EXPERIENCE ON USING THREE-PATH CORRELATION LIDAR MEASUREMENTS IN THE PROBLEM OF STATISTICAL FORECAST OF THE AVERAGE WIND COMPONENTS

V.S. Komarov, A.V. Kreminskii, N.Ya. Lomakina, and G.G. Matvienko

Institute of Atmospheric Optics,
Siberian Branch of the Russian Academy of Sciences, Tomsk
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A methodology is treated of a solution to the problem of supershort-term forecast of the average wind components within the planetary boundary layer, governing the spatial transport of atmospheric pollutants. It is shown by concrete examples that the statistical forecast from the measurements with a three-path correlation lidar developed at the IAO SB RAS are fairly acceptable for local atmospheric-ecological monitoring.

Investigations connected with a supershort-term forecast (for periods less than six hours) of a wind regime in the planetary boundary layer (i.e., at altitudes up to 1–2 km) occupy an important place in a wide class of fundamental and applied investigations on the problem of local and regional ecological monitoring due to the fact that the air circulation in this layer determines largely the state and evolution of the pollution level of a bounded air basin (e.g., of a city, an industrial zone, or a region as a whole).

The role of a wind in the formation and evolution of a pollution field can be judged, in particular, by the equation of balance (transport) of atmospheric pollutants. The equation is usually written for a specific pollutant and a turbulent atmosphere in the form

$$\frac{\partial s_a}{\partial t} + \left(u\,\frac{\partial s_a}{\partial x} + v\,\frac{\partial s_a}{\partial y} \right) + w\,\frac{\partial s_a}{\partial z} + \frac{\partial w_a s_a}{\partial z} - k_s \left(\frac{\partial^2 s_a}{\partial x^2} + \frac{\partial^2 s_a}{\partial y^2} \right) - \frac{\partial}{\partial z}\, k_z\, \frac{\partial s_a}{\partial z} = \varepsilon_a, \qquad (1)$$

where s_a is the volume concentration of pollutant a; u, v, and w are the components of the wind velocity vector in the coordinate system (x, y, z); w_a is the vertical velocity of the pollutant ($w_a < 0$); k_s and k_z are the turbulent exchange coefficients due to horizontal and vertical movements of particles, respectively; $\varepsilon_a = \varepsilon_a(x, y, z, t)$ is the source (sink) of the pollutant, i.e., the rate of its formation (decomposition) in a unit volume.

Indeed, according to equation (1) the horizontal components of the wind velocity vector play an important role as they cause advection of the pollutant (see the second term in the left side of the transport equation). These components are the input parameters of the transport model, so they are either calculated for any prognostic model (for instance, for a mesometeorological model that is usually used in local hydrodynamic weather forecast[1]) or determined from real wind measurements, as is most often done in practice of atmospheric-ecological investigations.

Since most anthropogenic pollutants are usually concentrated within the lower 1–2 km layer of the atmosphere, all the mathematical models of pollutant transport are constructed for the planetary boundary layer, as a rule. Therefore, it is necessary to estimate the horizontal wind velocity components u and v for the same layer because, according to Ref. 2, horizontal components of anthropogenic pollutant transport coincide with them. It should be noted that the horizontal displacement of a pollutant cloud in the planetary boundary layer, as shown in Ref. 3, is determined by the vector of wind velocity averaged over the vertical layers (or by the vector of the mean wind velocity) rather than by the wind velocity vectors of individual layers, that is,

$$\langle V \rangle_{h_0,h} = \frac{1}{h - h_0} \int\limits_{h_0}^{h} V(z)\, \mathrm{d}z \qquad (2)$$

(here, h_0 and h are the altitudes of the lower and upper boundaries of the pollution layer, and $h_0 = 0$, i.e., its lower boundary coincides with the earth's surface) whose zonal $\langle u \rangle_{h_0,h}$ and meridional $\langle v \rangle_{h_0,h}$ components can be obtained from the expressions

$$\langle u \rangle_{h_0,h} = \frac{1}{h - h_0} \int\limits_{h_0}^{h} u(z)\, \mathrm{d}z, \qquad (3)$$

$$\langle v \rangle_{h_0,h} = \frac{1}{h - h_0} \int\limits_{h_0}^{h} v(z)\, \mathrm{d}z. \qquad (4)$$

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The operator <•> in Eqs. (2)–(4) denotes the procedure of vertical averaging over the layer $h - h_0$.

We took into account all the above-stated in solving the problem of supershort-term forecast of the average wind components determining the spatial transport of the atmospheric pollutants. The present paper is devoted to the methodology and results of such a forecast.

It should be immediately noted that the problem of supershort-term forecast of atmospheric circulation in the planetary boundary layer was not solved up to now because the lack of the data about the vertical distribution of the wind with high spatiotemporal resolution. The data of standard network radiosounding usually used in practice of atmospheric ecological investigations are characterized by low spatiotemporal resolution and insufficient reliability at altitudes below 0.5 km (due to high ascention rates of radiosonde balloons). A real possibility to solve the problem of supershort-term wind forecast with accuracy sufficient for practice has appeared only nowadays, because the new methods of wind lidar sounding have been introduced only most recently. In particular, they are the Doppler and correlation methods described adequately in Refs. 4 and 5. The former requires complicated and expensive equipment but has some advantages in wind sounding at long distances. As for the correlation method, it can be easier realized and is competitive with the Doppler method in investigations of the wind field in the boundary layer of the atmosphere.

Since we use the data of a three-path correlation lidar[5] developed at the Institute of Atmospheric Optics of the SB RAS for a solution of the above-formulated problem, the question about the quality of the data obtained naturally arises. It was solved earlier in Ref. 6 where, based on statistical comparison of synchronous samples of lidar and radiosonde observations, it was shown that the measurements with a three-path correlation lidar can be successfully used for solving various problems of mesometeorology and local ecological monitoring.

Now we dwell on methodology of the supershort-term forecast (for periods less than six hours) of the average wind components.

We believe that this problem can be solved, like in the case of spatial (with respect to the altitude) forecast of the average wind components (see Ref. 7), by a modified version of the method of clustering of the arguments (MMCA) that is sufficiently simple for realization, takes into account the dynamics of atmospheric processes in the best way, and does not require large volume of initial information to create the optimal prognostic model. As a model, we use the hybrid difference dynamic-stochastic model of the form[8]

$$\xi_0(h, N + 1) = \sum_{\tau=1}^{N^*} A(h, \tau)\, \xi_i(h, N + 1 - \tau) + \sum_{j=1}^{h-1} B(h, j)\, \xi_0(j, N + 1) + \varepsilon(h, N + 1)$$

$$(\text{for } h = \bar{h} + 1, \bar{h} + 2, \ldots, h_k), \quad (5)$$

where $\xi_0(h)$ and $\xi_i(h)$ are the prognostic and initial profiles of random deviations of a meteorological parameter ξ (for simplicity, overbars are omitted here and below) taken at times $t = N + 1$ and $t = 1, 2, \ldots, N$, respectively; $\bar{h}$ is the altitude of the first level of the statistical forecast; N^* is the order of time delay ($N^* < [N - h - 1]/2$); $A(h, 1), \ldots, A(h, N)$ and $B(h, 0), \ldots, B(h, h - 1)$ are the unknown parameters of the prognostic model; $\varepsilon(h, N + 1)$ is the discrepancy of the model.

Algorithms for the selection and construction of the optimal prognostic model were adequately described in Refs. 9 and 10, so we do not dwell on them. The only unsolved problem in the given case is the choice of the optimal procedure for preliminary calculation (for the period $t = N + 1$) of the wind velocity components at an altitude of 140 m where the data of lidar measurements are lacking (in contrast to the problem of spatial forecast[7]).

In our opinion, they can be determined by the method of optimal linear extrapolation of a stochastic process, and the forecast of the average wind components can be performed, as in the case of spatial forecast, by the MMCA algorithm.

The procedure for determining any meteorological parameter (in our case, they are the zonal (u) and meridional (v) components of the wind velocity vector) at the instant $t + \tau$ (here, t is the time and τ is the period of forecasting) by the method of optimal extrapolation is, according to Ref. 11, to find it from the expression

$$\hat{\xi}(t+1) = \bar{\xi}(t) + \xi'(t + 1) = \bar{\xi}(t) + \sum_{k=0}^{n} a_k\, \xi(t - k), \quad (6)$$

where $\bar{\xi}(t)$ is the average value of meteorological parameter ξ (for stationary process,[11] $\bar{\xi}(t) = \bar{\xi} =$ = const); $\xi'(t + 1)$ are the deviations of the meteorological parameter from its average value at the instant $t + 1$; $\xi(t - k)$ are the deviations of the meteorological parameter from its average value at previous instants $t - k$ (here, $k = 0, 1, 2, \ldots, n$); a_k are the weight coefficients defined so that the parameter

$$\sigma_n^2 a_0, a_1, a_2, \ldots, a_n) = \\ = \min \left\{ \left[\xi(t + 1) - \sum_{k=0}^{n} a_k\, \xi(t + k) \right]^2 \right\} \quad (7)$$

was minimum.

Using the minimum condition for the function σ^2, i.e., the condition

$$[\partial\sigma_n^2(a_0, a_1, a_2, ..., a_n)]/(\partial a_k)=0 \quad \text{for } k=0, 1, ..., n, \qquad (8)$$

and differentiating Eq. (7) with respect to each variable, we arrive at the system of equations

$$\sum_{j=0}^{n} a_j\, \mu_\xi(k-j) = \mu_\xi(l+k), \quad k = 0, 1, ..., n, \qquad (9)$$

which can be used to determine the weight coefficients a_k for a stationary stochastic process (with the variance $D(t)$ = const).

Formulas (6)–(9) provided a basis for a computation code of the procedure of optimal extrapolation of the stochastic process at the lowest level (140 m) where minimum rms errors of supershort-term forecast of the wind characteristics were found.

Since the correlation functions μ_ξ were required to find the weight coefficients in formula (9), the analytic functions of the form

$$\mu_u(\tau) = \mu_v(\tau) = \exp\,[-\,\alpha(\tau)] \qquad (10)$$

obtained by us from the data of initial observations were used in order to determine these coefficients (here, $\alpha = 0.275$ for the zonal wind component and $\alpha = 0.537$ for the meridional one).

Now we turn to an analysis of the results of supershort-term forecast of the zonal ($<u>_{h_0,h}$) and meridional ($<v>_{h_0,h}$) average wind components made for the period τ = 4 h by the integrated algorithm.

This forecast was made from the data of lidar observations of wind (their number N = 90) with a three-path correlation lidar in the region of Tomsk (56°N, 85°E) between June 10 and August 12, 1994. Since the altitude resolution of the data was about 100 m, it enabled us to study the salient features of the average wind evolution in sufficient detail in almost entire boundary layer of the atmosphere (at altitudes up to 1140 m).

In order to estimate the accuracy of supershort-term forecast of the average wind components, we used rms error δ and the probability P that the prognostic error is less or greater than a preset value.

Table I lists the quality estimation of an integrated forecast of the components $<u>_{h_0,h}$ and $<v>_{h_0,h}$ represented by the rms error (δ) and probabilities (P) that the prognostic errors are less than ±1, ..., ±4 m/s or greater than ± 4 m/s. The same table gives the standard deviations (σ) of these components characterizing their variability.

TABLE I. Root-mean-square errors (δ) and probabilities (P) that the zonal and meridional wind velocities are less than ± 1, ..., ± 4 m/s *or greater than* ± 4 m/s *obtained by the MMCA from the measurements with a wind lidar performed every* 4 h, *prognostic values of these components at a level of* 140 m, *and their standard deviations* σ.

Reconstruction layer, m	Probability, P					δ	σ
	≤ ± 1 m/s	≤ ± 2 m/s	≤ ± 3 m/s	≤ ± 4 m/s	> ± 4 m/s		
Zonal wind							
140 – 240	0.84	0.96	0.98	1.00	0.00	0.6	1.6
140 – 340	0.76	0.94	0.98	1.00	0.00	0.8	1.8
140 – 440	0.66	0.88	0.98	0.98	0.02	1.0	2.0
140 – 540	0.64	0.88	0.94	0.98	0.02	1.2	2.1
140 – 640	0.60	0.86	0.94	0.98	0.02	1.4	2.2
140 – 740	0.56	0.84	0.90	0.98	0.02	1.6	2.3
140 – 840	0.50	0.78	0.88	0.98	0.02	1.6	2.5
140 – 940	0.50	0.78	0.88	0.98	0.02	1.6	2.6
140 – 1040	0.48	0.76	0.84	0.98	0.02	1.7	2.8
140 – 1140	0.46	0.66	0.84	0.98	0.02	2.0	2.9
Meridional wind							
140 – 240	0.84	1.00	1.00	1.00	0.00	0.6	1.7
140 – 340	0.78	0.98	1.00	1.00	0.00	0.8	2.1
140 – 440	0.70	0.92	1.00	1.00	0.00	1.0	2.4
140 – 540	0.76	0.90	0.98	1.00	0.00	1.1	2.5
140 – 640	0.74	0.92	0.98	1.00	0.00	1.1	2.7
140 – 740	0.72	0.86	0.94	1.00	0.00	1.3	2.9
140 – 840	0.70	0.88	0.94	1.00	0.00	1.4	3.0
140 – 940	0.66	0.86	0.94	0.98	0.02	1.4	3.2
140 – 1040	0.64	0.84	0.94	0.98	0.02	1.6	3.4
140 – 1140	0.60	0.82	0.92	0.98	0.02	1.8	3.5

Analysis of Table I shows that the statistical supershort-term forecast (for the period $\tau = 4$ h) of the average wind components in the planetary boundary layer performed on the basis of alternative methods and wind lidar data is fairly successful. Indeed, the accuracy of the integrated forecast of the parameters $<u>_{h_0,h}$ and $<v>_{h_0,h}$ is satisfactory for the above-mentioned period because the probability P that the error is less than ±1 m/s is rather large for such a forecast (especially for the meridional component) and varies from 0.46 to 0.84 for the zonal component and from 0.60 to 0.84 for the meridional one.

The advantages of the proposed integrated algorithm are confirmed by the fact that the rms error δ for all layers $h - h_0$ is much less than the standard deviation (cf. the values of δ and σ in Table I) and hence the condition

$$\delta^2 < \sigma^2 \quad (11)$$

(i.e., that the mean-square forecast error is less than the variance of the examined parameter) is fulfilled. In this case, as is well known, statistical forecast would be appropriate for use rather than persistence forecast.

It should be noted here that a better quality of statistical forecast based on combination of two alternative methods (optimal extrapolation and MMCA) can be naturally expected for periods $\tau < 4$h.

In conclusion we notice that although the forecast results obtained from the data of the three-path correlation lidar are fairly acceptable for practice of local atmospheric ecological monitoring, they will be much better if a more accurate Doppler lidar is used.

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