An Approach to Extract Effective Information of Monthly Dynamical Prediction–The Use of Ensemble Method①

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(Received February 23, 2000; revised October 30, 2000)

ABSTRACT

The approach of getting useful information of monthly dynamical prediction from ensemble forecasts is studied. The extended range ensemble forecasts (8 members, the initial perturbations of the lagged average forecast (LAF)(0000, 0600, 1200 and 1800 GMT in two consecutive days) of the 500 hPa height field with the global spectral model (T63L16) from January to May 1997 are provided by the National Climate Center of China. The relationship between the spread of ensemble measured by root–mean–square deviation of ensemble member from ensemble mean and forecast skill (the anomaly correlation or the root–mean–square distance between the ensemble mean forecast and the observation) is significant. The spread of ensemble can evaluate the useful forecast days *N* for the best estimate of 30 days mean. Thus, a weighted mean approach based on ensemble spread is put forward for monthly dynamical prediction. The anomaly correlation of the weighted monthly mean by the ensemble spread is higher than that of both the arithmetic mean and the linear weighted mean. Better results of the monthly mean circulation and anomaly are obtained from the ensemble spread weighted mean.

Key words: Monthly prediction, Ensemble method, Spread of ensemble

1. Introduction

The daily numerical weather forecast has an upper limit of approximately two weeks. Time and space averaging generally has higher predictability. Many extended–range forecast studies confirmed the practical feasibility of dynamical one–month forecast (Shukla, 1981; Tracton et al., 1989; Palmer et al., 1990; Zhang et al., 1997). Li and Ji (1996) demonstrated that the most predictable components are characterized by slow evolution. In order to eliminate the effect of fast growing errors of high–frequency perturbations and reserve the low–frequency processes, the application of the low–frequency filtering method in monthly extended–range forecast significantly improved the forecast skill (Yang and Ji, 1997a, 1997b). It is a main part of extended–range forecast how to extract more useful information from daily numerical forecasts and improve the skill of monthly forecast. In order to eliminate the influence of the less predictable high frequency components of the circulation, Tracton et al.

①Supported by the Excellent National State Key Laboratory Project (49823002), the National Key Project 'Study on Chinese Short–Term Climate Forecast System' (96–908–02) and IAP Innovation Foundation (8–1308).

(1989) suggested that the average of only the first 7–10 days is the best estimate of the 30–day mean circulation. Although the skill of daily forecast concentrates in the earlier time ranges, the useful information can be extracted from the later time ranges (Miyakoda et al., 1986; Shukla, 1981). Consequently, Zhang et al. (1996, 1997) considered that more skillful monthly mean forecast can be got when the time filtering mean was used. The optimum value of useful forecast days for monthly prediction varies largely with individual cases and is uncertain. If we knew the optimum value in advance, we would get a better monthly mean numerical forecast by fully utilizing the useful information. The spread of ensemble members is the manifestation of difference among the forecasts of ensemble members initiated from different values. What relationship between the spread of ensemble and forecast skill is ? Is the optimum days for estimating monthly prediction related with the spread of ensemble members ?

The accuracy of numerical weather forecast is deteriorated by two kinds of errors. The first is initial error. The second is model error. Through studying the error growth of numerical weather forecast and its sensitivity to initial data, scientists well recognized that a nonlinear dynamical system is inherently stochastic. In order to deal with the stochastic nature of forecast problem, both research and operational atmospheric modeling groups have utilized ensemble forecasts to advance probability of prediction. In the extended–range forecast, when the predictability of baroclinic disturbances is completely lost, a statistical or probabilistic approach based on an ensemble of forecasts may give us more convincing information.

In postprocessing of an ensemble of model output, an ensemble mean of forecasts is generally used. The weighted mean of the climate and the ensemble forecasts has proven to get better results (Houtekamer, 1995). Probability forecast provides relative probability of a selected prediction object and various possible states of future atmosphere from ensemble forecasts. Cluster analysis (Brankovic et al., 1990; Murphy, 1990) collects the resemble output of ensembles, and difference flow regimes can arise. Nevertheless, we need more effective forecast result for operation and user requirements.

2. Data

The data used in the present study consist of the daily extended–range ensemble forecasts of the 500 hPa height field with the global spectral model from January to May 1997 provided by the National Climate Center of China. The global spectral model has a resolution of rhomboidal truncation 63 and 16 unequally spaced layers. The lagged average forecast (LAF) method is applied in which the LAF includes 8 ensemble members, each ensemble member being an ordinary dynamical forecast starting from some different initial states at a time interval of 6 hours (0000, 0600, 1200 and 1800GMT in two consecutive days).

3. Assessment of the useful information length N

In the extended–range, daily forecasts normally evolve from rather accurate to rather useless. Figure 1 presents the anomaly correlation (R_{AC}) of the Northern Hemisphere (NH) (20–90°N) 500 hPa height field between $1-N$ day ensemble mean forecast and the 30–day mean observation for 15–case average (Equation (2)). The R_{AC} of 500 hPa height field between $1-N$ day mean ($N=1$ to 30) forecast and the 30–day mean observation first increases and then reaches its maximum and then declines as the averaging period N is extended. Note also that N varies considerably from case to case. The R_{AC} reaches maximum 0.4601 at

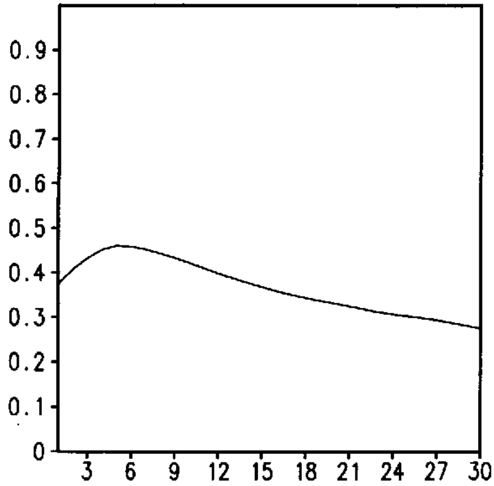

Fig. 1. Northern Hemisphere anomaly correlation of 500 hPa height field between 1– N day mean forecast and 30–day mean observation for 15–case average.

Table 1. The maximum R_{AC} and N for each case

Initial Date	Ensemble Mean	
	R_{AC}	N
09–10 Jan 1997	0.453	4
19–20 Jan 1997	0.684	5
30–31 Jan 1997	0.476	29
09–10 Feb 1997	0.781	2
19–20 Feb 1997	0.526	1
27–28 Feb 1997	0.516	10
09–10 Mar 1997	0.403	7
19–20 Mar 1997	0.619	5
30–31 Mar 1997	0.283	7
09–10 Apr 1997	0.762	16
19–20 Apr 1997	0.347	2
29–30 Apr 1997	0.422	8
09–10 May 1997	0.332	5
19–20 May 1997	0.348	9
30–31 May 1997	0.595	22–24

N= 5 days. In other words, the first 5 days of the integration provide the best estimate of the complete 30–day mean. Table 1 gives the maximum R_{AC} and the optimum N for each case. The best proxy N can be from 1 to 29 days. N equals 5 days when the maximum R_{AC} (0.5017) arrives for the 9–case mean of January–March. But for the 6–case mean of April–May, the R_{AC} gains the maximum 0.4067 when N= 6. Therefore, the N value when the R_{AC} reaches the maximum changes greatly from case to case, and has uncertainty. It is noted that one did not a priori know N and N is not determined in forecasting. N is the reflection of the increasing of the forecast error with time. If N was estimated or forecasted, the first N–day average of the integration would provide the best estimate of the complete 30–day mean, fully utilize the useful information from the forecast results, and improve the monthly numerical weather forecast.

4. Relationship between the ensemble spread and forecast skill

The above–mentioned results showed that the first N days mean of integration is able to substitute for the monthly weather forecast. Zhang et al. (1996, 1997) showed that the non–skillful later part of the integration includes useful information to monthly weather forecast in spite of less accurate daily forecasts of all scales. The still better monthly mean results are obtained from a larger weight of the former part and a smaller weight of the later part of the integration because the anomaly correlation R_{AC} of daily forecast declines as the integrating time progresses. But how is the useful prediction length estimated? For this, we define the ensemble spread (S), the anomaly correlation (R_{AC}), and the root–mean–square error (E_{RMS}) of ensemble mean forecast as follows:

$$S=\sqrt{\frac{1}{N_E}\frac{1}{M}\sum_{i=1}^{N_E}\sum_{j=1}^{M}(H_{ij}-\overline{H}_j)^2}\ , \tag{1}$$

where H_{ij} is the forecast of the ith member of the ensemble at the jth point of the space, N_E is the size of the ensemble, M is the space size of the Northern Hemisphere (20–90°N), and the overbar signifies an ensemble members mean.

$$R_{AC}=\frac{\sum\{[(H-C)-\overline{(H-C)}][(O-C)-\overline{(O-C)}]\}}{\sqrt{\sum[(H-C)-\overline{(H-C)}]^2\sum[(O-C)-\overline{(O-C)}]^2}}\ , \tag{2}$$

$$E_{RMS}=\sqrt{\frac{1}{M}\sum(H-O)^2}\ . \tag{3}$$

In Equations (2) and (3), $H=\frac{1}{N_E}\sum_{i=1}^{N_E}H_i$, is the ensemble mean for N_E–member ensemble forecasts. The C and O are respectively climatological and observed (analyzed) values. The overbar "—" signifies a spatial average.

Figure 2 is the time evolution of S (solid line), E_{RMS} (long dashed line) and R_{AC} (dashed line) of the NH 500 hPa height ensemble forecast for the 15–case average. The growth rate of spread approaches zero after day 18 of integration. The growth rate of the root–mean–square error (E_{RMS}) is close to zero beyond 11 days. The E_{RMS} increases faster than the ensemble spread. The anomaly correlation of ensemble mean forecast (R_{AC}) decreases with time progressing and has little change after day 12 of integration. This indicates that the spread of ensemble members has the capability of estimating the forecast skill. Table 2 shows the correlation coefficient between R_{AC}, E_{RMS} and S for each case. The correlation coefficient between R_{AC} and S is negative with the largest absolute value 0.980, the smallest absolute value 0.746. The correlation coefficient between E_{RMS} and S varies from 0.424 to 0.954. The largest correlation coefficient is for the case of 19–20 March 1997. It can be seen that this is the case of the best improvement for monthly forecast by using the ensemble spread weight. All correlation coefficients between R_{AC} and S greatly exceed the significance level of 99% of t–test. This indicates that the ensemble spread can estimate the useful information length N, and provides the estimate of the growth of forecast error. Consequently, the

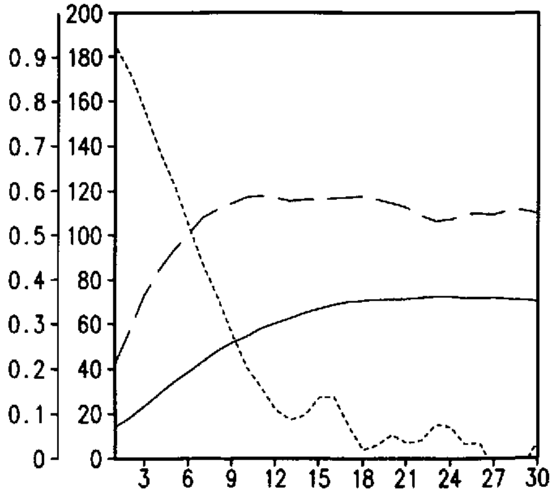

Fig. 2. S (solid line), E_{RMS} (long dashed line) and R_{AC} (dashed line) of the NH 500 hPa height ensemble forecast for the 15–case average.

spread of ensemble members could be used as weights to extract useful information of monthly dynamic prediction.

Table 2. Correlation coefficient between R_{AC}, E_{RMS} and S

Initial Date	Arithmetic mean	
	R_{AC} and S	E_{RMS} and S
09–10 Jan 1997	–0.750	0.650
19–20 Jan 1997	–0.848	0.424
30–31 Jan 1997	–0.746	0.746
09–10 Feb 1997	–0.809	0.802
19–20 Feb 1997	–0.945	0.594
27–28 Feb 1997	–0.779	0.550
09–10 Mar 1997	–0.899	0.644
19–20 Mar 1997	–0.980	0.954
30–31 Mar 1997	–0.935	0.691
09–10 Apr 1997	–0.904	0.542
19–20 Apr 1997	–0.951	0.945
29–30 Apr 1997	–0.882	0.886
09–10 May 1997	–0.955	0.765
19–20 May 1997	–0.917	0.713
30–31 May 1997	–0.872	0.575

5. The filtering monthly dynamic prediction by the ensemble spread weight

Ensemble forecasts starting from somewhat different initial states provide various probabilities of future atmosphere. An ensemble mean can filter the unpredictable random processes and should be on an average closer to the reality than a single deterministic prediction. But the traditional mean is one of the possible states. The problem is how to gain more useful information of monthly dynamical prediction from the ensemble forecasts.

A few weighted filtering means for monthly dynamical prediction are listed for comparison.

(1) Arithmetic mean: it is a general way that each member forecast is equally useful for ensemble mean forecasts and every daily forecast is equally useful for 30–day means monthly forecast.

The arithmetic mean of an ensemble of 8–member forecasts is defined as the average field:

$$H_t = \frac{1}{8}\sum_{i=1}^{8} H_{it} \ , \tag{4}$$

$$\overline{H_{30}} = \frac{1}{30}\sum_{t=1}^{30} H_t \ , \tag{5}$$

where t is the forecast time, H is the forecast.

(2) Linear weight: utilizing the method by Zhang et al. (1996, 1997) in which larger weight of former part integration and smaller weight of latter part integration are considered and each ensemble member has equal weight.

$$W_t = 1 + \frac{15.5 - t}{15.5} \ . \tag{6}$$

$$\overline{H_{30}} = \frac{\sum_{t=1}^{30} W_t H_t}{\sum_{t=1}^{30} W_t} \ . \tag{7}$$

(3) Weight based on the ensemble spread: In the first short range of integration, the ensemble members will be closer to each other. But as the integrating time goes on, the nonlinear processes become important, and the ensemble members may be scattered. Thus the spread of ensemble members can be used as weight. Two groups of formulas have been adopted:

(a)

$$\overline{H_{30}} = \frac{\sum_{t=1}^{30} \frac{H_t}{S}}{\sum_{t=1}^{30} \frac{1}{S}} \ , \tag{8}$$

(b)

$$S_{it} = \frac{1}{M}\sum_{j=1}^{M} \left| H_{itj} - H_{tj} \right| \ , \tag{9}$$

$$\overline{H_{30}} = \frac{\sum_{t=1}^{30}\sum_{i=1}^{8}\frac{H_{it}}{S_{it}}}{\sum_{t=1}^{30}\sum_{i=1}^{8}\frac{1}{S_{it}}} \quad . \tag{10}$$

In (a) the reciprocal of the ensemble spread S is used as weight for the monthly mean (see Equation (8)). While for (b) the weight is obtained from the distance of the ith ensemble member from the ensemble mean because there is some correspondence between small ensemble scattering and high forecast skill. Relative contribution of each ensemble member to monthly prediction is considered (see Equations (9) and (10)).

Table 3. The monthly Northern Hemisphere 500 hPa geopotential height scores for each case and forecasting methods

Initial Date	Arithmetic Mean		Linear Weight		Ensemble Spread Weight (a)		Ensemble Spread Weight (b)	
	R_{AC}	E_{RMS}	R_{AC}	E_{RMS}	R_{AC}	E_{RMS}	R_{AC}	E_{RMS}
09–10 Jan 1997	0.214	76.2	0.284	76.1	0.351	74.3	0.351	74.7
19–20 Jan 1997	0.442	62.9	0.590	56.0	0.681	50.4	0.679	50.6
30–31 Jan 1997	0.499	70.8	0.494	73.6	0.506	74.3	0.509	74.3
09–10 Feb 1997	0.417	70.1	0.484	67.6	0.591	60.7	0.599	60.2
19–20 Feb 1997	0.243	79.6	0.322	80.6	0.356	76.2	0.365	57.8
27–28 Feb 1997	0.312	68.5	0.397	68.9	0.423	66.8	0.425	66.8
09–10 Mar 1997	0.119	66.6	0.241	66.5	0.224	67.3	0.237	67.7
19–20 Mar 1997	0.223	57.9	0.388	54.8	0.506	50.5	0.514	50.6
30–31 Mar 1997	−0.009	70.4	0.14	71.4	0.132	70.4	0.128	71.5
09–10 Apr 1997	0.669	37.0	0.762	33.9	0.745	34.8	0.739	35.5
19–20 Apr 1997	0.022	59.1	0.092	65.2	0.175	61.0	0.173	61.4
29–30 Apr 1997	0.145	60.0	0.258	60.4	0.228	60.5	0.230	60.8
09–10 May 1997	0.031	56.8	0.133	56.7	0.158	55.5	0.166	55.6
19–20 May 1997	0.235	43.1	0.287	44.0	0.283	43.4	0.276	43.5
30–31 May 1997	0.559	29.7	0.569	33.3	0.560	31.8	0.557	32.5
15 cases average	0.275	60.6	0.363	60.6	0.395	58.5	0.397	57.6

Table 3 lists the monthly ensemble prediction skill using the above methods. It shows that the filtering monthly forecast obtained by the ensemble spread weighted mean performs better than the arithmetic mean and linear weighted mean, where method (3b) is the best. The 15–case mean monthly prediction improvement introduced by method (3b) over method (3a) is 0.002 in the anomaly correlation R_{AC}. The monthly forecast skills of 9 cases are higher by method (3b) than by method (3a). The best one is for the case of 19–20 February 1997 in which R_{AC} using method (3b) increases 0.009 comparing with method (3a). R_{AC} of the 15–case mean monthly prediction by method (3b) filtering increases by 0.1222 compared with arithmetic mean and 0.0342 compared with linear mean. Still better results are obtained from method (3b) of the ensemble spread weight.

Table 3 also shows that the improvement in R_{AC} varies with season by method (3b). The improvement in R_{AC} is larger during January–March, and smaller during April–May. In January–March, the mean R_{AC} by method (3a) increases by 0.1456 compared with arithmetic mean, 0.0478 compared with linear weight, and by method (3b) increases by 0.1497

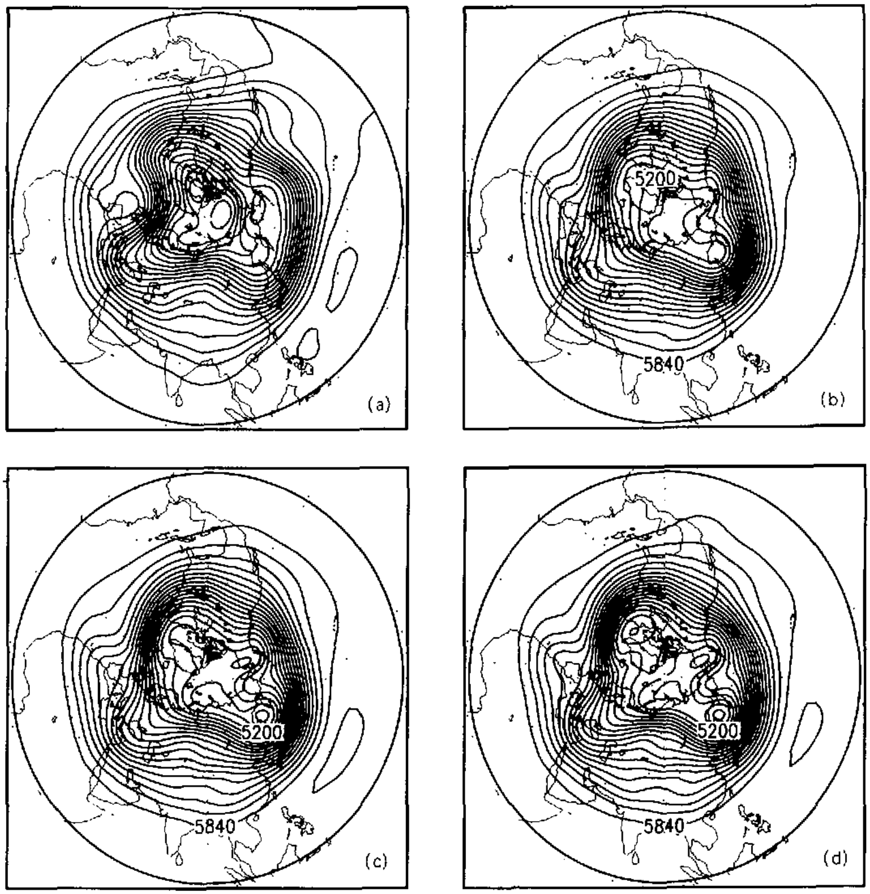

Fig. 3. 21 March–20 April mean 500 hPa geopotential height for an extremely skillful case (19–20 March 1997). Analysis (a), arithmetic mean (b), linear weight (c) and method (3b) (d).

compared with arithmetic mean, 0.0519 compared with linear weight. During April–May, the mean R_{AC} by method (3a) increases by 0.0813 compared with arithmetic mean, 0.008 compared with linear weight, and by method (3b) increases by 0.081 compared with arithmetic mean, 0.0077 compared with linear weight. The better improvement is during January–March. It seems that the barotropic and baroclinic instability at middle–high latitudes is larger in winter, and the spread of ensemble members reflects the growth of forecast error because of the initial perturbation. Therefore the ensemble method of monthly dynamical forecast using the spread weights may be useful to increase the skill of monthly mean forecast.

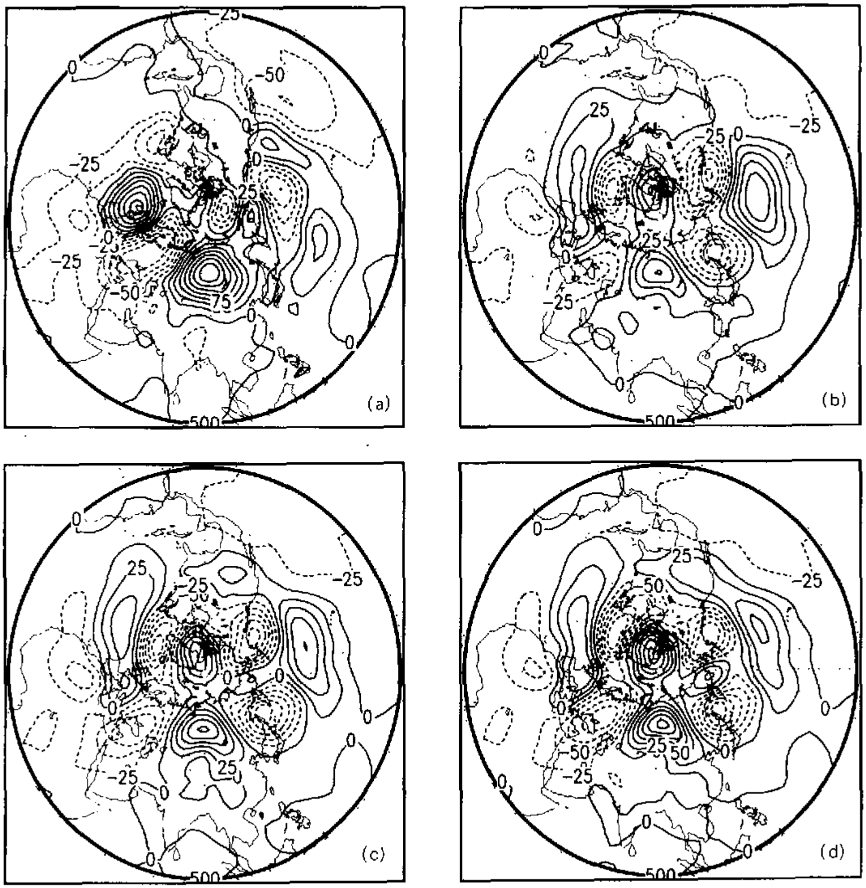

Fig. 4. 21 March–20 April mean 500 hPa geopotential height anomaly for an extremely skillful case (19–20 March 1997). Analysis (a), arithmetic mean (b), linear weight (c) and method (3b) (d).

6. Case study

The above study showed the skill scores of the monthly ensemble forecast using arithmetic mean, linear weight and spread weights. A set of fifteen cases is too small to draw a statistically significant conclusion, so we try to look into a very good case. It is an extremely good case for 19–20 March 1997 initial fields by method (3b) filtering, whose anomaly correlation R_{AC} of monthly mean forecast by method (3b) is 0.514, 0.291 higher than that by the arithmetic mean, and 0.126 higher than that by the liner weight. The monthly mean 500 hPa height and anomalies of the analysis and the forecasts by different weighted mean for 19–20 March 1997 case are shown in Fig. 3 and Fig. 4, respectively. There is a 4–wave pattern along middle and high latitude band for the analysis of 1–30 days mean 500 hPa geopotential height

(Fig. 3a). The troughs over Europe, the eastern Pacific and the east coast of North America are stronger than normal. But the trough over the east coast of Asia is weaker than normal. The ridges over the west coast of Europe and Lake Baikal are stronger than normal. These features are showed clearly by the anomalies (Fig. 4a). The largest positive height anomalies prevail over the west coast of Europe and Siberia. The negative height anomalies are located over Europe, the eastern Pacific and the east coast of North America. In middle latitudes, the Pacific is occupied by positive height anomalies, and the other areas are dominated by negative height anomalies. The locations of troughs and ridges of monthly mean forecasts by arithmetic mean, linear weight and method (3b) are basically consistent with the monthly analysis (Figs. 3b–d). But the amplitude of the troughs and ridges by method (3b) filtering is closer to the analysis. Specially in the Eurasian continent, the amplitude of ridges over the west coast of Europe and Lake Baiker is enhanced compared with arithmetic mean and linear weight. Figure 4b shows that the height anomalies signal over Europe and the west coast of Europe and Siberia are induced using arithmetic mean and linear weight, but the intensity of the anomalies is much weaker than the analysis. These anomalies are enhanced by method (3b) and close to the analysis anomalies. In the mid–latitude Pacific, the intensity and range of the positive height anomalies by method (3b) are greatly improved compared with arithmetic mean and linear weight (Fig. 4d).

7. Conclusion

The main purpose of this work is to discuss the most useful forecast days N for the best estimate of the monthly mean and how to get better monthly dynamical prediction utilizing the ensemble method. The data of the 500 hPa height field are from the National Climate Center of China, in which 15–case extended–range ensemble forecasts were generated for the period January to May 1997 using the T63L16 (Triangular truncation of 63 waves, 16 levels) global spectral model. The size of ensemble forecasts is 8 members. The method of lagged average forecast (LAF)(0000, 0600, 1200 and 1800GMT in two consecutive days) is applied to the initial perturbations. The results obtained by verifying the 15–case are summarized as follows:

(1) Forecast skill (the anomaly correlation or the root–mean–square distance between the ensemble mean forecast and the observation) is related to the spread of ensemble members (root–mean–square deviation of ensemble member from ensemble mean). The spread of ensemble members can evaluate the useful forecast days N for monthly dynamical prediction and reflects the increasing of forecast error because of uncertainty in initial fields.

(2) The anomaly correlation (R_{AC}) of monthly dynamical prediction is considerably increased using weight based on the spread of ensemble. The R_{AC} of monthly dynamical prediction by the spread weight means is higher than that of both arithmetic mean and liner weight mean. The R_{AC} of monthly dynamical prediction by method (3b) filtering is 0.1222 higher than that by the arithmetic mean and 0.0342 higher than that by the liner weight for the 15–case average. It shows that improvement in the R_{AC} of monthly dynamical prediction using method (3b) varies with season. The R_{AC} using method (3b) filtering monthly forecast increases by 0.1497 compared with the arithmetic mean and 0.0519 compared with the liner weight for January–March cases mean. The R_{AC} by method (3b) filtering monthly dynamical prediction is 0.081 higher than that by the arithmetic mean and 0.0077 higher than that by the liner weight for April–May cases mean. So monthly dynamical prediction using the ensemble spread weighted mean is effective for practical use.

(3) From the case study of very well enhanced case by method (3b) of the ensemble

spread weight on 19–20 March 1997, the monthly mean circulation and anomaly are improved significantly especially in Eurasia.

The data were provided through the National Climate Center of China. The authors wish to thank Ms. Chen Lijuan for her assistance.

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集合方法在月动力预报信息提取中的应用

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摘 要

本工作将集合方法应用于提取月动力预报有用信息。利用中国气象局国家气候中心T63L16全球谱模式的500百帕高度场月集合预报产品(集合成员数为8个,初始场的选取采用滞后方法(LAF),即相邻两天的0000,0600,1200和1800GMT的初始化资料),就1997年1月至5月共15次预报,分析了集合预报成员间的离散度与预报评分(距平相关系数和均方根误差)的关系,研究了用集合各成员预报离散度作为各个成员逐日预报的权重对月预报效果的影响。结果表明集合预报成员的离散度与预报评分有显著的相关,是有效预报长度 N 的一个很好估计;用离散度作为权重平均的月预报高度距平相关系数明显高于算术平均和线性权重,此外个例分析表明月平均环流及其异常的预报得到明显的提高。

关键词: 月预报,集合方法,离散度