Experience of Using a Dynamic Stochastic Approach for Solving the Problem of Very Short-range Forecasting of State Parameters of the Atmospheric Boundary Layer

V. S. Komarov, A. V. Lavrinenko, N. Ya. Lomakina, and S. N. Il’in

Zuev Institute of Atmospheric Optics, Siberian Branch, Russian Academy of Sciences,
pl. Akademika Zueva 1, Tomsk, 634021 Russia, e-mail: gfm@iao.ru

Received May 20, 2013

Abstract — Discussed are the results of applying a dynamic stochastic method based on the use of the two-dimensional model and the Kalman filtering algorithm for solving the problem of the very short-range (from 0.5 to 6 hours) forecast of air temperature and orthogonal components of the wind speed in the atmospheric boundary layer realized using the data of radiometric, sodar, and increased-frequency radiosonde measurements. It is demonstrated that the proposed technique and the appropriate algorithm give a rather high accuracy of very short-range forecasting of temperature and wind within the lead time range under consideration.

DOI: 10.3103/S1068373914020022

1. INTRODUCTION

The growing requirements of economic sectors of the country in meteorological services result in the need in obtaining new types of information on atmospheric conditions. The importance of prognostic information for the atmospheric boundary layer with the small lead time (from 0.5 to 6 hours) is especially high. In particular, the forecast of air temperature and wind is used for solving such practical problems as the meteorological support for the safety of the takeoff and landing of aircrafts, the forecast of short-range variations in the pollution of limited air basins, the provision (using prognostic data) of the all-weather operation of lidar sounding systems, etc.

In spite of the high need in increased-frequency prognostic data on the thermal and wind regimes of the atmospheric boundary layer, the problem of the very short-range forecasting of air temperature and wind in the atmospheric boundary layer has not been practically studied so far. The research was impeded by the absence of both high-resolution data on the vertical distribution of temperature and wind in the atmospheric boundary layer and of reliable methods of their forecasting with the small lead time.

In fact, the radio sounding data used in the practice of meteorological studies of the atmospheric boundary layer are characterized by low vertical resolution and low sounding frequency (usually, at 00:00 and 12:00 UTC). Recently, new tools of remote sounding (lidars, radiometers, and sodars) have been widely introduced into the practice of the atmospheric monitoring which enable estimating the vertical distribution of temperature and wind in the atmospheric boundary layer with high vertical and temporal resolution. Besides, the use of dynamic stochastic methods in the practice of short-range weather forecasts has not lost its urgency so far. Using these methods, the possibilities are considered in [3, 7, 8] of using low-parameter models (regression, polynomial, etc.) and the Kalman filter algorithm for solving the problems of diagnosis and forecast of mesoscale meteorological fields.

In the present paper, the method is studied of the very short-range forecast of meteorological parameters based on the two-dimensional model and Kalman filter algorithm within the framework of the dynamic stochastic approach.

2. THE FORMULATION OF THE PROBLEM AND THE METHOD OF ITS SOLUTION

The two-dimensional dynamic stochastic model of the following form was used for the very short-range forecasting of air temperature and the orthogonal components of the wind speed in the atmospheric boundary layer:
where $\xi_{z,k}$ is the observed value of the meteorological parameter $\xi$ at the height $z$ at the time moment $k$; $\xi_{m,k-j}$ are the observed values of the meteorological parameter at the height from $z-j$ to $z+j$ at the time moments from $k-1$ to $k-1$; $d_{m,j}$ are the unknown coefficients of the model; $e_{z,k}$ is the residual of the model caused by the stochasticity of atmospheric processes; $m$ is the relative number of the current level within the specified atmospheric layer which data are taken into account for forecasting the field of the parameter $\xi$ at the forecast level $z$.

The use of the double sum in (1) enables taking account of the joint impact of temporal correlations between atmospheric processes and interlevel relationships arising under the influence of the processes of turbulent mixing and ordered vertical motions.

The presence of parametric dependence between the values of the meteorological variable $\xi$ at the time moment $k$ and at preceding time moments $k-j$ does not enable using directly the expression (1) for forecasting because the coefficients $d_{m,j}$ are unknown. Therefore, the problem of forecasting is divided into two stages. At the first stage, the coefficients of the model $d_{m,j}$ are estimated using the Kalman filter and the measured values of the meteorological variable $\xi$ that have been taken since the time moment $k$ to $k-j$ at the specified height $z$ and at neighboring heights. At the second stage, proceeding from the supposition on the stationarity of the atmospheric process within the lead time range under consideration and using the prognostic model of the following form

$$\hat{\xi}_{z,k+1} = \sum_{m=z-j}^{z+j} \sum_{j=0}^{K-1} d_{m,j} \xi_{m,k-j} + e_{z,k+1},$$

(2)

the forecast of this meteorological parameter is carried out for the time moment $k+1$. In (2), $\hat{\xi}_{z,k+1}$ is the estimate of meteorological variable $\xi$ at the time moment $k+1$; $d_{m,j}$ are the unknown coefficients of the model estimated at the $k$th time step.

To estimate the model coefficients $d_{m,j}$ (according to [9]), a model of the state of the dynamic system and a mathematical model of observation should be specified. In this case, the model of the state has the following form:

$$x_k' = \Psi_{k-1} x_{k-1} + \omega_{k-1},$$

(3)

where $x_k' = [d_{0,1}, d_{0,2}, \ldots, d_{2i+1,K}]^T$ is the true state vector including the unknown coefficients of the model (1); $\Psi_k$ is the transition matrix for the discrete model taking account of the dependence between the state variables and their spatiotemporal variability; $\omega_k' = [\omega_{0,1}', \omega_{0,2}', \ldots, \omega_{n,1}']^T$ is the column vector of random disturbances of the model (the vector of state noises) and $\langle \omega \rangle = 0$, $\langle \omega \omega^T \rangle = Q$, where $Q$ is the covariance matrix of the model noises and $\langle \cdot \rangle$ is the expectation operator. Proceeding from the supposition that the estimated coefficients $x_k'$ on average do not vary during the time interval equal to the forecast lead time, it is assumed that the transition matrix $\Psi_k$ is equal to the unit matrix $I$.

The mathematical model of observations used in the Kalman filter algorithm for assessing the system state is described in the general case with the adaptive mixture of the useful message and observational error:

$$\xi^o_k = H_k x_k' + e^o_k,$$

(4)

where $\xi^o_k$ is the vector of observations or actual observations of a meteorological parameter; in this case, this is a scalar; $H_k$ is the transition matrix defining the functional relationship between the true values of state variables and actual observations; $e^o_k$ is the observational error at the time moment $k$ (observational noise) also being a scalar and $\langle e \rangle = 0$, $\langle ee^T \rangle = R$, $\langle ee^o \rangle = 0$, where $R$ is the covariance matrix of observational noises.

As a result of the comparison of expressions for the prognostic model (1) and mathematical model of observations (4), the matrix $H_k$ can be written in the following form: $H_k = [\xi_{z-i,k-1}, \xi_{z-i,k-2}, \ldots, \xi_{z,k-1}, \xi_{z+i,k-1}, \xi_{z+i,k-2}, \ldots, \xi_{z+i,k}]$. 

RUSSIAN METEOROLOGY AND HYDROLOGY Vol. 39 No. 2 2014