Development of the Analogue-Dynamical Method for Error Correction of Numerical Forecasts

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ABSTRACT

Due to the increasing requirement for high-level weather and climate forecasting accuracy, it is necessary to exploit a strategy for model error correction while developing numerical modeling and data assimilation techniques. This study classifies the correction strategies according to the types of forecast errors, and reviews recent studies on these correction strategies. Among others, the analogue-dynamical method has been developed in China, which combines statistical methods with the dynamical model, corrects model errors based on analogue information, and effectively utilizes historical data in dynamical forecasts. In this study, the fundamental principles and technical solutions of the analogue-dynamical method and associated development history for forecasts on different timescales are introduced. It is shown that this method can effectively improve medium- and extended-range forecasts, monthly-average circulation forecast, and short-term climate prediction. As an innovative technique independently developed in China, the analogue-dynamical method plays an important role in both weather forecast and climate prediction, and has potential applications in wider fields.

Key words: analogue-dynamical method, numerical model, error correction, historical data

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1. Introduction

Since numerical forecasts were successfully realized by Charney et al. (1950), their capability has been much developed (Chen and Xue, 2004). While forecast errors are still significant, the forecast accuracy for high-impact weather events remains very low (Wu et al., 2007). The two factors restricting the accuracy of numerical forecasts are initial error and model error (Zhong et al., 2011), so improving the quality of the initial field and reducing model errors are two ways to improve forecast capability. In recent years, numerical forecasts have been developed in the direction of elaborate models and accurate initial fields. This trend has resulted in more intensive observational data, more sophisticated assimilation technology, more elaborate numerical models, and more reasonable parameterization. These efforts have much improved forecasting accuracy, but with the increasing economic and social development, current forecasting capabilities still cannot satisfy the growing demand (Wu et al., 2007).

No matter how elaborate the model, forecast errors are inevitable, and the efforts required to make further improvements are considerably greater. Along with the development of assimilation technology, another effective way to improve forecast accuracy is to conduct error correction. Much work has been done in developing error correction technology, and it is worth mentioning that Chinese scientists combined statisti-

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cal and dynamical methods (Chou, 1986) and obtained a series of innovative theories and methods (Gu, 1958a, b; Zheng and Du, 1973; Chou, 1974; Qiu and Chou, 1990; Huang and Yi, 1991; Zhang and Chou, 1991; Cao, 1993; Zhang and Chou, 1997; Gu, 1998). Particularly, by combining the analogue evolution law of the atmosphere and the dynamic model, the analogue-dynamical method (ADM) was developed (Chou, 1979). This has played an important role in improving the prediction theory and raising the level of operational forecast capability. Error correction technology using the ADM has been widely used in medium-range, extended-range, and short-term climate predictions.

This paper first reviews the progress in research on error correction strategies in Section 2. The principle and evolution of the implementation scheme of the ADM, and its development on different-scale weather and climate forecasts are systematically introduced in Section 3. Finally, a summary is provided in Section 4.

2. Progress in research of the error correction technology

Generally, forecast errors can be divided into systematic and non-systematic errors (Shao et al., 2009). The former is independent of time variation, can usually be calculated by the time average of some forecast errors, and represents the bias between the equilibrium of the numerical model and the actual climate state. The latter is flow-dependent (dependent on atmospheric state) and includes random errors. Focusing on both types of errors, correction techniques can also be divided into systematic and flow-dependent correction (Dalcher and Kalnay, 1987).

2.1 Systematic correction

The size of systematic correction is independent of model variable, and the common method is to calculate the mean of a large amount of hindcast errors (considering seasonal and diurnal variations) and to add them to the corresponding forecast results. Zeng et al. (1990) adopted a convenient method to remove climate drift by replacing the forecast climate mean with the actual climate mean, then adding the anomaly of the forecast field to the actual climate mean to give the corrected forecast field. Afterwards, they proposed a series of error correction schemes (Zeng et al., 1994), such as the maximum-likelihood correction, minimum bias correction, empirical orthogonal function (EOF) correction, and so on, applied them in the Institute of Atmospheric Physics (IAP) two-level atmospheric circulation model, and obtained some reasonable results (Lin et al., 1998; Zhao et al., 1999; Zhou et al., 1999; Wang et al., 2000; Li et al., 2005). Moreover, establishing statistical relations on the basis of hindcast data and historical actual data is also common, such as the approach using Perfect Prediction (PP) and Model Output Statistics (MOS) (Klein et al., 1959; Klein, 1971; Glahn, 1972), which are forecasted by establishing the relationship between the circulation pattern and the weather phenomena. These methods are all postprocessings after numerical integration, and are usually called after-the-fact correction (Danforth et al., 2007). This is widely used for its convenient operation, while its shortcoming is not considering the nonlinear interaction between external and internal errors in model integration (Danforth et al., 2007).

The online correction differs by adding a forcing term in the numerical integration to offset the model tendency error and to restrain the nonlinear growth of the forecast error (Danforth et al., 2008a). As it corrects the variation tendency of the model variable in the integration, it is also called the tendency error correction. The most common technique for tendency error correction is nudging, which originates in data assimilation by adding a nudging term to bring the forecast close to the observational data (Hoke and Anthes, 1976; Jeuken et al., 1996). Some scholars have compared the nudging with the after-the-fact corrections, and the result indicates that these two types of correction can both improve forecast abilities, but uncertainty exists in the correction performance. Danforth et al. (2008a) indicated that nudging was better beyond one day; Saha (1992) indicated that nudging had no superiority for forecast skills; Johansson and Saha (1989) indicated that nudging had better effects on small scales, but may destroy the conservativeness of transient energy. These differences illustrate that the performances of these two correction methods are largely dependent on the model used, and when the magnitude of the forcing term in the online correction is too large, coordination among model variables may be destroyed (Danforth et al., 2008a).

To reasonably estimate the magnitude of the forcing term, Klinker and Sardeshmukh (1992) used the mean result of one-step integration to estimate the tendency error, by closing each parameterization in turn to obtain the contribution of each term, and found that the gravity wave parameterization played an important role. Kaas et al. (1999) nudged some low-resolution global circulation models (GCMs) toward a high-resolution GCM to obtain the empirical interaction function of the horizontal diffusion, and reduced the large-scale systematic errors. The above two methods are complex in operation, and empirical estimation is usually adopted in practical numerical models, i.e., the ensemble mean of the ratios of some forecast errors and forecast time is set as the forcing term. This method assumes that the forecast error grows linearly (Yang et al., 2008), and it demands that the forecast time be not too long. As for the selection of forecast time, different investigations have shown different results. Danforth et al. (2007) set it to 6 h, same as the interval of the reanalysis dataset, and averaged all of the 6-h forecast errors from the same month from the previous 5 years as the estimation. To avoid the influence of diurnal variation, Saha (1992) averaged all the 24-h forecast errors from the month before the initial time. Yang et al. (2008) averaged a large amount of 6-, 12-, 18-, and 24-h forecast errors from different years, to estimate the current forecast error, which avoids the variation in the tendency error from different forecast times.

The above empirical correction method is easy to realize, but cannot ensure that the introduced forcing term is optimal. The optimal is usually related to variation assimilation. In the traditional four-dimensional variational data assimilation (4DVar) system, the model is assumed to be perfect, and the effect of model errors is not considered. The weak-constraint 4DVar developed by Bennett et al. (1996, 1997) has considered the existence of model errors. By introducing a term of tendency model error, both the initial error and model error are reduced. This kind of technique has achieved remarkable effects in both simple and complex numerical models (Derber, 1989; Zupanski, 1993; Trémolet, 2007; Akella and Navon, 2009), but the format of the tendency error needs to be assumed as a priori and tested by experiments. Additionally, the solution of 4DVar is usually restricted by the necessity to establish an adjoint model, and the appended term of the model error undoubtedly increases the calculation load.

2.2 Flow-dependent correction

Some studies (Saha, 1992; DelSole and Hou, 1999; DelSole et al., 2008) have indicated that systematic correction can reduce systematic errors, but has little effect on non-systematic errors, which makes it necessary to develop flow-dependent correction.

Leith (1978) established the relationship between tendency errors and state variables using a statistical approach, which expressed the forcing term as the linear function of the state variables, and provided a statistical model with a large number of samples. Though the derivation was under a linear assumption, the results showed that it also had effects on nonlinear models. Delsole and Hou (1999) applied this method in a quasi-geostrophic model and effectively improved the forecast results, but the error covariance matrix required a large amount of calculation. Danforth et al. (2007) and Danforth and Kalnay (2008a, b) reduced the dimension of this method by using singular value decomposition (SVD). The 6-h forecast results from a quasi-geostrophic model indicated that this method could reduce errors in some areas with high values, but the global improvement is little. A common step in the above studies is to establish an error covariance matrix by using a large number of training samples, meaning that the established statistical relationship depends highly on the selected samples, and the stability is difficult to ensure. Once the forecast model is changed or corrected, the rebuilding of the error covariance matrix needs large amounts of computation and is difficult to transplant (Zheng, 2013).

With a linear system, establishing the statistical relationship is an effective approach, and the more the samples, the more stable the relationship. With a nonlinear system, the relationship between the correction effect and the samples is not stable, and a larger number of samples may not be better. Therefore, the selection of samples is important (Chou and Ren, 2006).

The analogue phenomenon exists widely in the evolution of atmosphere and ocean (Zhao et al., 1982; Wang et al., 1983). For two similar atmospheric states, their evolutions are usually similar. This phenomenon provides a reference for selecting samples. For example, Chen and Ji (2003) and Chen et al. (2006a, b) utilized phase space reconstruction theory and a prediction method based on nonlinear time series, searched for the analogue history information to forecast the current state. They thus constructed a regional nonlinear dynamic forecast model on zonal average on the monthly scale, and conducted the correction in the process of model integration. The results indicated that it not only reduced the zonal averaged error, but also had effects on some wave components. They showed that the analogue phenomenon has reference values for improving model forecasting ability.

Based on the above ideas, some investigators combined the analogue phenomenon with the dynamical models, and developed an analogue-dynamical method (ADM) to correct forecast errors. In the following section, the principle and evolution of this method will be systematically introduced, with a focus on its development in different forecast ranges.

3. Development of the ADM

3.1 Analogue phenomenon and forecast

The analogue phenomenon exists in the atmosphere and ocean, and the analogue forecast based on this phenomenon has long been used widely. The basis of this method is, for two similar initial fields, when the atmosphere is in a stable flow pattern, the analogue will be maintained on synoptic timescales. On monthly and seasonal scales, the analogue rhythm phenomenon also exists; i.e., the atmosphere circulation experiences an alternate process of analogue-disanalogue-analogue in the long-term evolution, while the formation of this phenomenon is different from the law of analogue on synoptic scales. As for the dynamical form, Huang and Chou (1990), Huang (1991), and Huang et al. (1990a) studied this form with a coupled ocean-atmosphere model. Their results showed that the analogous rhythm is a non-uniform oscillation of analogous deviation disturbance, caused by the nonlinear coupled interaction of the ocean-atmosphere system and the seasonal variation of monthly mean circulation. They found that the analogue phenomenon is not formed by the evolution of atmosphere or ocean, but that the ocean-atmosphere interaction plays an important role and the seasonal variation of monthly mean circulation increases the amplitude of the disturbance markedly. They also indicated that the ocean and the seasonal variations are important factors when choosing analogues.

Analogue forecasting is widely used in weather and climate forecasting. Lorenz (1969) used natural analogue samples to study the predictability of forecast error growth, and showed that finding strict analogue samples is difficult. This conclusion was confirmed by Van den Dool (1994). While this does not mean that analogue forecasting lacks scope, Van den Dool sequentially proposed regional analogue (Van den Dool, 1989, 1991), construction analogue (Van den Dool et al., 2003), and other methods. Barnett and Preisendorfer (1978) reduced the dimensions of the state space by EOF, and extracted the "analogue climate state vectors," which are used to describe the climate system evolution to select analogues. The analogue forecast was put into operation at NCEP as reported by Livezey and Barnston (1988).

It may be too simple to regard the future state as a repetition of past states (Ren and Chou, 2007a). By combining the analogue forecast and dynamical models, the ADM became an effective means for improving the accuracy of numerical forecasts.

3.2 Principle of the ADM

The ADM was proposed in 1979, and the basic thought was "regarding the forecast field as a small disturbance superimposed on historical analogue fields, so historical analogue errors can be used to estimate and correct forecast errors" (Chou, 1979). This method acknowledged the existence of tendency error, and estimated it by historical analogues. Its principle is as follows.

The numerical forecast is proposed as the initial problem of a partial differential equation, expressed as:

$$\frac{\partial \psi}{\partial t} = L(\psi), \tag{1}$$

$$\psi(t_0) = \psi_0, \tag{2}$$

where ψ is the model state variable, L is the numerical model operator, t_0 is the initial time, and ψ_0 is the initial value. Because of the existence of model errors, the evolution of model atmosphere is different from that of the actual atmosphere. By expressing the tendency of the model error as E, the evolution of the actual state variable φ can be described as:

$$\frac{\partial \varphi}{\partial t} = L(\varphi) + E(\varphi), \tag{3}$$

where E is the functional of the state variable, which is consistent with the view of Leith (1978). Comparing Eqs. (1) with (3), it can be seen that, if $E(\varphi)$ is known, adding it to the model can force the model tendency in each step toward the actual state. An analogue state can be found in the historical dataset, and the current state variable is regarded as a disturbance of the historical analogue, i.e., $\varphi = \tilde{\varphi} + \hat{\varphi}$, where $\tilde{\varphi}$ is the analogue state variable, and $\hat{\varphi}$ is the analogue deviation. With consideration of the historical evolution of the actual atmosphere, the analogue reference state satisfies:

$$\frac{\partial \tilde{\varphi}}{\partial t} = L(\tilde{\varphi}) + E(\tilde{\varphi}). \tag{4}$$

Subtracting Eq. (4) from Eq. (3), the deviation equation becomes:

$$\frac{\partial \hat{\varphi}}{\partial t} = L(\tilde{\varphi} + \hat{\varphi}) - L(\tilde{\varphi}) + E(\tilde{\varphi} + \hat{\varphi}) - E(\tilde{\varphi}). \tag{5}$$

Calculating the tendency error is difficult; to avoid calculating it, the ADM replaces the current tendency error with the tendency error of historical analogues, resulting in

$$\frac{\partial \hat{\varphi}}{\partial t} = L(\tilde{\varphi} + \hat{\varphi}) - L(\tilde{\varphi}). \tag{6}$$

The control variable of Eq. (6) has changed from φ to $\hat{\varphi}$. After obtaining $\hat{\varphi}$ by solving Eq. (6), adding it to the $\tilde{\varphi}$ produces the current forecast field. Comparing Eqs. (1), (4), and (6) reveals a clear difference: the original forecast Eq. (1) has omitted the whole tendency error, while Eq. (6) has omitted the difference between the current tendency error and the tendency error of the analogue reference state. Equation (6) considers the effect of the analogue evolution of the circulation anomaly, and thus theoretically has higher accuracy. Meanwhile, it identifies certain analogue selections, i.e., analogous initial value, analogous climate state, and analogous boundary (Qiu and Chou, 1989).

3.3 Early development of the ADM

Qiu and Chou (1989) introduced forcing errors, topography height errors, and subgrid errors into a quasi-geostrophic barotropic vorticity equation model, and showed that the ADM could reduce the mean square errors. By defining an analogue index, this method need not be hugely analogous, though the improvement is increased by an increase in both the forecast time and the degree to which it is analogous.

Being a stationary wave (Yi et al., 1990), the atmospheric circulation anomaly has the characteristic of barotropy (Huang and Chou, 1988; Zhou et al., 1989; Huang et al., 1990b; Yang et al., 1990), and is analogue in the long-term evolution. Huang (1990) introduced these features into the long-term range numerical forecasts, developed a quasi-geostrophic baroclinic ocean-atmosphere coupled model (Huang, 1992), and established the corresponding analogue deviation equation. They first used the ADM to perform experimental seasonal forecasts (Huang et al., 1993a), monthly forecasts (Huang and Wang, 1991a), and flood season forecasts. Their results indicated that the anomaly centers at 500 hPa were precisely produced. The 8-yr mean results (Huang and Wang, 1991b) in summer (August), forecasted from winter (January), indicated that the accuracy rate (represented by the consistency of anomaly symbols) was 56.8% for the 500-hPa height field, and 55.4% for surface temperature. The 8-yr mean results (Huang et al., 1993b) in winter (February), forecasted from summer (July), indicated that the accuracy rate was 57% for the 500-hPa height field, and 55.7% for surface temperature. The forecast effect was obviously better than the traditional analogue forecast. The advantage was more evident with increasing forecast time. This study provided a new method for seasonal forecasting.

The above work was based on a simple model. To investigate the effectiveness in complex models and improve the accuracy of monthly operational forecasts, Bao et al. (2004) applied this method to the T63L16 monthly extended-range operational model (Li et al., 2005) of the National Climate Center (NCC) of China, and established an analogue-dynamical monthly forecast model. They selected multiple analogue reference states in the historical dataset to create the analogue-dynamical forecast. The results indicated that the ensemble mean had a better effect than a single analogue member. The global averaged anomaly correlation coefficient (ACC) was improved by 0.2, and the root mean square error (RMSE) was reduced by 12 gpm. From the results of different regions and scales, the tropics and subtropics had the most obvious correction effect; the correction effect on the planetary scale was improved beyond the 15-day forecast, while the accuracy was not improved on the synoptic scale.

3.4 The simplified analogue correction

Besides the development of ADM, D'Andrea and Vautard (2000) (abbreviated as DV2000) independently proposed a tendency error estimating method by historical analogues. They adopted the 4DVar technique to obtain the optimal estimation of tendency model errors of analogue samples, and added them to the equation as the approximation of the current forcing term. The basic idea was equivalent to the ADM; i.e., they approximately replaced the current tendency error with that of analogue reference states. The difference is, this method adopted the variational technique to solve Eq. (4) to obtain $E(\tilde{\varphi})$ and then used it in Eq. (3), while the ADM subtracted Eq. (4) from Eq. (3), and established a new equation. This means that the ADM is a reasonable and effective method and some related early leading work has been completed (Ren, 2006).

The heavy computation load of the 4DVar restricted application of the DV2000 method in the quasi-geostrophic baroclinic model. The DV2000 method was also difficult to be applied in sophisticated operational models. Though the early-developed ADM has avoided compiling an adjoint model, an analogue deviation equation still needs to be established, which is also too complex to facilitate its application in operational models.

Aiming at this problem, Ren et al. (2009) simplified the early ADM by replacing the analogue of the tendency error with the analogue of the forecast error. That is, assuming analogue samples have analogous forecast errors, the current forecast error can be estimated by that of analogues, thus avoiding the calculation of tendency error. In practice, the forecast time is divided into intervals. At each interval, the ensemble mean of the forecast errors of some analogue samples is superposed on the current forecast results, i.e., the forcing is not by step and the after-the-fact correction is done at intervals of some steps. As the duration of the analogue is limited, the analogues are reselected after some time. These simplifications have avoided the rebuilding of a new model, have enhanced the operability, and are easier to transport to other sophisticated models. A total of 24 cases were selected to perform the monthly forecast experiment with the T63L16 model (Ren et al., 2006). The results indicated that the global mean ACC was improved by 0.1, and the RMSE was reduced by 7.49 gpm; the improvement was more evident in the tropics. The improvement of daily forecasting was concentrated beyond 7 days and on the scale of planetary wave; there was no improvement on synoptic scales. Additionally, the precipitation forecast for summer has been examined by using the NCC/IAP T63 ocean-atmosphere coupled model (Ren and Chou, 2007b); the mean result of 23 cases revealed that the global pattern correlation coefficient was improved by 0.092, and by 0.124 for eastern Asia.

The above sections systematically introduced the fundamentals of the ADM and the evolution of practical schemes. When the ADM is applied to different forecast fields, it needs to be further adjusted based on the characteristics of the particular field. The following section describes application of the ADM to different range forecasts.

3.5 Application of the ADM in extended-range forecasts

For the ADM and traditional analogue forecasts, the selection of analogue fields is always the core problem. On the one hand, the numerical model is sensitive to the initial field, and it is difficult to ensure the consistency of the forecast error evolution between the current state and the analogue state. On the other hand, the numerical model has a large degree of freedom, and it is difficult to choose ideal initial analogue values (Zheng et al., 2013).

Based on the chaotic characteristic of the atmosphere, Chou et al. (2010) proposed a theory to separate the predictable components that are not sensitive to initial error from the random components that cannot be predicted. Based on this theory, Zheng et al. (2009, 2010) extracted the basis of the climate attractor (Huang et al., 1989; Wang et al., 1989) by decomposing the historical data with EOF. The model variable was expanded, the predictable components were retained, and the random components were filtered. The ADM was developed, based on the predictable components, to avoid the impact of rapid growth of small-scale component errors. As the predictable components are not sensitive to the initial errors and have a small degree of freedom, using them to select analogues can avoid the two difficulties mentioned in the preceding paragraph. A 6–15-day forecast experiment was carried out with the T63L16 model (Zheng et al., 2013). Comparison results showed that the ADM, based on predictable components, improved the forecast accuracy beyond 10 days, and offerred a slight improvement on synoptic scales. This contrasts with the result described in the preceding section. The reason for this may be that this method can to some extent restrain the growth of small-scale components errors. It may also be that the improvement on planetary scales can partly restrain the error growth on synoptic scales by the interaction between high and low frequencies. As for the random components, the probability distribution can be calculated by using a large amount of historical data. Compared with the operational extended-range ensemble forecast system of the NCC (Zheng et al., 2012), the mean ACC of 6–15 days was improved by 0.12, and the RMSE was reduced by 12.36 gpm.

The above study used the climate attractor from the historical data as the basis, which is easy to operate. There is a climate drift between the model atmosphere and the actual atmosphere, and their climate attractors are naturally different. No time evolution of the atmospheric pattern can be considered when fixing the climate attractor (Wang et al., 2014). As a result, the large-scale components determined by the historical data do not correspond to the model components, whose errors grow slowly. To solve this problem, Wang et al. (2012a) calculated the levels of the predictable components under given initial values using conditional nonlinear optimal perturbation (CNOP) (Mu et al., 2003; Wang and Tan, 2009). The analogue-dynamical correction was conducted for the predictable components, and the random components corresponding to the historical analogues were averaged. The combination of these two parts formed the corrected forecast results. The 10–30-day forecast experiments were also conducted with the T63L16 model (Wang et al., 2014), and the global mean ACC of the 500-hPa field was improved from 0.06 to 0.32. As for different scales, the effect on the planetary scale was the most marked.

3.6 Application of the ADM in short-range climate forecasts

The summer precipitation forecast is an important aspect of short-range climate forecasting, as it relates to the prevention and reduction of flood disasters. So far, this practice has been difficult. The ADM plays an important role in improving the forecast accuracy for the flood season. Unlike the above monthly and extended-range forecasts, the flood season forecast is a boundary problem affected most by external forcing, and presents as low frequency. Therefore, selecting the initial field as the analogue factor is not suitable, and the external forcing and low-frequency variation should be considered. Feng et al. (2013)

used the forecast errors of analogue years to estimate and correct the forecast errors of the current year, based on the Beijing Climate Center's coupled general circulation model (BCC-CGCM), and developed a dynamical-statistical quantitative precipitation forecast method for the flood season. The core of this method is the filter and combinatorial arrangements of analogue forecast factors. In normal years, the corrections are conducted by optimal multi-factor combination; when these factors are unusual, the abnormal factors correction scheme is adopted. Working in different regions, Wang et al. (2011, 2012b) established the dynamical-statistical ensemble forecast schemes for the middle and lower reaches of the Yangtze River, Xiong et al. (2011, 2012) established the optimal multi-factor forecast scheme in Northeast China, and Yang et al. (2011, 2012) established the multi-factor combination forecast scheme in North China. This forecast system has provided good predictions of the location of the main summer rain band in China, as confirmed by the verification following the annual national conference on the flood season in 2009. The mean of the predictive scores (PS) from 2009 to 2012 was 73, and the corresponding ACC was 0.16, both higher than the systematic corrected forecast results of the BCC-CGCM (the mean PS score was 63 and the mean ACC was 0.01) (Feng et al., 2013). The dynamical-statistical integrated forecasting system for seasonal precipitation (FODAS1.0), based on this method was also put into operational forecasting (Feng et al., 2013). In the flood season forecast of 2013, the forecast result had a PS of 74 and an ACC of 0.20; it generally captured the location of the summer drought and flood of China in 2013. After the flood season of each year, the forecast results from this method were checked and summarized, and the reason for any climatic anomaly was diagnosed (Zhao et al., 2011, 2013a, 2014). In addition to the above flood season forecast, this method has also been applied to the seasonal forecast of geopotential height field for some critical regions of China, and it reduced the forecast errors to some extent (Zhao et al., 2013b).

The El Ninõ–Southern Oscillation (ENSO) is one of the strongest indicators of climate change and is associated with an anomalous change in atmosphere circulation. Sun et al. (2006) applied the ADM to the ENSO forecast, and conducted some experiments using the Ninõ3 index with the simplified ocean-atmosphere coupled model of the NCC. With regard to the particularity of the ENSO forecast, the partial analogue selection, which considered only sea surface temperature (SST), and the entire analogue selection, which considered both SST and surface wind field, were compared. The results indicated that the entire analogue selection more accurately reflected the analogue degree of the ocean-atmosphere coupled system than did the partial analogue selection. When selecting five analogue samples, and setting the oceanic analogue update period as 20 days and the atmospheric analogue update period as 10 days, the best effect was achieved. The experiment with the Ninõ3 index from 1998 to 2003 indicated that the ADM had a greater effect than the control forecast for the whole forecast time. It had a mean ACC of 0.45 and an accumulative absolute error of 10.69℃, while the corresponding accuracy of the control forecast was 0.29 and 13.78℃.

3.7 Application of the ADM in medium-range forecasts

From the above discussion, it can be seen that the ADM has effectively improved the accuracy in short-term climate, monthly mean, and extended-range forecasts, but its improvement in the medium range is not evident, as indicated by Ren et al. (2006). This can be attributed to the essence of ADM, which considers the dynamical process of analogue circulation anomalies. This process has a large timescale, the impact of the initial field is small, and the low-frequency variation is evident, the analogue evolution of which is easy to grasp. Regarding medium-range forecasts, these are sensitive to initial values, the internal error grows nonlinearly, and it is much more difficult to carry the flow-dependent correction by analogues. Therefore, developing and realizing the ADM for medium-range forecasting is urgently needed.

Working on this problem, Yu et al. (2014) modified the ADM to correct the medium-range operational forecast model. The above simplified ADM assumed that analogous samples have analogous forecast errors, which is more of an approximation to that in the early ADM; the reason of this needs to be verified. By introducing the continuity theorem of forecast errors, it is proved under some assumptions that forecast errors can constitute a continuous curved surface in hyperspace when the volume of the historical data is large enough. It is also shown that the current forecast error can be interpolated with the corresponding hindcast errors of some selected analogue reference states, which means that the simplification is reasonable. In extreme conditions, the analogue-dynamical correction can be converted into control forecast and systematic correction. In the operational scheme, considering that the medium-range forecast is sensitive to the initial field and the global model is dependent on the SST, the seasonal and diurnal variations, atmospheric circulation pattern, and SST pattern are all considered when choosing analogue samples. To avoid the nonlinear growth of errors that could destroy the analogue, the optimal update period was selected as 5 days in sensitivity experiments. Forty cases were selected from summer and winter to carry out 10-day forecast experiments with GRAPES (Global and Regional Assimilation and Prediction System; Chen et al., 2009). The results (Yu et al., 2014) demonstrated that this method extended the period of validity of the global 500-hPa height field by 0.8 day, the most remarkable being 1.25 days in the tropical region. The correction effect became more significant as the lead time increased. Although the analogues were selected by using the height field at 500 hPa, the forecast ability at all vertical levels was improved. The average increase in ACC was 0.07, and RMSE decreased by 10 gpm, on average, at a lead time of 10 days. The magnitude of errors for most forecast fields such as height, temperature, and kinetic energy decreased considerably by inverse correction. These all show the effectiveness of the method for medium-range forecasts.

4. Summary

The development of numerical models does not conflict with the development of error correction technology; on the contrary, they supplement each other. On the one hand, the forecast error is not a simple superposition of internal error (initial error) and external error (model error), but the result of their nonlinear interaction (Chen and Ji, 1990). It is difficult to locate the error origin from the forecast output and to correct it positively, thus it is necessary to change the point of view. This needs to acknowledge the existence of forecast errors, summarize their evolution pattern, and establish the empirical relationship to estimate and correct the errors. On the other hand, the numerical forecast treats the atmosphere as a certain system (Chen, 2007); i.e., the future state is determined by the current state and certain physical rules. Actually, both the numerical model and the initial field are approximate descriptions of the real atmospheric state and have large uncertainties; thus, the forecasted future state must also have a large uncertainty. In contrast, the statistical forecast admits the future uncertainties, and infers the future state probability from the information on current and historical states. The disadvantage of this line of thoughts is that the physical rules are not considered. Therefore, the dynamical and statistical methods have respective advantages and disadvantages, and combining them (Chou, 1986) to develop a better error correction technique is naturally advantageous.

To this end, the ADM was developed by combining the statistical method with dynamical models and utilizing the analogue information from historical data. This paper reviewed the creation and development of this method, and discussed associated key issues, corresponding solutions, and improvement of this method for forecasts on different timescales.

This review and related discussion indicate that the ADM has been developed and modified considerably over several decades. It has greatly improved the ability of numerical models in medium-range, extended-range, monthly mean circulation, and short-range climate forecasts, and has shown broad application potentials. This method not only considers systematic errors but also includes the information on the evolution of flow-dependent model errors, avoiding the establishment of the statistical relationship between forecast error and model variable, and is easy to operate and translate to other sophisticated models (Li et al., 2013).

By comparing the recent ADM with the earlier one, the recent method has been shown to be simplified for application to sophisticated models through replacing tendency errors with forecast errors and replacing the online correction with after-the-fact correction. These simplifications also induce a problem; i.e., there is no consideration of the interaction between external and internal errors (Danforth and Kalnay, 2008a). Therefore, a meaningful direction for future research is to combine the advantages of both recent and earlier methods, and further improve the ADM to make it easy to operate while still restraining the nonlinear growth of forecast errors.

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