem defined by the governing equations and initial conditions of atmosphere and ocean both. The boundary conditions are only given on the top of the atmosphere and the bottom of soil and ocean. Of course the initial conditions are not taken from one individial day but from a data set if an ensemble prediction is made. In this sense the ensemble prediction is a generalized initial value problem.

VIII. ABOUT THE ENSEMBLE PREDICTION

General speaking, ensemble prediction should be represented as an integral or a sum of individual predictions with a weighting function (probability). In our case the predictions are made from different initial day τ. Assuming that the weighting function is $P(\tau)$, we have the ensemble prediction $<a>$ as follows

$$<a> = \int_{\tau_1}^{\tau_2} a(\tau)P(\tau)d\tau \Big/ \int_{\tau_1}^{\tau_2} P(\tau)d\tau \ . \tag{16}$$

$P(\tau)$ should be determined by empirical way based on the statistics of existing set of historical predictions and some theoretical consideration. For example, suppose that we know the root mean squired error $\delta(\tau)$ of prediction $a(\tau)$ initiated from day τ and obtained from the existing set of historical predictions, say set h, we can take

$$P(\tau) = \beta^{-1}\delta^{-1}(\tau) \ , \tag{17}$$

$$\beta \equiv \int_{\tau_1}^{\tau_2} \delta^{-1}(\tau) d\tau \ . \tag{18}$$

In general, $P(\tau)$ depends also on the geographical location, but it is a function of τ alone if δ is averaged over the region where the prediction is made.

$\delta(\tau)$ such averaged might reach its minimum on day τ_0. However this does not mean that every individual prediction is the best initiating from day τ_0. Therefore, an ensemble prediction is more beneficial.

It is obvious that $P(\tau)$ depends on τ if a monthly mean prediction is made. For example, when a monthly prediction for March is made, $P(\tau)$ should be larger for those τ, closed to March but smaller for τ, in earlier February. What will be the function $P(\tau)$ for a prediction for one or two seasons? It can be determined only by empirical way, but $P(\tau)$ will be more or less independent of τ for such cases because the period of prediction is far away from the predictability limit of the atmospheric variability.

Since we have only a small prediction set, we take $P(\tau)$=constant in our present real-time monthly, seasonal and extraseasonal predictions.

IX. CONCLUSION REMARKS

So far the results of our semi-operational real-time seasonal and extraseasonal predictions by GCMs are encouraging. The prediction of disastrous climatic events such as severe flood and drought is successful in most cases, although the statistical quantitative verification shows that the prediction is only satisfactory, and that the predicted intensity of anomaly is less than the observed one.

Our experiment seems to indicate that the correctness of SSTA prediction (by CGCM) or prescription (in the boundary conditions for uncoupled AGCM) is very important. A good prediction of SSTA in the Pacific Ocean, especially in the Tropical Wesernt Pacific Oceans, is necessary in order to have a correct prediction of summer precipitation in East Asia. Besides, the influence of initial atmospheric conditions also cannot be neglected.

In order to have operational seasonal and extraseasonal predictions, the models, especially the oceanic GCM, the method of coupling and the 4-dimensional data assimilation for getting correct and consistent oceanic dynamical fields, should be improved, and the real time data (initial conditions) of high quality are also required.

There are always systematic errors in the climate simulation and prediction. It is favorable to remove such systematic errors first, and the introduction of additional corrections to the GCM's prediction output by using some statistical considerations is also desirable. Some such techniques are under examination now.

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