Forecasting temperature profile based on blending of measurement data and numerical prediction models

Nikolay A. Baranov, and Ekaterina V. Lemishchenko

***Abstract*—** The work is devoted to the presentation of the approach to the construction of a short-term forecast of the dynamics of the atmospheric surface temperature profile. The forecast is based on the correction of the results of a numerical global forecast issued from temperature profile measurement data with the use of remote temperature sensing means. The data from the microwave temperature profiler MTP-5 applied for Pulkovo Airport (ICAO ULLI code) was used as the source of the measurement data. The relevance of this study is determined by the high requirements to the accuracy of the short-term forecast of weather hazards, for example, for the terminal area control. This approach provides the possibility of correcting the short-term forecast of weather hazards carried out by the data from real-time observations and does not require significant computational resources.

***Keywords*—** remote temperature sensing, nowcasting, temperature profile, forecasting modelling, blending, spline-interpolation.

I. Introduction

One of the active users of weather forecasts is aviation. Qualitative and timely weather forecasts define both flight safety in general, and efficiency and, for example, the effectiveness of take-off and landing operations at the aerodrome. In particular, short-term weather forecasts have a significant impact on the effectiveness of the terminal traffic management. In this regard, the Global Air Navigation Plan (GANP), which involves the phased upgrade of the entire air navigation system until 2028 [1], includes the improvement and expansion of meteorological information for air navigation services as an element of this modernization. The key concept of the ASBU methodology, the aviation system block upgrade, is the so-called "trajectory-based operations", which imply the rapid integration of high-resolution forecasts and short-term forecast products into the air traffic management (ATM) system. In this regard, projects are being actively developed in many countries to create systems for the nowcasting of weather hazards for airports [2-5].

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The quality of nowcasting systems is largely determined by the condition for effective assimilation of the current observations of meteorological parameters, since the short-term forecasts have a relatively strong dependence on the initial conditions. Forecast errors in a very short time range (several hours) have a strong correlation with the error of the initial data.

In this regard, the creation of effective algorithms for recording current observation data while constructing a short-term forecast is of considerable interest.

In the framework of this work, one of the approaches to solving this problem, which allows taking into account the data of current observations while constructing a short-term forecast in real time, is presented. The implementation of this approach is considered using the example of constructing a short-term forecast of the dynamics of the atmospheric surface temperature profile from remote sensing data.

As a data source, we consider the MTP-5 temperature profiler, manufactured by ATTEX, that provides a temperature profile measurement with a high spatial resolution (at least 50 m vertically) and a frequency of the measurement data every five minutes [6]. The urgency of applying the proposed approach with respect to forecasting the temperature profile is dictated by a number of considerations.

1. Temperature profile is one of the important factors determining the formation of such weather hazards as fogs, low clouds, freezing precipitation [7, 8].
2. Numerical prediction models have a low spatial resolution in the atmospheric surface layer, which does not allow to reliably identify the temperature inversion, which is an important predictor, for example, while forecasting fogs or freezing precipitation

To forecast the temperature profile, we use the extrapolation method of observed values based on the construction of smoothing cubic splines for a given set of heights (usually the heights at which measurements are made).

The proposed technology of blending observation data and numerical modeling is that the combined time interval is considered: a certain observation time interval plus the required forecasting interval. The functional dependence of the analyzed meteorological time parameter on the basis of weighted spline interpolation is formed on this combined time interval.

As an approximable set of values in the forecast interval, the forecasted temperature values obtained from the data of the global (or regional) numerical prediction model are used and adjusted according to the measured values in the observation interval.

II. Background

Currently approaches to the construction of short-term weather forecast based on data assimilation of observations into numerical prediction models are widely widespread. At the same time, a wide range of data assimilation methods is used, among which the methods of variatonal data assimilation prevail [9].

In addition, to improve the efficiency of the forecast, ensemble methods are widely used. They form the final forecast as an weighted- average value based on the set of models, and the weight coefficients of the models are statistical estimates of the reliability of forecasts for each model [10].

The peculiarity of the short-term forecast of aviation hazards is that the time scales of phenomena in the lower troposphere that influence air traffic planning often amount to minutes or tens of minutes. This applies, for example, to the variability of visibility and altitude of the cloud base – the main factor in the delay of flights at airports of moderate latitudes.

The application of approaches that use assimilation of observational data requires not only significant computational resources for their effective application, but also a high density of the observational network, which forms a continuous stream of input data for assimilation. The formation of such an observational network is associated with significant material costs. Nevertheless, the direct data assimilation of the observational network now allows only hourly updating the forecast, for example, Rapid Refresh (RAP) is the operational system of hourly assimilation/modeling adopted by the National Centers for Environmental Prediction (NCEP), USA.

In this regard, the algorithms of adaptive mixing of these models and observations are actively developing. The essence of these algorithms is that the prognostic value for each parameter is determined on the basis of the calculation of the weighted-average trend. In its turn, the value of the weighted-average trend is calculated as a combination of the trend value from observational data and trend values from modeling data taken with their weights. Weight coefficients are calculated based on the analysis of the quality of the forecast for the previous observation period.

III. Extpapolation methodology

Suppose that in the time interval$[t_0 - \tau_O, t_0]$ which will call the observation interval, there are a number of measurements of the temperature T_j at a given height H at instants of time t_j. In the time interval$[t_0, t_0 + \tau_F]$ which we will call the forecast interval, there are a number of predicted temperature values $\hat{T}_k$ at the same height at instants $\hat{t}_k$. In addition, the predicted temperature is also known at the time point $\hat{t}_{-1} \leq t_0$.

We construct the functional dependence $S(t)$ of the temperature change on the time interval $[t_0 - \tau_O, t_0 + \tau_F]$, using the blending of the available data: on the observation interval we use the measurement data and on the forecast interval we use the numerical simulation data.

Due to errors in the prediction model for the current time, the predicted value of the temperature differs a priori from the observed one, we perform a correction of the forecast from the available observational data. To do this we calculate the smoothed value of the temperature at the current instant of time (to compensate the influence of measurement errors):

$$\tilde{T}_0 = \frac{\sum_{t_j \in [t_0 - \tau_S, t_0]} T_j}{\sum_{t_j \in [t_0 - \tau_S, t_0]} 1},$$

where $\tau_s \leq t_O$ – is a certain interval of smoothing.

The corrected predicted temperature values are calculated by numerically integrating the predicted temperature gradient with an initial condition equal to the smoothed measured value:

$$\tilde{T}_1 = \tilde{T}_0 + \frac{\hat{T}_1 - \hat{T}_{-1}}{\hat{t}_1 - \hat{t}_{-1}} (t_0 - \hat{t}_{-1}),$$

$$\tilde{T}_k = \tilde{T}_{k-1} + \hat{T}_k - \hat{T}_{k-1} \text{ for } k > 1. \quad (1)$$

Thus, the smoothing spline $S(t)$ is built on a composite data set:

$\{\{(t_j, T_j)\}, \{(\hat{t}_k, \tilde{T}_k)\}\}$ as a function satisfying the following conditions:

- on each time interval$[t_{j-1}, t_j]$, $[t_0, \hat{t}_1]$, $[\hat{t}_k, \hat{t}_{k+1}]$ the function $S(t)$ is a polynomial of the third degree;
- the function $S(t)$ is twice continuously differentiable on the interval$[t_0 - \tau_O, t_0 + \tau_F]$;
- the function $S(t)$ ensures a minimum of the functional

$$J(S) = \int_{t_0 - \tau_O}^{t_0 + \tau_F} [S''(t)]^2 dt + \sum_j \frac{1}{w_j} \{S(t_j) - T_j\}^2 + \sum_k \frac{1}{\hat{w}_k} \{S(\hat{t}_k) - \tilde{T}_k\}^2. \quad (2)$$

As additional conditions ensuring the correctness of the problem to determine the approximating spline$S(t)$, we accept conditions where the second derivative at the ends of the interval is zero$[\bar{t}_0, \bar{t}_L]$:

$$S''(\bar{t}_0) = S''(\bar{t}_L) = 0.$$

In the presented relation for the minimized functional (2), the second and third summons are specially singled out to show that when constructing a smoothing spline the measured values of temperature and the predicted values obtained from the data of the numerical model are taken with different weights w_j and $\hat{w}_k$ respectively. In this case, the values of w_j are taken in such a way as to provide a greater weight of the observational data and, accordingly, a more accurate approximation of the data in the observation interval.

To simplify the notation, we introduce the general numbering $\bar{t}_l$ of the observation times t_j and the times at which the numerical prediction data $\hat{t}_k$ is available. Accordingly, the temperature value (measured or predicted) for the time instant $\bar{t}_l$ will be denoted by $\bar{T}_l$, and the weight coefficients by ρ_l.

For each interval of interpolation $[\bar{t}_{l-1}, \bar{t}_l]$ the value of the smoothing spline $S(t)$ is calculated by the formula [11]

$$S(t) = M_{l-1}\frac{(\bar{t}_l - t)^3}{6\Delta t_l} + M_l\frac{(t-\bar{t}_{l-1})^3}{6\Delta t_l} +$$
$$+\left(T_{l-1} - M_{l-1}\frac{\Delta t_l^2}{6}\right)\frac{\bar{t}_l - t}{\Delta t_l} + \left(T_l - M_l\frac{\Delta t_l^2}{6}\right)\frac{t-\bar{t}_{l-1}}{\Delta t_l}, \quad (3)$$

where

$\Delta t_l = \bar{t}_l - \bar{t}_{l-1}$,

and the coefficients M_l are calculated as a solve simultaneous equations of the form

$$a_0M_0 + b_0M_1 + c_0M_2 = d_0,$$
$$b_0M_0 + a_1M_1 + b_1M_2 + c_1M_3 = d_1,$$
$$c_{l-2}M_{l-2} + b_{l-1}M_{l-1} + a_lM_l + b_lM_{l+1} + c_lM_{l+2} = d_l, \quad (4)$$
$$c_{L-3}M_{L-3} + b_{L-2}M_{L-2} + a_{L-1}M_{L-1} + b_{L-1}M_L = d_{L-1},$$
$$c_{L-2}M_{L-2} + b_{L-1}M_{L-1} + a_LM_L = d_L,$$

where

$$a_l = \frac{1}{3}(\Delta t_{l-1} + \Delta t_l) + \frac{1}{\Delta t_{l-1}^2}\frac{1}{\rho_{l-1}} +$$
$$+\left(\frac{1}{\Delta t_{l-1}} + \frac{1}{\Delta t_l}\right)^2\frac{1}{\rho_l} + \frac{1}{\Delta t_l^2}\frac{1}{\rho_l}, \; l = 1,\dots,L-1,$$
$$b_l = \frac{1}{6}\Delta t_l - \frac{1}{\Delta t_l}\left[\left(\frac{1}{\Delta t_{l-1}} + \frac{1}{\Delta t_l}\right)\frac{1}{\rho_l} + \left(\frac{1}{\Delta t_l} + \frac{1}{\Delta t_{l+1}}\right)\frac{1}{\rho_{l+1}}\right],$$
$$l = 1,\dots,L-2,$$
$$c_l = \frac{1}{\Delta t_l}\frac{1}{\Delta t_{l+1}}\frac{1}{\rho_{l+1}}, \; l = 1,\dots,L-3,$$
$$d_l = \frac{\bar{T}_{l+1} - \bar{T}_l}{\Delta t_{l+1}} - \frac{\bar{T}_l - \bar{T}_{l-1}}{\Delta t_l}, , \; l = 1,\dots,L-1,$$
$$a_0 = a_L = 1, b_0 = c_0 = c_{L-2} = b_{L-1} = d_0 = d_L = 0.$$

The presented system of equations (4) is easily solved by the sweep method. After solving it the temperature values are calculated by formula (3) for an arbitrary moment of time.

IV. Results and discussion

The measurement data obtained by the MTP-5 temperature profile in the area of Pulkovo Airport (ICAO ULLI code) from 12.2017 to 01.2018, as well as the results of the numerical model GFS with a grid step of 0.25°, interpolated for the point of installation of the measuring device, were used for the analysis.

The results of applying the above approach for calculating the temperature forecast for the time interval $\tau_F = 4$ hours are presented below.

The following notation is used in these figures:

- magenta color markers indicate predicted temperature values according to the global forecast model (GFS);
- dashed green color line shows the values of the forecast value adjusted for observational data $\widetilde{T}_k$ (1);
- red line with markers is measured temperature values (MTP-5 data);
- dashed magenta color line is the temperature forecast based on the smoothing spline-extrapolation described above (3).

As the moment of the forecast on the presented schedules the moment of time is $st_0 = 16{:}00$.

Fig. 1, 2 show the results reflecting the effect of the observation interval used on the construction of the approximating spline. The observation intervals $t_O = 1$ and $t_O = 2$ are considered. It can be seen that although the influence of the observation interval on a large forecast interval is feebly marked, it can nevertheless be noted that the use of the observation interval $t_O = 2$ hours gives slightly better convergence of observational and forecast data in the time interval $[t_0, t_0 + \tau_F]$, and the trend is manifested at large intervals of forecast time (3-4 hours).

It can also be noted that the forecast based on the numerical model (magenta color markers), even with correction based on observation data, can give a significant error of 2-3 degrees on the observation interval.

The forecast based on spline extrapolation, gives a fairly high degree of convergence with observation data especially in the ultra-short range prediction (up to two hours). On a larger forecast range, the accuracy of the forecast is influenced by the adequacy of predicting the temperature dynamics.

From the presented comparison results it is clearly seen that the error of the GFS model of calculating the temperature profile in the surface layer can be 3-4° and in certain adverse situations 5-6° as fig. 3, 4 show. These figures show the results of calculation of the forecast error in comparison with the data of the temperature profiler measurements for heights 0 (blue), 100 (red), 200 (magenta), 500m (green).

Fig. 5 shows the results of calculations based on the spline-extrapolation of temperature profiles and their comparison with the obtained measurement data. It can be seen that the use of the proposed method for constructing a short-term weather forecast gives a fairly high accuracy of forecasting the profile: the profile forecast error does not exceed two degrees in the surface layer.

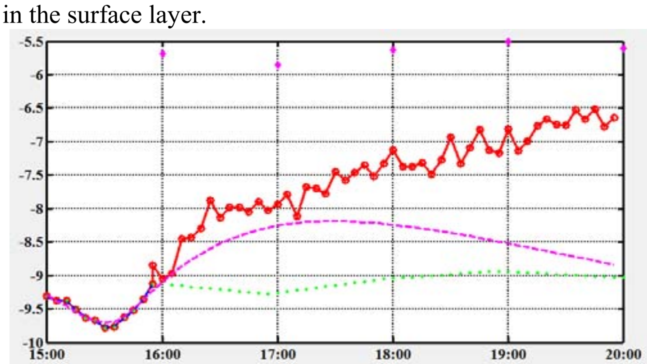

Fig.1 temperature forecast at the observation interval of 1 hour.

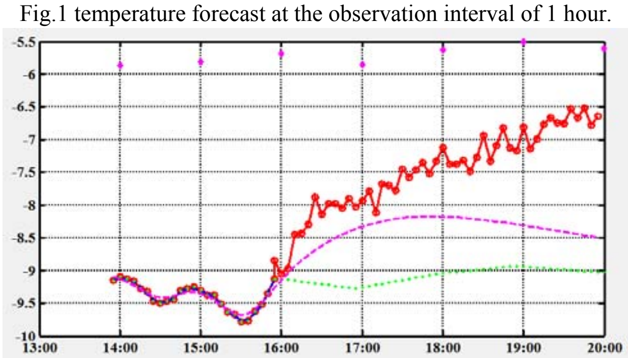

Fig.2 temperature forecast at the observation interval of 2 hours.

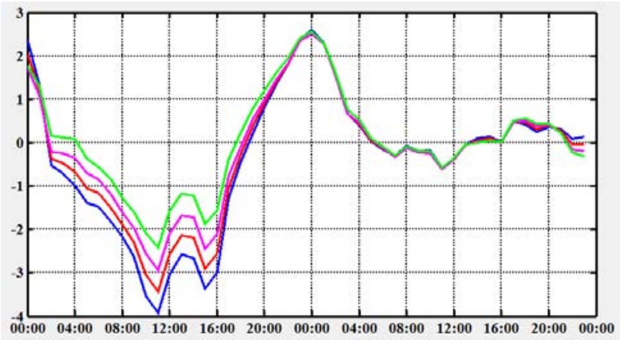

Fig.3 the error of the forecast temperature profile (20-21.12.2017, ULLI).

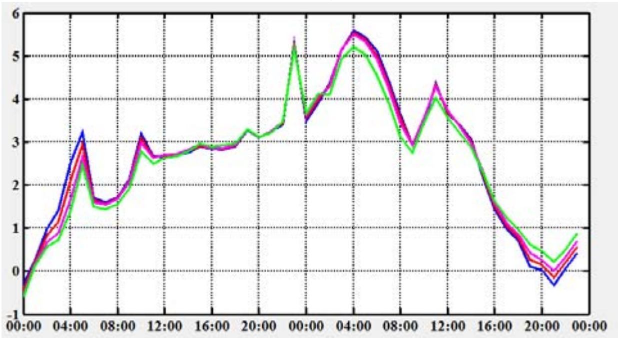

Fig.4 the error of the forecast temperature profile (12-13.01.2018, ULLI).

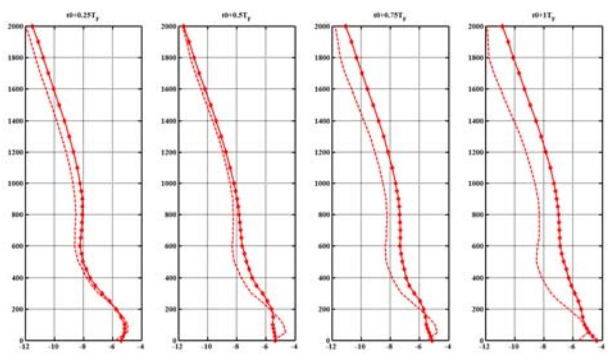

Fig.5 hourly forecasts of temperature profile in comparison with the measured values of the profiles at the same time points.

It should be noted that due to the fact that the reference data used to form the final short-term forecast is the data of a numerical forecast model that is weakly sensitive to the altitude distribution of temperature in the surface layer, the forecast formed at a specific observation moment for the next few hours may not reflect the dynamics of changes in temperature stratification.

In particular, Fig. 4 reflects this result, where it can be seen that the surface inversion in the lower 100-m layer, which existed at the time of the forecast compilation, continues to change. Two hours later, surface isotherm is formed in the lower layers, which then transforms into a temperature profile close to the adiabatic temperature profile.

Nevertheless, the predicted temperature profile retains the type of stratification that existed at the time the forecast was compiled. Although, at large, the discrepancy between the predicted and observed temperature profile over the entire prediction interval (4 hours) does not exceed 2°, nevertheless, an inadequate forecast of the stratification type can lead to unreliable forecasting of weather hazards. In particular, as shown by the analysis of observational data, the presence of temperature inversion in the lower 100-m layer is a factor determining the possibility of formation of a radiation fog [12]. An error in determining the type of stratification can cause inadequate prediction of this dangerous meteorological event.

An error in predicting the type of stratification is due to the fact that at the time of the forecasting (16:00) a trend of a sharp change in temperature is formed (Fig. 2, a red line with markers, observational data). However, the results of the numerical prediction do not reflect this trend (magenta color markers), showing a constant temperature trend. Correspondingly, the same trend (with a zero time gradient) has data corrected from the results of observations (see formula (1)), which are the initial data for the formation of forecast values.

Nevertheless, the conducted analysis shows that due to the implementation of operational assimilation of observational data, it is possible to provide an operative correction of the short-term forecast.

For example, Fig. 6-9 show the dynamics of the change in the predicted temperature. Note that at the observation interval of 14:00 - 16:00 the numerical model produced a significant error in the forecast of temperature (3-4°), predicting a trend of maintaining these values. However, around 16:00, an intensive increase in temperature begins. The increase cannot be identified by the original forecast or the corrected and described above algorithm (Fig.6).

However, already at 16:10 due to the operational assimilation of observational data the presented algorithm correction of short-term forecast captures the trend of temperature increase and gives a more adequate hourly forecast, the error of which does not exceed 0.5°. However, over a long period of 4 hours, the corrected forecast still provides a significant discrepancy with observation data.

Data assimilation in the subsequent moments of time allows to obtain an adequate estimation of the formed trend of temperature change and to improve the quality of the forecast on a longer interval of time (Fig. 8-9). It should be noted that the adjustment of short-term forecast occurs almost at reception rate of the observational data

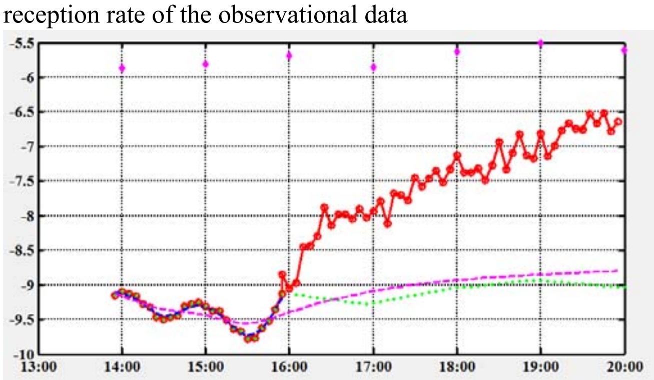

Fig.6 temperature forecast in a time of 16:00.

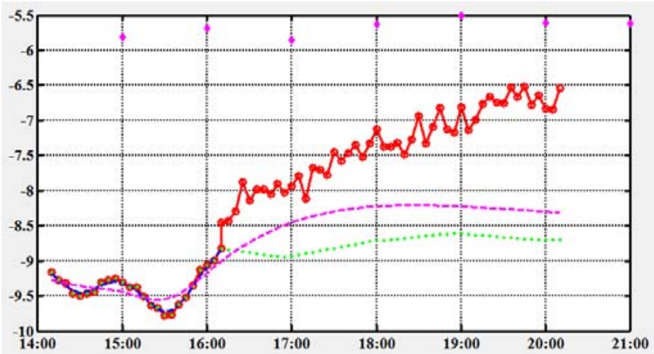

Fig.7 temperature forecast in a time of 16:10.

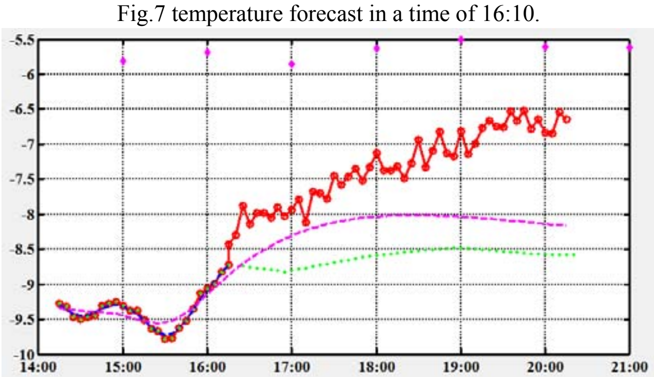

Fig.8 temperature forecast in a time of 16:20.

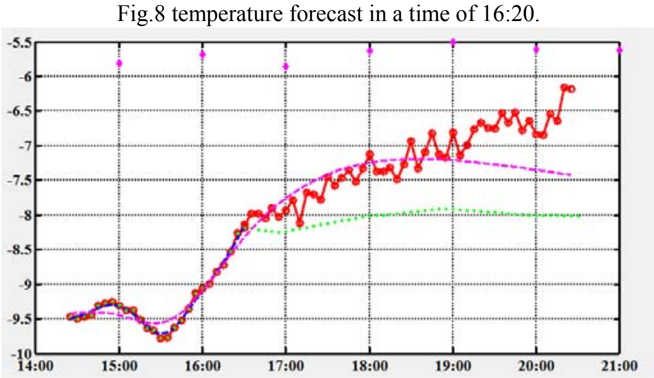

Fig.9 temperature forecast in a time of 16:30.

V. CONCLUSION

The work describes an approach to the formation of a short-term forecast of meteorological parameter values by adjusting the data of numerical models of the forecast according to operational observations. The calculation methodology is based on the application of weighted interpolation methods. As an interpolated set of data, a collection of observational data on a certain time interval that precedes the moment of forecasting and numerical modeling data for the prediction time interval are considered. Observation data are taken with much greater weight than the modeling data, which ultimately provides an improvement in the quality of the short-term forecast.

The presented results on the example of forecasting the dynamics of the atmospheric surface temperature profile show the possibility to improve the quality of the forecast with a reduction of errors in predicting the temperature values by a factor of two. The presented results show that the application of this approach is expedient in the formation of a short-term forecast on a time interval of up to 4 hours, while it is rational to use observation data for a 2-hour period preceding the moment of making the forecast.

The described approach has a high operational efficiency, which allows correcting the forecast of weather hazards practically in real time by taking into account the observational data. Despite the fact that the results are presented on the example of forecasting the dynamics of the stratification of the atmospheric surface layer, this approach can be used for a short-term forecast of other meteorological parameters.

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