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Application of retrospective time integration scheme to the prediction of torrential rain*

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The retrospective time integration scheme presented on the principle of the self-memory of the atmosphere is applied to the mesoscale grid model MM5, constructing a mesoscale self-memorial model SMM5, and then the short-range prediction experiments of torrential rain are performed in this paper. Results show that in comparison with MM5 the prediction accuracy of SMM5 is obviously improved due to its utilization of multiple time level past observations, and the precipitation area and intensity predicted by SMM5 are closer to observational fields than those by MM5.

Keywords: mesoscale numerical model, short-range weather prediction, atmospheric self-memory, retrospective time integration scheme, torrential rain

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1. Introduction

In the study of a prediction presented as an initial value problem of a differential equation, the differential equation is generally transformed into a difference equation, and then numerically solved by using a difference scheme. The search for an efficient scheme has produced active investigation and numerous articles: for example, those of James [1] and Feng *et al.*[2,3] Liu *et al*[4] put forward a Lattice Boltzmann method for two-dimensional (2D) convection. Cao *et al*[5] discussed the conditions of stability and convergence of the six-point weighted difference scheme for generalized nonlinear SchrÖdinger equations. In terms of statistical physics, a fluid such as the atmosphere is a many-body system, which has a vast amount of degree of freedom and thus obeys the second law of thermodynamics. Liu *et al*[6,7] made a noticeable improvement of the prognostic outputs by reconstructing the terms of the horizontal diffusion in a nested grid version of PSU/NCAR's mesoscale model (MM5) according to the principles of the second law of thermodynamics. In addition, the computational noise is effectively and significantly suppressed since the physical dissipative technique for reconstructing suggested is based on physical law rather than on the computational method such as the artificial viscosity. Generally speaking, Euler's scheme, the leapfrog scheme, the Lax–Wendroff scheme, etc., are commonly used, and these schemes involve two or three time levels; although the linear multi-step method for ordinary differential equations requires several time level values before the initial time, which are still obtained from the initial value of one time level by computation; that is to say, the principle of one initial value is abided in prediction.[8−11] In weather prediction, only the last time level observation data are used, and a vast amount of the observations before the last time level are not utilized. Therefore, from the viewpoint of fully utilizing the information of observations, the traditional method for solving differential equations has obvious deficiency.

The atmospheric self-memory idea [12] based on the irreversible property of atmospheric motion is a new development of the multiple time level model:[13,14] it is able to improve weather prediction

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in terms of historical observational data, and is also a fruitful way to combine dynamics and statistics in the operational numerical prediction. The retrospective time integration scheme is just the concrete manifestation of the idea,[15−23] and also an extension of existing difference schemes. It is able to improve the accuracy of prediction due to abstracting the information of the historical data of multiple time levels, and is thus suitable for mesoscale numerical models. A global self-memory T42 model was established using a T42L9 spectral model as the dynamic kernel,[24] and 12 one-month (30 day) integration experiments were performed. For the sake of comparison, integration of the T42L9 model for the same time period was also performed. Results showed that the self-memory T42 model has a good prospect of applications:

(a) The forecast of the self-memory T42 model depends on its dynamic kernel model. Its forecast effect manifests in that the improvement in winter and autumn is better than in spring and summer; the improvement in the Northern Hemisphere is better than in the Southern Hemisphere; the improvement in long wave prediction is better than in short wave; and the improvement in the upper and lower levels is better than in the middle level.

(b) The anomaly correlation coefficient (A_c) of daily circulation is 0.6, and the A_c of monthly forecast 0.5. The self-memory T42 model possesses a higher skill in the 500 hPa geopotential height forecast, and on average it extends the valid time of daily forecast for 0.4 day. i.e. the valid time of T42 is 3.0 days while that of the self-memory T42 is 3.4 days.

(c) The self-memory T42 improves the forecast skill of monthly averaged circulation quite significantly. It raises the A_c by 8%, and reduces the RMSE from 60.9 geopotential metres (gpm) to 40.9 gpm by 33.3%.

(d) The increase in computation for the self-memory T42 is about 1/15 of that for the T42.

In this paper, this effective time integration scheme is applied to MM5 so as to validate the efficiency of the scheme. Based on the principle of self-memory property and the idea of retrospective time integration, the concrete expression for the model is derived, and called the self-memory MM5 model (hereafter SMM5). Aiming at the exceptionally torrential rain of the July 1998 over the middle reach of the Changjiang River, numerical experiments are performed by using SMM5 and MM5, respectively, and the results, especially precipitation fields of prediction in the torrential rain process, are compared.

2. Retrospective time integration scheme

A differential equation,

$$\frac{\partial u}{\partial t} = F, \tag{1}$$

can be calculated with various difference schemes, e.g. a central difference scheme,

$$(u(t+\Delta t) - u(t-\Delta t))/2\Delta t = F(t). \tag{2}$$

Rewrite Eq.(2) as

$$\begin{aligned} u(t+\Delta t) =& u(t-\Delta t) + 2\Delta t F(t) \\ =& \alpha_0 u(t) + \alpha_{-1} u(t-\Delta t) \\ &+ \theta_0 \Delta t F(t) + \theta_{-1} \Delta t F(t-\Delta t), \end{aligned} \tag{3}$$

where α_0=0, α_{-1}=1, θ_0=2, θ_{-1}=0. Equation (2) is deduced on the basis of numerical mathematics. But, unfortunately, from an information view, the information contained in terms $u(t)$ and $F(t-\Delta t)$ is neglected, as $\alpha_0 = 0$ and $\theta_{-1} = 0$, which should have provided much information useful for predicting $u(t+\Delta t)$ at t_0. Predicting $u(t+\Delta t)$ should utilize total information at times t and $t-\Delta t$, including both variable u and field F. From this idea, we generalize Eq.(3) to the following:

$$\begin{aligned} u(t+\Delta t) =& \alpha_0 u(t) + \alpha_{-1} u(t-\Delta t) \\ &+ \cdots + \alpha_{-p} u(t-p\Delta t) + \theta_0 \Delta t F(t) + \cdots \\ &+ \theta_{-p} \Delta t F(t-p\Delta t) \\ =& \sum_{i=0}^{p} \alpha_i u(t-\mathrm{i}\Delta t) + \sum_{i=0}^{p} \theta_i \Delta t F(t-\mathrm{i}\Delta t). \end{aligned} \tag{4}$$

We call Eq.(4) a retrospective scheme of time-integration with an order p ($p \geq 2$) in the numerical model. A key problem in the scheme is to determine the coefficients α_i and θ_i. If the variable u is regarded as a state variable of the system and the function F as an exogenetic variable of the system, Eq.(4) is just the general equation in discipline of the system's identification. So numerous methods in the system's identification can be introduced to determine the coefficients in Eq.(4), for example, stochastic approximation, the relaxation algorithm, the least square and even the genetic programming which has been developed recently. We will take the least square in the following computation.

In fact, using the multi-level data has been already implied in numerical weather forecast, which consists of two procedures, the time integration and the time filtering. We exemplify the European Centre for Medium Range Weather Forecasts (ECMWF) model as follows.

In the ECMWF spectral mode, the time integration scheme is

$$x(t+\Delta t) = \overline{x}(t-\Delta t) - 2\Delta t(A(t) + S(t-\Delta t)), \quad (5)$$

in which A and S denote the adiabatic and non-adiabatic terms respectively. Equation (5) refers to three-time levels $\tilde{p} = p+2 = 3, \overline{x}(t)$ is a filtering value at time t, i.e.

$$\overline{x}(t) = x(t) + \alpha(\overline{x}(t-\Delta t) - 2x(t) + x(t+\Delta t)). \quad (6)$$

Similarly, we have

$$\begin{aligned}\overline{x}\,(t-\Delta t) =& x(t-\Delta t) + \alpha(\overline{x}(t-2\Delta t) \\ & - 2x(t-\Delta t) + x(t)).\end{aligned} \quad (7)$$

From Eqs.(5)–(7), it is shown that $x(t+\Delta t)$ in Eq.(5) also contains the information of $x(t-2\Delta t)$, though there is less information from $x(t-2\Delta t)$, because the weight α is small, α=0.06. This enlightens us to formulate a new time integration scheme, which can contains more time levels, for example $t+\Delta t$, t, $t-\Delta t$, $t-2\Delta t$, $\cdots, t-p\Delta t$, i.e. $p \geq 2$, and may withdraw the time filtering procedure from the integration of numerical weather prediction. This implies that the new scheme possibly has two functions: time integration and time filtering. Without time filtering in the integration process, weakening of atmospheric waves will not appear, so it obtains accurate favourite solutions of the atmospheric equations.

There are two ways to determine the coefficients α_i and θ_i in Eq.(4). One is direct, namely by utilizing observed data by means of the least square, stochastic approximation etc., to determine them as mentioned above; the other is indirect, as described in the following, which is deduced from memorial dynamics. Generally speaking, the atmospheric dynamics–thermodynamics equations can be written as

$$\frac{\partial x_i}{\partial t} = F_i(x, \lambda, t) \qquad i = 1, 2, \cdots, j, \quad (8)$$

where j is an integer, x_i the ith physical quantity, and λ a physical parameter. For simplicity, only one physical quantity x is considered hereafter, and x and λ in $F_i(x, \lambda, t)$ are dropped. Equation (8) expresses the relationship between a local change of x and a source function F. Obviously, x is a scalar function at the space r_0 and the time t. Introducing a weight $\beta(r,t)$ as a memory function, a weighting integration for Eq.(8) is made from t_0 to t as follows:

$$\int_{t_0}^{t} \beta(\tau)\frac{\partial x}{\partial \tau}\mathrm{d}\tau = \int_{t_0}^{t} \beta(\tau)F(\tau)\mathrm{d}\tau, \quad (9)$$

where r in $\beta(r,t)$ is dropped because of fixing at the spatial point r_0. Following the calculus in mathematics, making an integration by parts for the left of Eq.(9) yields

$$\begin{aligned}\int_{t_0}^{t} \beta(\tau)\frac{\partial x}{\partial \tau}\mathrm{d}\tau =& \beta(t)x(t) - \beta(t_0)x\,(t_0) \\ & - \int_{t_0}^{t} x(\tau)\beta'(\tau)\mathrm{d}\tau,\end{aligned} \quad (10)$$

where $\beta'(\tau) = \partial\beta(t)/\partial t$. Applying the median theorem in calculus to the third term on the right-hand side of Eq.(10), we obtain

$$-\int_{t_0}^{t} x(\tau)\beta'(\tau)\mathrm{d}\tau = -x^m(t_0)(\beta(t) - \beta(t_0)), \quad (11)$$

where the median $x^m(t_0) \equiv x(t_m)$, $t_0 < t_m < t$. Substituting Eqs.(10) and (11) into Eq.(9) and carrying out algebra operation, we obtain

$$\begin{aligned}x(t) =& \frac{\beta(t_0)}{\beta(t)}x(t_0) + \frac{\beta(t) - \beta(t_0)}{\beta(t)}x^m(t_0) \\ & + \frac{1}{\beta(t)}\int_{t_0}^{t} \beta(\tau)F(\tau)\mathrm{d}\tau.\end{aligned} \quad (12)$$

The first and second terms in Eq.(12) are related to x value only at the fixed point r_0 itself at the initial time t_0 and the middle time t_m, therefore they are called self-memorization terms. It is natural to call the third term an exogenetic effect term, i.e. the total effect contributed by other spatial points to the point r_0 in an interval $[t_0, t]$.

For multi-level t_i, $i = -p, -p+1, \cdots, t_0, t$, similar to Eq.(10), we have

$$\begin{aligned}&\int_{t_{-p}}^{t_{-p+1}} \beta(\tau)\frac{\partial x}{\partial \tau}\mathrm{d}\tau + \int_{t_{-p+1}}^{t_{-p+2}} \beta(\tau)\frac{\partial x}{\partial \tau}\mathrm{d}\tau + \cdots \\ &+ \int_{t_0}^{t} \beta(\tau)\frac{\partial x}{\partial \tau}\mathrm{d}\tau \\ &= \int_{t_{-p}}^{t} \beta(\tau)F(\tau)\mathrm{d}\tau.\end{aligned} \quad (13)$$

By eliminating the same terms $\beta(t_i)x(t_i)$, $i = -p +$

$1, -p+2, \cdots, 0$, we obtain

$$\begin{aligned}&\beta(t)x(t)-\beta(t_{-p})x(t_{-p})\\&-\sum_{i=-p}^{0}(\beta(t_{i+1})-\beta(t_i))x^m(t_i)\\&-\int_{t_{-p}}^{t}\beta(\tau)F(\tau)\mathrm{d}\tau=0.\end{aligned}\tag{14}$$

This is a difference-integral equation, which is called a self-memorization equation with the retrospective order p. This is a basic equation under study.

Setting $p=0$, we have time t and t_0, and Eq.(14) becomes Eq.(12), which is called a zeroth-order self-memorization equation. If p=1, we have time t, t_0 and t_{-1} and Eq.(14) becomes

$$\begin{aligned}&\beta(t)x(t)-\beta(t_{-1})x(t_{-1})-(\beta(t_0)-\beta(t_{-1}))x^m(t_{-1})\\&-(\beta(t)-\beta(t_0))x^m(t_0)\\&-\int_{t_{-1}}^{t}\beta(\tau)F(\tau)\mathrm{d}\tau=0,\end{aligned}\tag{15}$$

which is called a first-order self-memorization equation. For example, the one-dimensional advection equation

$$\frac{\partial u}{\partial t}+C\frac{\partial u}{\partial x}=0,\tag{16}$$

i.e.

$$\frac{\partial u}{\partial t}=-C\frac{\partial u}{\partial x}\equiv F,\tag{17}$$

where x stands for a spatial coordinate, C is a constant velocity of advection. For the spatial point r, the self-memorization equation similar to Eq.(14) reads as

$$\begin{aligned}\beta(j,t)u(j,t)=&\beta(j,t_{-p})u(j,t_{-p})\\&+\sum_{i=-p}^{0}[(\beta(j,t_{i+1})-\beta(j,t_i)]u^m(j,t_i)\\&-C\int_{t_{-p}}^{t}\beta(j,\tau)\frac{\partial u(j,\tau)}{\partial x}\mathrm{d}\tau.\end{aligned}\tag{18}$$

While we make a forecast with Eq.(14), the model utilizes p values of $u(t_i)$ and p fields of $F(t_i)$ before t_0; therefore, $\beta(t_i)$ in Eq.(14) are functions in memorizing $p+1$ of u-values and $p+1$ of F-fields. That is why we call it a memory function. It is the mathematical basis in proposing the memory function.

3. Self-memory mesoscale model

3.1. Unification of model equations

MM5 is represented in the flux form of the primitive fluid dynamical basic equation system, and variables in the governing equations are p^*u, p^*v, p^*w, p^*p', p^*T, where u and v are the meridional and zonal components of horizontal velocity respectively, and w is the vertical component of the velocity. P' is the perturbation pressure. We have

$$p'=p_s-p_t,$$

where p_s is the surface pressure in a reference state, and p_t is the pressure at the top of the atmosphere.

If all the variables are denoted by Z, then the governing equations of MM5 may be written briefly as

$$\frac{\partial Z}{\partial t}=F.\tag{19}$$

For horizontal momentum equations, the following equalities hold:

$$Z_u=p^*u,$$

$$\begin{aligned}F_u=&-m^2\left[\frac{\partial p^*uu/m}{\partial x}+\frac{\partial p^*vu/m}{\partial y}\right]\\&-\frac{\partial p^*u\dot{\sigma}}{\partial\sigma}+u\mathrm{D_i}\\&-\frac{mp^*}{\rho}\left[\frac{\partial p^*}{\partial x}-\frac{\sigma}{p^*}\frac{\partial p^*}{\partial x}\frac{\partial p'}{\partial\sigma}\right]+p^*fv+D_u,\end{aligned}\tag{20}$$

where F_u denotes the temporal change of horizontal momentum, D_u the horizontal diffusion coefficient, and D_i the mass divergence. The D_i term does not exist in the hydrostatic balance equation. Now the D_i term appearing for p^* does not change with time, and therefore the hydrostatic continuity equation cannot be used any more. The only one omitted in the governing equation of MM5 is the diabatic heating term, which contributes to the trend of perturbation pressure. Because the term produces only a small quantity of divergence in heating, it may generally be omitted. Other equations are for Z_v, Z_w, $Z_{p'}$, Z_T and F_v, F_w, $F_{p'}$, F_T. For these equations, according to Steppeler's idea, we may take them as the dynamic kernel and thus obtain its self-memory equation.

3.2. Variable series and source functions of the computational model

At first, MM5 is integrated for a certain time period so as to gain the time series of predictands at the prescribed example time interval required by the retrospective difference scheme.

Write the value at grid (i,j) at time n as $Z_{i,j,n}$, let t_0 be the starting time, and integrate the MM5 forwards to obtain the value at time $t_l=t_0+R_T$, where $R_T=k\Delta t$, Δt is the time step, and k the number of

integration step. If denoting t_0 as n, and t_1 as $n+1$, we have

$$F_{i,j,n} = (Z_{i,j,n+1} - Z_{i,j,n})/R_T. \quad (21)$$

Integrating the MM5 forwards for a time period of R_T yields a predicted field, and integrating successively the MM5 for L times (i.e. the total integration time is $L \times R_T$) yields L predicted fields. Therefore $F_{i,j,n+1}, F_{i,j,n+2}, \cdots, F_{i,j,n+l}, \cdots$ can be obtained from Eq.(21), and its sample length is L. Obviously, this is an approximate method, and the direct method should be the series of F which is calculated from observational data by using Eq.(20).

The corresponding series of Z, i.e. $Z_{i,j,n}, Z_{i,j,n+1}, Z_{i,j,n+2}, \cdots, Z_{i,j,n+l}, \cdots$ in Eq.(21) has been obtained in the integration process. According to the requirement of the self-memory model, the sampling interval of observational data may take one to twelve hours. The interval of 12 hours is used in the experiments in this paper due to the limitation of real observational data. Thus the two series of F and Z are obtained.

3.3. Establishment of self-memory model SMM5

According to Section 2, the following prediction equation may be obtained from the two series by using the retrospective difference scheme:

$$Z_{i,j}(t + R_T) = \sum_{k=-p-1}^{-1} \alpha_k Z(t_0 + kR_T) + \sum_{k=-p}^{0} \theta_k F(t_0 + kR_T) R_T, \quad (22)$$

where $Z \equiv Z_u$, Z_v, Z_w, $Z_{p'}$, Z_T; $F \equiv F_u$, F_v, F_w, $F_{p'}$, F_T; and p is the retrospective order. Because the sampling interval R_T is given in advance, it is incorporated into θ_k. After determining the coefficients α_k and θ_k by using the Z, F series of sampling length L and the least square method, Eq.(22) may be used in prediction. It is worth noting that here the retrospective order and the sampling length may be variable. The value of p may be dynamically debugged according to the quantity of real samples and the sample data. It is generally adequate to take the value of p to be 2–5.

3.4. Comparison of results of the two integration methods

After the specification of the retrospective order, the self-memory model SMM5 is also determined. In the following we just use the observed meteorological fields and SMM5 to make prediction.

4. Prediction experiments of precipitation

4.1. Model parameters

The centre of computational domain in the model is located at (115°E, 30°N), and the grid number is 45 in the S–N direction and 51 in the E–W direction. A time step of 4min is used. The period of validity is 48h, and predicted fields are output once every 12h. The nested mesh model is used.

4.2. Physical processes of the model

In the model, the Anthes–Kuo scheme is used in cumulus parametrization; the Blackder scheme of high resolution in the planetary boundary layer; a simple cooling scheme in atmospheric radiation; the mixed ice phase scheme in moisture; and the multi-layers soil temperature model in soil temperature.

4.3. Data

The T106 analysis data from 16th to 26th July 1998 are used as the first guess field. The vertical plane is divided into 17 layers with a horizontal grid spacing 1.125°×1.125°. The physical variables are latitudinal wind component u, longitudinal component v, temperature T, geopotential height H, and relative humidity R_H. Also incorporated are the conventional sounding and surface observational data, their time levels are 00, 12h (GMT) and 00, 06, 12, 18h (GMT) respectively. Twenty-three semi-sigma layers are taken, and the pressure at the top of the model is 10 hPa.

4.4. Assimilation computation by using SMM5

4.4.1. Contrast analysis between MM5 and SMM5

Determining the retrospective order by using the trial computation method, the observational field of sample length L and Eq.(22) are used to establish SMM5, which is next used to make the forecast field at a certain time q (hereafter MM5-S). Meanwhile MM5 is integrated forwards from the observed meteorological field at time q-R_T to the forecast field at time q (hereafter MM5-O).

The historical observational data from 00h GMT 16th to 12h GMT 21th July 1998 (L=12) are used to

establish SMM5, which is next used to make a 12h-forecast, i.e. the forecast field at 00h GMT 22th. Meanwhile MM5 is also integrated for 12h from the initial (observed) field at 12h GMT 21th to the forecast field at 00h GMT 22th. Comparison results of MM5-O and MM5-S are listed in Table 1. It can be seen from Table 1 that MM5-S is better than MM5-O.

Table 1. Comparison of 700hPa forecast fields at 00h GMT 22th July 1998.

Variables	Correlation coefficients (R)		Root-mean-square errors σ_R	
	MM5-O	MM5-S	MM5-O	MM5-S
u	0.6234	0.7805	0.1369	0.1234
v	0.5019	0.6121	0.1303	0.0814
w	0.9886	0.9887	4.2768	4.1762
T	0.9997	0.9998	0.0422	0.0291

MM5-O denotes the 12h forecast of MM5; MM5-S denotes the 12h forecast of SMM5.

4.4.2. Using the prediction of SMM5 as the initial field

Data assimilation has been one of the topics of general interest in the domain of numerical weather prediction studies,[25] and various data assimilation methods such as the four-dimensional variational assimilation, Karman filtering etc. have been developed. Therefore, in the second part of this paper, the prediction field of SMM5 is taken as the initial field of MM5 so as to investigate the possibility of developing data assimilation by using the self-memory model. After the moment, MM5 is integrated forward for 48h from the two initial fields of MM5-S and MM5-O. The forecasting fields of MM5 of the two kinds are output every 12h and denoted as MM5-SF and MM5-F respectively. MM5-SF and MM5-F are compared and wind, pressure, temperature and precipitation fields forecasted are tested with forecast scores so as to investigate, after replacing the forecast field of MM5 (i.e. MM5-O) with one of SMM5 (i.e. MM5-S), whether the forecast accuracy of MM5 is increased or not. It is worth mentioning that the sample interval R_T and sample number L may vary with forecast cases. Then MM5 is integrated forwards for 48h respectively from both MM5-S and MM5-O, and eight forecast fields of MM5 at every 12h are obtained.

The correlation coefficients between the real observed fields and the predicted fields and the root-mean-square (hereafter RMS) errors of the two predicted fields, MM5-F and MM5-SF, are listed in Tables 2–5. Figures 1 and 2 display the temporal variations of the correlation coefficients of 700 hPa predicted and observed pressure and temperature fields, respectively.

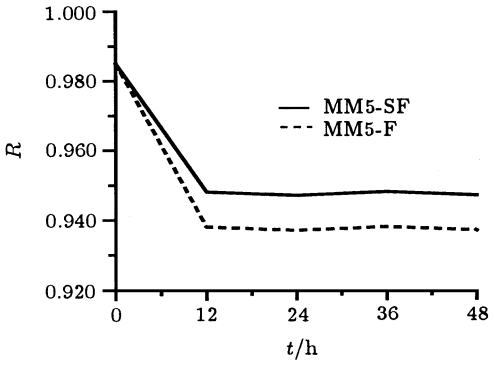


Fig.1. Temporal variations of the correlation coefficients between predicted and observed fields of 700 hPa pressure.

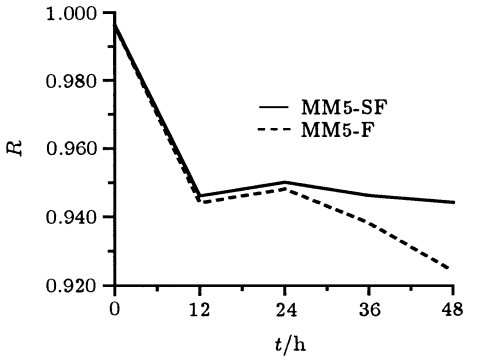


Fig.2. Temporal variations of the correlation coefficients between predicted and observed fields of 700hPa temperatures.

4.4.3. Contrast analysis

The wind, pressure, temperature and precipitation fields of MM5-SF and MM5-F are analysed in the following. MM5-SF denotes the 48h forecast of MM5 integrated from MM5-S, and MM5-F the 48 forecast from MM5-O.

Table 2. RMS errors σ_R of u fields.

Time/h	12	24	36	48
MM5-SF	0.0482	0.0431	0.0463	0.0435
MM5-F	0.0484	0.0489	0.0483	0.0459

Table 3. Correlation coefficients R of v fields.

Time/h	12	24	36	48
MM5-SF	0.4674	0.3926	0.3960	0.3170
MM5-F	0.4397	0.3789	0.3425	0.2950

Table 4. RMS errors σ_R of pressure fields.

Time/h	12	24	36	48
MM5-SF	2.9320	2.9621	2.9829	2.9542
MM5-F	3.1701	3.1849	3.1933	3.1644

Table 5. RMS errors σ_R of temperature fields.

Time/h	12	24	36	48h
MM5-SF	0.0262	0.0262	0.0263	0.0264
MM5-F	0.0265	0.0261	0.0283	0.0269

(1) Wind fields

In regard to the four times of u forecast fields, the correlation coefficient of MM5-SF is 2% higher than MM5-F within 24h, and it is 4% higher at 36h, and 6% higher at 48h. Viewing from RMS errors, the σ_R difference of MM5-SF and MM5-F is not obvious at 12h, while after 36h the σ_R of MM5-SF is about 5% less than that of MM5-F. In brief, viewing from wind fields, MM5-SF is improved in comparison with MM5-F within 24h; however, the effect is not obvious and is also not stable. MM5-SF is relatively better than MM5-F in the period after 24h up to 48h and is also stable. This may be related to the fact that the time interval of observational data is 12h. If the time interval is reduced, the result of MM5-SF might be even better within 24h.

(2) Pressure and temperature fields

In regard to the results of pressure field forecasts, since the forecast effect of MM5 is fairly good, the correlation coefficient of MM5-SF is higher than MM5-F, but not distinct. The σ_R of MM5-SF is generally about 7% less than MM5-F. Similar to the pressure field forecasts, results of temperature field forecasts of MM5-SF and MM5-F are both good, but the forecast result of the former is still slightly better than the latter. And considering the extent of improvement, whether the correlation coefficient or RMS error is considered, the result of MM5-SF after 24h is better than that of MM5-F.

(3) Precipitation fields

On the observed rainfall fields, whether it is the 24h or 48h rainfall field, there are two precipitation centres. The 48h maximum rainfall centre lies at (30°N, 115°E) with the maximum rainfall of 395 mm, and another submaximum rainfall centre at (28°N, 110°E) with a rainfall of 360mm (Table 6).

Table 6. Observed and predicted 48h rainfall on 24th July 1998.

	Maximum rainfall centre		Submaximum rainfall centre	
	Location	Intensity/(mm/48h)	Location	Intensity/(mm/48h)
Observed	30°N 115°E	395	28°N 110°E	360
MM5-SF	30°N 115°E	400	28°N 113°E	360
MM5-F	32°N 116°E	400	25°N 110°E	330

There are also two rainfall centres in the 48h precipitation field (Fig.3) of MM5-SF: the maximum rainfall centre lies at (30°N, 115°E) with the maximum rainfall of 400mm, and the other submaximum rainfall centre at (28°N, 113°E) with a rainfall of 360mm.

There are two corresponding rainfall centres in the 48h precipitation field (Fig.4) of MM5-F: the maximum rainfall centre lies at (32°N, 116°E) with the maximum rainfall of 400 mm, and the other submaximum rainfall centre lies at (25°N, 110°E) with a rainfall of 330mm.

As far as 48h precipitation forecast is concerned, MM5-SF shows improved result in comparison with MM5-F. The precipitation intensities of the maximum precipitation centres in MM5-SF and MM5 are identical. However, the forecast result of the submaximum precipitation centre in MM5-SF is better than that in MM5-F, and the central precipitation area in MM5-SF is obviously closer to the observed. Furthermore, in view of the trend of the whole precipitation area, the result of MM5-SF is very similar to the observed. Because people pay more attention to the distribution features of precipitation, i.e. precipitation location, in large-scale short-range forecast of flood season precipitation, the forecast result of MM5-SF is of more significance (Fig.5).

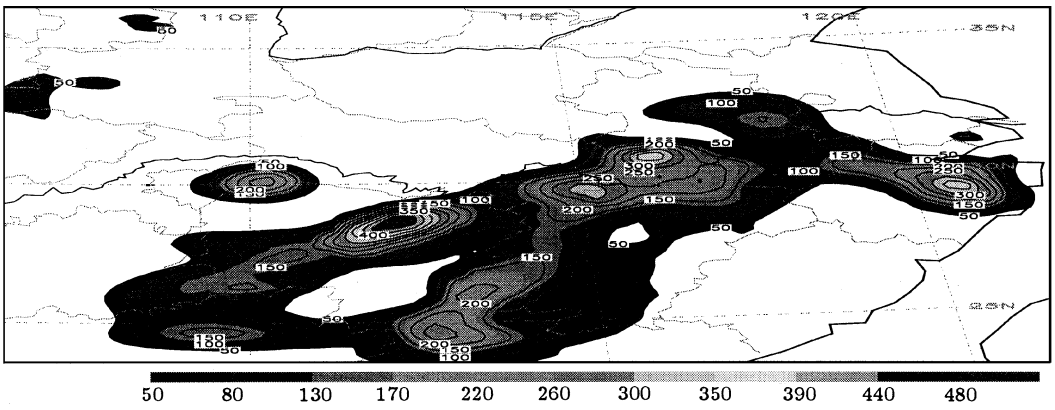


Fig.3. The 48h precipitation of MM5-SF from 22th to 24th July 1998 (units: mm).

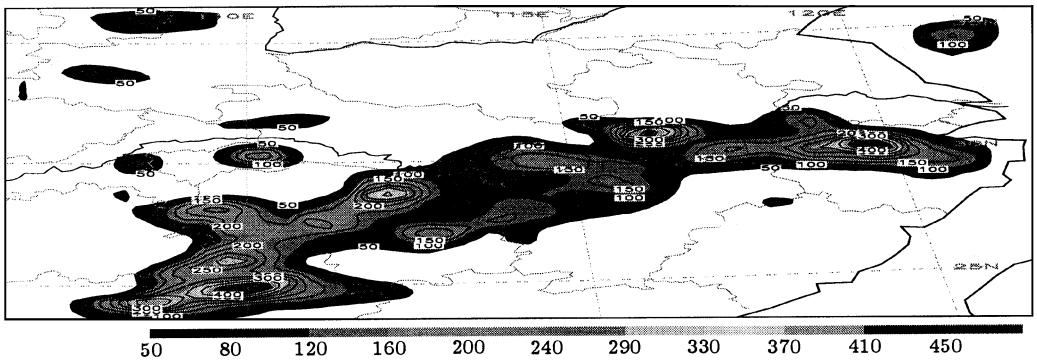


Fig.4. The 48h precipitation of MM5-F from 22th to 24th July 1998 (units: mm).

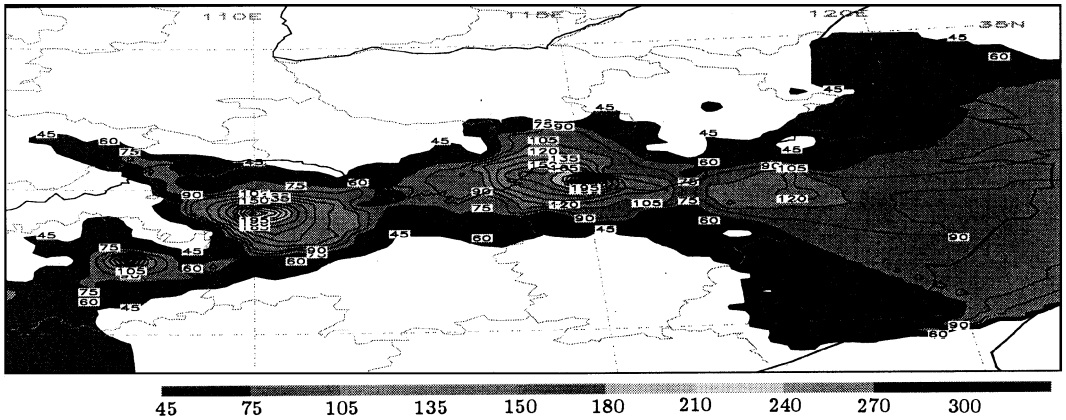


Fig.5. Observed 48h precipitation from 22th to 24th July 1998 (units: mm).

Forecast results of MM5-SF and MM5-F are quantitatively examined with T_s score as follows. As far as the 24h rainfall fields is concerned, the T_s scores of precipitation location for MM5-SF and MM5-F are 0.6994 and 0.6564 respectively. If viewing from the angle of torrential rain (the daily rainfall is equal to or greater than 50 mm) forecast, the T_s scores of precipitation location for MM5-SF and MM5-F are 0.2358 and 0.1603 respectively. Therefore, whether the precipitation or torrential rain location forecast is con-

cerned, MM5-SF is better than MM5-F. As far as the 48h rainfall forecast field is concerned, the T_s scores of precipitation location forecast for MM5-SF and MM5-F are 0.7890 and 0.7369 respectively. If viewing from the angle of torrential rain forecast, the T_s scores of precipitation location for MM5-SF and MM5-F are 0.3812 and 0.3062 respectively. So far as field correlation is concerned, the correlation coefficient between the predicted rainfall field of MM5-F and the observed is 0.1747, while the correlation coefficient of MM5-SF is 0.2120, the latter is obviously higher than the former. As is well known, it is very difficult to raise the forecast accuracy of torrential rain; however, as seen from the above, the only thing done here is that the 12h forecast field (MM5-SF) of SMM5 is taken as the initial field of MM5, and its forecast accuracy of torrential rain is then obviously raised. This is surprising. In fact, this result can be interpreted with atmospheric self-memorization property, i.e. when MM5-SF is taken as the initial field of MM5, the information several days ago has merged into the MM5-SF. This point of view is in agreement with that of Michaud.[26] He considered that, when the air–sea coupled model and the initial field of December 1982 were used to make the atmospheric general circulation forecast of January 1983, because the initial field had been modulated by the El Nino and its circulation in summer, i.e. the initial field memorized the previous atmospheric state, the forecast was accurate. In fact, the period from summer 1982 to January 1983 was a period of El Nino events.

5. Conclusion

To sum up, the improvement in the 12h forecasts of meridional wind and temperature fields by SMM5 is more obvious than the forecast of zonal wind field. As far as the pressure field forecast is concerned, the forecast result of MM5 itself is fairly good, therefore the forecast result of SMM5 is slightly better than MM5, but not obvious. In the experiments of MM5 using the 12h forecast field of SMM5 as the initial field, the improvement in wind, pressure and temperature field forecasts is overall not obvious within 24h, and is also not stable. After 24h, the improvement is distinct, and becomes stable. This result is in accord with those of self-memory spectral models and self-memory barotropic models, i.e. if the period of validity is extended, the forecast improvement of the self-memory model becomes obvious. This is a shining point of the self-memory model.

The improvement in precipitation field forecast by using MM5-SF is obvious, and whether it is precipitation location forecast or torrential rain location forecast, the forecast of MM5 using MM5-S is closer to the observed field than that using MM5-O, which is encouraging because it is a difficult thing to raise the accuracy of precipitation forecast. Since the time interval of data used is 12h, this is obviously not enough for short-range forecasts. With use of an even shorter time interval, for example 1–3h, the observed data might be expected to further improve the forecast result of the model.

The specification of the retrospective order is critical in the forecasting process of SMM5, and it is directly related to the forecast results. The order here is specified with 2–5, and when the order is specified within 3–4 the forecast effect will generally be ideal. The experiments of MM5 using the forecast of SMM5 (MM5-S) as the initial field aim at investigating the possibility of using SMM5 as a model for data assimilation, and the results show that using self-memory equations to develop a four-dimensional assimilation scheme shows much prospect.

Finally, only the observational data in 1998 are used in the numerical experiments in this paper, and therefore there might be some limitations in the representativeness of the experimental results. However, at least the experimental results here can show the feasibility and effectiveness of retrospective time integration scheme in mesoscale models. More experiments using different cases remain to be done in the future.

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