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A New Way to Predict Forecast Skill

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ABSTRACT

Forecast skill (Anomaly Correlated Coefficient, ACC) is a quantity to show the forecast quality of the products of numerical weather forecasting models. Predicting forecast skill, which is the foundation of ensemble forecasting, means submitting products to predict their forecast quality before they are used. Checking the reason is to understand the predictability for the real cases. This kind of forecasting service has been put into operational use by statistical methods previously at the National Meteorological Center (NMC), USA (now called the National Center for Environmental Prediction (NCEP)) and European Center for Medium-range Weather Forecast (ECMWF). However, this kind of service is far from satisfactory because only a single variable is used with the statistical method. In this paper, a new way based on the Grey Control Theory with multiple predictors to predict forecast skill of forecast products of the T42L9 of the NMC, China Meteorological Administration (CMA) is introduced. The results show: (1) The correlation coefficients between "forecasted" and real forecast skill range from 0.56 to 0.7 at different seasons during the two-year period. (2) The grey forecasting model GM(1,8) forecasts successfully the high peaks, the increasing or decreasing tendency, and the turning points of the change of forecast skill of cases from 5 January 1990 to 29 February 1992.

Key words: forecast skill; grey control theory; anomaly correlated coefficient

1. Introduction

It is well known that after the first numerical weather chart was put into operational use in 1956, our numerical weather forecasting models and computer capacity have improved dramatically. However, the forecast skill of the products has not improved at the same rate to match this progress. Lorenz (1969a, b) and Smagoringsky (1969) pointed out that there exists a limit for this issue, which is called the predictability of medium range numerical weather forecasting. This theory has some positively significant meaning to avoid the unrealistic idea to submit numerical weather forecasting products longer than two weeks. Leith (1974) challenged the classic predictability theory by showing some facts in which the atmosphere keeps not so unstable a state as the classic predictability shows us for the real atmosphere, since the behavior of the atmosphere changes from an unblocked weather situation to a blocked one. Therefore, it is very easy for us to consider that the predictability limit should be longer than two weeks since the lifespan for a blocked weather situation for the atmosphere can be longer than four weeks or so. For example, Li et al. (2001) carefully checked the maintenance mechanism of the blocking over the Ural mountain during the second Meiyu period in the summer of 1998. After more and more specific information on the blocking situation is obtained, we might extend the forecast time for forecasting products to a longer time than the current limit in the near future. However, to many meteorological centers, it is a dream to submit numerical weather forecasting even only longer than 10 days because an extremely low forecast skill exists for the majority of real forecasting cases. Even for European Centre for Medium-Range Weather Forecast (ECMWF), the forecast skill of cases longer than 10 days changes dramatically from case to case (Palmer, 1987). It is an indirect way to improve the forecasting quality of our NWP models if we can predict the forecast skill immediately after the forecasting product has been made. As we know, we can extend the forecast time of our NWP model by one or two days longer than the original time if we work out an effective method to identify those cases which might have a high forecast skill.

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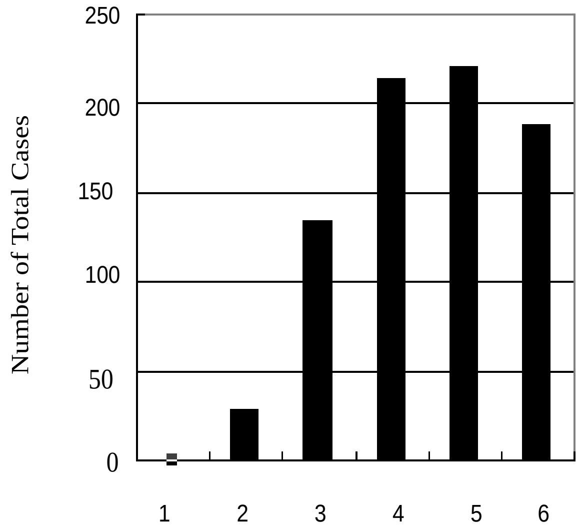

Grade	ACC Range
1	0.9≤ACC
2	0.8≤ACC<0.9
3	0.7≤ACC<0.8
4	0.6≤ACC<0.7
5	0.5≤ACC<0.6
6	ACC<0.5

Class of Forecast Skill Level (Grade)

Fig. 1. The number distribution of different cases at different grade levels accoding to their Anomaly Correlation Coefficient (ACC).

For NWP in the National Meteorological Center in China, the forecast skill for operational forecasting cases is far from satisfactory even for 5-day forecasting (see Fig. 1). From Fig. 1, we can see that only for a small ratio of cases (28 cases out of 790) is the forecast skill noteworthy.

On the other hand, as we know, regarding the predictability problem for extended and medium range weather forecasting, one of the technique policies is ensemble forecasting. However, this brings a new problem of identifying those cases which are good and those which are bad.

Because of the two requirements of operational use and theoretic progress (ensemble forecasting), the idea came to predict forecast skill. This idea came from Cats, G. J. and O. Akesson (1983), Hoffman and Kalnay (1983), Palmer and Tibaldi (1986), and Kalnay and Dalchur (1987). And in their work (Cats, G. J. and O. Akesson (1983), Hoffman and Kalnay (1983), and Molteni, F. and T. N. Palmer (1991), a statistical method was used to predict forecast skill. Hoffman and kalnay used the spread of twin forecasting cases (at day 5 of yesterday's and at day 4 of today's) as a single predictor to predict forecast skill. Some sort of success was achieved but not so satisfactory because the correlation coefficient between the time series of the "forecasted" and "real value" of the forecast skill is about 0.3–0.5.

Tan and Ji (1996) found that the forecast skill at day 5 is highly correlated with the specific pattern of circulation and the change of circulation. Therefore, if some more predictors are employed, the forecasting quality for predicting the forecast skill will probably be improved. On the other hand, the results from the purely statistical methods strongly depend on the amount of historical data. Therefore, it is reasonable to seek a new method. Here, we try a new way to predict forecast skill by introducing grey control theory (Deng, 1992) to establish an operational scheme.

2. Data, power spectrum analysis, and predictors

2.1 *Data*

In this study, both the forecast and analysis data (790 continuous cases) of T42L9 at 500-hPa geopotential height during the period from 1 January 1990 to 28 February 1992) are used to calculate the forecast skill (ACC).

2.2 *Power spectrum analysis of ACC*

Figures 2a, b, c show the power spectrum analysis of different regions' ACC. From Fig. 2a, we can see that there are peaks which show us some significant periods (5 days, 7 days, 9 days, 12.5 days) for forecast skill in Asia.

From Fig. 2b, we can see that there are also some peaks which show us some significant periods (4.5 days, 6 days, 7 days, 12 days and 16 days) for forecast skill in North America. Figure 2c gives us some significant periods (5.5 days, 6 days, 10 days, 13.5 days and 16 days) for forecast skill in Europe.

These periods show us that there are some patterns of circulation which the T42L9 model can and cannot successfully describe. Since these patterns of circulation come periodically, there exist periods for forecast skill also.

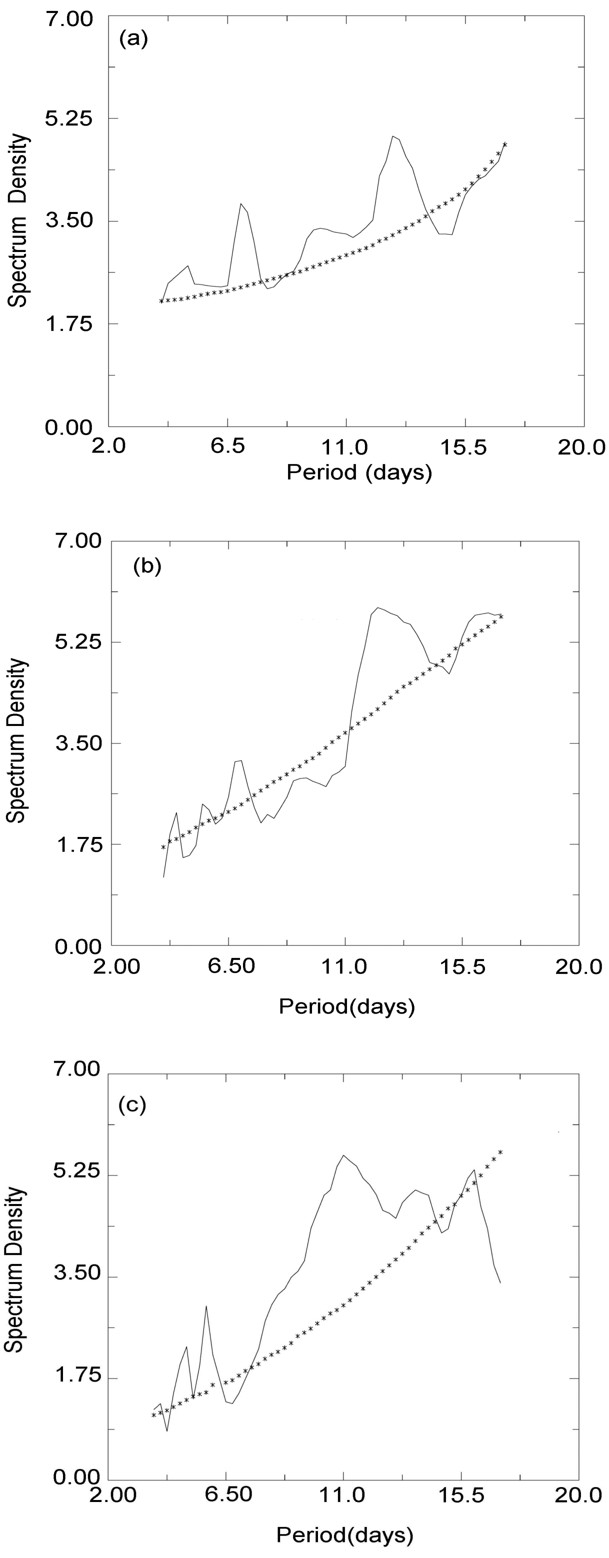

Fig. 2. Power Spectrum Analysis of ACC at day 5 for (a) Asia, (b) Europe, and (c) North America.

2.3 *Predictors*

Cats, G. J. and O. Akesson (1983), Hoffman, R. N. and E. Kalnay (1983), Molteni, F. and T. N. Palmer (1991) used statistical methods to forecast forecast skill with the predictors which are highly correlated with the forecast skill of their models. In their work, only the spread of twin forecasts were chosen as a circulation predictor. This might be the reason why this statistical method is not so successful, since the correlation coefficient between the forecasted forecast skill and the real forecast skill is between 0.3 and 0.5 (Molteni, F., and T. N. Palmer (1988). In order to make use of this information, we express the 790 cases' initial fields by EOFs. In calculating the correlation coefficient between ACC and the time coefficient of the first ten EOFs, we have identified some circulation predictors (see Table 1). Tan and Ji (1996) showed that the T-index, which gives the relationship between the forecast skill and the change in the pattern of circulation, is highly correlated with the change of the circulation. Therefore, in order to make use of this information as a predictor, some pattern predictors reflecting the change of circulation are defined below.

The term "twin forecast products" means that we output the forecasting products for a case at the same date in different ways: sometimes we use different analysis data from different sources to run our NWP model at the same length of integration time; sometimes we use the same analysis data from a single source but run our NWP model at different lengths of integration time.

Suppose that there are n days between the initial fields for a twin forecasting products. The spread field we have is $\delta(n,i,j)$. $f^*(n+1,i,j)$ and $f(n,i,j)$ are the twin forecasting products. Thus,

$$\delta(n,i,j) = f^*(n+1,i,j) - f(n,i,j) \quad (n = 1,2,3,4) \, .$$

If $n = 0$, then $\delta\,(0,i,j) = f^*\,(1,i,j) - f\,(0,i,j)$ and $\delta(0,i,j)$ is the forecast error field for a 24-hour forecasting product. If $n = 1$, then $\delta(1,i,j) = f^*(2,i,j) - f(1,i,j)$ and $\delta(1,i,j)$ is the spread field for a twin forecasting (last day's 48-hour forecast and today's 24-hour forecast), and so on.

We express the spread field in EOFs and we find the 9th EOF of $\delta\,(1,i,j)$ and first EOF of $\delta\,(4,i,j)$ are better correlated with ACC than the others.

Table 2 shows the correlation coefficient between the predictors and the ACC at day 5 for geopotential height at 500 hPa. From the table, we can see these pattern predictors can be very helpful to forecast forecast skill.

Table 1. The correlation coefficients between time series coefficients of EOFs and ACC

	EOF									
Season	1	2	3	4	5	6	7	8	9	10
Winter (89)	–0.30	–0.52	–0.32	0.14	–0.05	0.18	–0.10	0.09	–0.05	0.07
Spring (90)	–0.28	–0.55	–0.29	–0.4	0.00	–0.44	–0.12	0.11	0.03	–0.21
Summer (90)	–0.21	–0.07	–0.22	–0.14	0.33	0.03	–0.10	–0.40	0.07	–0.06
Autumn (90)	–0.58	–0.36	–0.56	0.07	0.08	–0.02	–0.05	0.25	0.06	–0.07
Winter (90)	0.24	0.15	0.04	–0.11	0.04	–0.15	0.16	0.26	0.11	0.09
Spring (91)	0.14	–0.04	0.25	–0.20	0.03	–0.09	0.13	0.13	0.01	–0.03
Summer (91)	0.17	0.02	0.05	0.26	0.18	–0.17	–0.09	0.20	0.11	0.03
Autumn (91)	0.10	0.22	–0.03	0.14	–0.05	–0.07	0.33	0.01	–0.04	0.16
Winter (91)	0.06	–0.00	0.04	–0.2	–0.11	0.15	–0.17	–0.16	–0.06	–0.16

Table 2. The correlation coefficients between the predictors and ACC at day 5 for geopotential height at 500 hPa

	EOF		
Season	24 h Forecast error pattern predictor	The pattern predictor of $\delta(1, i, j)$	The pattern predictor of $\delta(4, i, j)$
Winter (89)	0.38	0.22	0.35
Spring (90)	0.56	0.49	0.42
Summer (90)	0.54	0.61	0.61
Autumn (90)	0.48	0.49	0.46
Winter (90)	0.48	0.25	0.33
Spring (91)	0.29	0.29	0.41
Summer (91)	0.31	0.26	0.31
Autumn (91)	0.51	0.50	0.49
Winter (91)	0.31	0.32	0.49

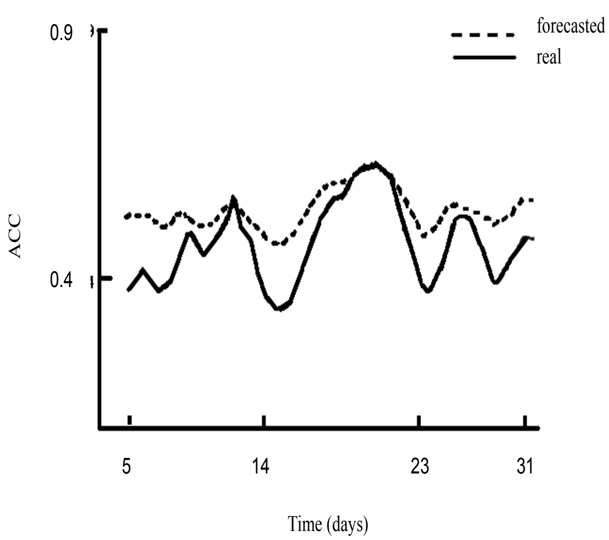

Fig. 3. The "forecasted" and "real" forecast skill for geopotential height of 500 hPa of cases from 5 January 1990 to 31 January 1990.

3. Method

According to the above-mentioned results, we just know the "grey" relation between the predictors and forecast quantity. Therefore, here we employ the new control theory of grey systems put forward by to establish our grey forecasting model to predict forecast skill.

According to Deng's theory, the general form of the grey forecasting model for an nth-order differential equation and $m-1$ predictors is GM (n, m):

$$\frac{d^n x_1^{(1)}}{dt^n} + a_1 \frac{d^{n-1} x_1^{(1)}}{dt^{n-1}} + a_2 \frac{d^{n-2} x_1^{(1)}}{dt^{n-2}} + \cdots + a_{n-1} \frac{dx_1^{(1)}}{dt}$$

$$+ a_n x_1^{(1)} = b_1 x_2^{(1)} + b_2 x_3^{(1)} + \cdots + b_m x_m^{(1)} , \quad (1)$$

where a and b are constant while $x_1(k)$, $x_2(k)$, $x_3(k)$ $\cdots, x_m(k)$ are variables in the array

$$x_1 \equiv \{x_1(k)\} \quad k = 1, 2, 3 \cdots , \quad (2)$$

where x_1 is the forecasted quantity and $x_2, x_3, \cdots, x_m$ are the predictors.

In this study, we set up GM (1, 8) and

$$\frac{dx_1^{(1)}}{dt} + a_n x_1^{(1)} = b_1 x_2^{(1)} + b_2 x_3^{(1)} + \cdots + b_7 x_8^{(1)} , \quad (3)$$

Table 3. The correlation coefficients between "forecasted" and "real" values of forecast skill

Season	1989 Winter	1990 Spring	1990 Summer	1990 Autumn	1990 Winter	1991 Spring	1991 Summer	1991 Autumn
Corrdation coefficient	0.62	0.69	0.70	0.65	0.61	0.65	0.7	0.56

The method to determine coefficients can be obtained in (Deng, 1992). The seven predictors are: the time coefficient of the EOF of circulation; the time coefficient of the EOF of $\delta(1, i, j)$; the time coefficient of the EOF of $\delta(4, i, j)$; the time coefficient of the EOF of the 24-hour forecast error; and the other three predictors (spread, 24 RME, and 24 ACC) which were used by Molteni and Palmer (1988).

4. Results and discussion

Figure 3 gives the results of day 5's forecasted forecast skill for the geopotential height. From the figure we can see three sorts of success:

(1) The grey control model successfully forecasted the high peaks of forecast skill of the cases during the period from 5 January 1990 to 31 January 1990.

(2) The grey control model forecasted the tendency of the change of forecast skill of the cases during the period.

(3) Although the grey control model did not forecast the true value of the lowest points of forecast skill of the cases during the period, it successfully forecasted the location of these values.

The features of other forecasted values for other periods are similar to these three points mentioned above. Table 3 gives the correlation coefficients between the "forecasted" and real values of forecast skill for the above-mentioned cases. From the table, we know that it shows a very nice quality for the new way to forecast forecast skill because the correlation coefficients between forecasted and real forecast skill range from 0.56 to 0.7.

5. Conclusion

One of the most important factors to affect the forecast skill of the NWP models might depend on the ability of the NWP model to predict the change of a weather system for the model. In this study, we define some pattern predictors to enlarge the signal of the correlated relationship between the change of a weather situation. After introducing the method to set up a forecast model by grey control theory, we successfully improve the way to predict the forecast skill for the geopotential height field at 500 hPa of T42L9 at the NMC, CMA. The results show that:

(1) The correlation coefficients between "forecasted" and real forecast skill range from 0.56 to 0.7 at different seasons during the two-year period.

(2) The grey forecasting model GM(1,8) forecasted successfully because it showed the high peaks, the increasing or decreasing tendency, and the turning points of the change of forecast skill of the cases during the period.

Of course, some problems still exist. One such problem is that although we can predict the turning points of the lowest points of forecast skill, we fail to determine how low it might be. Operationally, we might make some sort of compensation for this shortcoming by simply adding some experienced values. However, the reason should be checked further in more detail, which will be helpful to improve our NWP models if predictors can be found.

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