RESEARCH PAPER

STATISTICAL MODELING OF THE EFFECTS OF WIND SPEED, AIR TEMPERATURE AND RELATIVE HUMIDITY ON THE CONCENTRATION OF CARBON MONOXIDE IN THE URBAN ATMOSPHERE

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ABSTRACT. The high carbon monoxide content in the urban atmosphere is one of the most important indicators of poor air quality in megacities such as Moscow. This study is to evaluate the importance of wind speed, air temperature, and relative air humidity for predicting the concentrations of carbon monoxide for the day ahead using a simplified one-dimensional quasistationary statistical model. It is shown that the concentration of carbon monoxide in the Moscow atmosphere is determined by a combination of internal (previous days CO concentration) and external (meteorological conditions) factors. The variation of carbon monoxide concentration at one station differs from the variation at another station due to the differences in local conditions. Taking into account wind speed and air temperature increases the predictive value of the one-dimensional quasi-stationary statistical model for most of the stations. In contrast to wind, relative air humidity decreases the predictive value of the model for most of the stations. This means that meteorological factors considered in this study could have different effects on predicting carbon monoxide concentration in the case of Moscow. The data from the Balchug weather station, located in the city center, offers a more accurate CO concentration forecast for most Moscow stations compared to the VDNKh weather station. For a more complete description of the influence of meteorological conditions on the predicted low concentration of gases, it is useful to take into account the model wind direction, surface air pressure, and the intensity of mixing in the urban boundary layer.

KEYWORDS: statistical forecasting, regression-autoregression model, urban air, atmospheric pollution, carbon monoxide, meteorological factors

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INTRODUCTION

Modeling and forecasting the content of gas pollutants in the urban atmosphere is one of the most important, interesting, and difficult problems of urban meteorology. As is known, the concentrations of gaseous pollutants in urban air are determined by the magnitude and spatial distribution of their emissions from stationary and mobile sources, atmospheric diffusion, and mesoscale meteorological processes. The assessment of the influence of meteorological factors on the measured and predicted concentrations of gas pollution is a rather non-trivial research task due to the uncertainty of the spatial and temporal variability of emissions and their propagation conditions. Modern meteorological models (WRF, COSMO, ICON, etc.) may not always justify their use due to the complex configuration of the urban surface layer and the multitude of stationary and mobile sources of gas pollution in megacities like Moscow. In many large cities around the world, especially in South and Southeast Asia, machine learning methods based on multiple regression and autoregression equations are widely used for short-term forecasting of urban air pollution, which give results comparable to those of meteorological models but require significantly lower computational costs. In Russia, the methods for calculating the dispersion of emissions of polluting substances in atmospheric air were approved by the Order of the Ministry of Natural Resources and Ecology (Order No. 273 from June 6, 2017) replacing the "Methodology for calculating concentrations of harmful substances, contained in emissions from enterprises, in the atmospheric air" (OND-86) that had been valid since 1986. Urban transport is the primary source of carbon monoxide. The spatial and temporal distribution of this CO source is difficult to describe in sufficient detail for numerical modeling. Thus, for example, the decrease in the concentration of CO in Moscow due to a sharp decrease in ground transport flows during the lockdown associated with the COVID-19 pandemic was much stronger in residential areas than near highways (Ginzburg et al. 2020). Due to the complex pattern of CO sources, in previous works (Demchenko et al. 2015; Zavalishin et al. 2018) co-authored by the authors of this article, the method of multiple regression-autoregression was suggested for using in short-term forecasting of the average daily concentration of CO and other gas and aerosol pollutants in the urban atmosphere and to address the effect of the main meteorological factors (temperature, wind speed and air humidity).

The carbon monoxide increase in an urban environment leads to the formation of tropospheric ozone and serves as an indicator of global atmospheric changes (Grechko et al. 2009). Variations in carbon monoxide concentration in the Moscow air basin are significantly affected by meteorological conditions (Vilfand et al. 2014; Golitsyn et al. 2015; Kuznetsova 2010; Demchenko et al. 2015; Elansky et al. 2015; Rakitin et al. 2021) such as wind speed (Grechko et al. 2009, Demchenko et al. 2015, Elansky et al. 2015, Rakitin et al. 2021, Berlyand, 1991, Comrie & Diem 1999, Đurić & Vujović 2020, Li, R. et al. 2020, Ruan 2021), air temperature (Benavides et al. 2019, Berlyand 1991, Comrie & Diem 1999, Czerwińska & Wielgosiński 2020, Đurić & Vujović 2020, Li et al. 2020, Ruan et al. 2021), air humidity (Comrie & Diem 1999), and atmospheric pressure (Comrie & Diem 1999, Czerwińska & Wielgosiński 2020, Ruan et al. 2021).

Besides, carbon monoxide variations reflect the weekly cycle of economic and business activity (Gorchakov et al. 2010a). On weekends, the concentration of carbon monoxide decreases (Gorchakov et al. 2006) to an average of 87.5% of the concentration on weekdays (Gorchakov et al. 2010b). The factors that determine "calendar" variability (Gorchakov et al. 2010c) are included in a non-linear regression-autoregression model developed for reproducing the temporal evolution of the observed concentrations of various pollutants in the Moscow air basin (Demchenko et al. 2015).

Modeling the temporal evolution of air pollutants in the urban atmosphere serves for many purposes: for making forecasts of their concentrations at different time scales (Arya 1990, Baklanov et al 2007), for air quality management, and for relating the concentrations observed at stationary or mobile monitoring stations to the intensity and localization of emission sources (Bornstein, Johnson 1977). The models of the temporal evolution of air pollutants may be divided into statistical, simplified one-dimensional quasi-stationary models (Berlyand 1985), integral box models (Agirre-Basurko et al. 2006, Poggi, Portier 2011), and Euler or Lagrangian three-dimensional photochemical models (Arya 1990, Revokatova et al 2012) such as the COSMO-ART model, which is used by The Russian Federal Service for Hydrometeorology and Environmental Monitoring (Roshydromet) (Revokatova et al. 2012). Statistical models, in contrast to three-dimensional models, do not require information on the intensity of emission sources. Obtaining such information is a difficult task. Statistical models are also much more computationally effective. Some studies (Dias-Robles et al. 2008, Gardner, Dorling 1998) also demonstrate that the accuracy of statistical and three-dimensional models practically do not differ when they are used to predict the concentrations of pollutants for the upcoming day.

However, due to regional variations in the relationship between air pollution and meteorological conditions, the performance of a statistical model depends on the factors taken into consideration (Liu et al. 2020). This study is to reveal the contribution of such meteorological factors as wind speed, air temperature, and air humidity to the ability of a regression-autoregression model to reproduce the observed carbon monoxide concentrations.

MATERIALS AND METHODS

The prognostic equation of nonlinear regression-autoregression proposed by Demchenko et al. (2015) includes both external and internal factors. The internal factors include the concentrations of atmospheric pollutants for the days during a certain period preceding the day for which the forecast is made, and the external factors include meteorological factors.

The simplest way to predict any pollutant concentration on the one day ahead is using so-called inertial forecast, that is, to assume that tomorrow there will be the same concentration as today. It means that if in day before measured concentration is y_{i-1}, in the next day concentration $Y_i = y_{i-1}$ Bellow this forecast will be called "inertial".

In simplest autoregression model the one day ahead prediction of a pollutant concentration Y_i is based on the measured concentrations on the two previous days y_{i-1} and y_{i-2}.

The model will be represented by the following Eq. (1):

$$Y_i = a_1 y_{i-1} + a_2 y_{i-2} \quad (1)$$

where a_1 and a_2 are the coefficients that provide the best approximation in terms of the standard deviation of the predicted values from the observed values, Y_i is predicted value of CO concentration for the i-th day, y_{i-1} and y_{i-2} are concentrations of pollutant of previous 2 days, i is the index of the array containing the observed values of CO concentrations.

To study the role of wind speed, a term describing the effect of wind speed is added to the right side of Eq. (1) (Eq. (2)):

$$Y_i = a_1 y_{i-1} + a_2 y_{i-2} + a_3 \left(v_i + a_4 \right) \quad (2)$$

where is the average daily wind speed (m/s) at the day of forecast, a_1, a_2, a_3 and a_4 are the coefficients that provide the best approximation in terms of the standard deviation of the predicted values from the observed values. a_4 – additional coefficient for better accounting of calm conditions.

To study the role of air temperature (°C) a term describing the effect of air temperature is added to the right side of Eq. (2) (Eq. (3)):

$$Y_i = a_1 y_{i-1} + a_2 y_{i-2} + a_3 \left(v_i + a_4 \right) + a_5 T_i \quad (3)$$

where T_i – the daily mean air temperature, a_1, a_2, a_3, a_4 and a_5 are the coefficients that provide the best approximation in terms of the standard deviation of the predicted values from the observed values.

To study the role of relative air humidity (%), a term describing the effect of relative air humidity was added to the right side of Eq. (3) (Eq. (4)):

$$Y_i = a_1 y_{i-1} + a_2 y_{i-2} + a_3 \left(v_i + a_4 \right) + a_5 T_i + a_6 u_i \quad (4)$$

where u_i is the average daily air humidity, a_1, a_2, a_3, a_4, a_5 and a_6 are the coefficients that provide the best approximation in terms of the standard deviation of the predicted values from the observed values.

For a more complete consideration of the influence of meteorological conditions on the predicted concentration of gaseous pollution, it is helpful to include in the statistical model wind direction, surface air pressure, and preferably temperature at a certain height (for example, on the Ostankino tower), verbal gradations of stratification types (unstable, stable, weakly stable) and mixing intensity (intense, moderate, weak, strong). However, it is difficult to consider all these factors within the framework of a single article. This is the subject of further research and publications.

The observed values of carbon monoxide concentrations are provided by the Budgetary Environmental Protection Institution "Mosecomonitoring". The air quality monitoring system includes a network of automatic air pollution monitoring stations (AAPMS), specialized meteorological complexes for monitoring dispersion conditions, mobile laboratories, and an analytical laboratory accredited for laboratory analysis of a wide range of pollutants in the air. The atmospheric air pollution monitoring system in Moscow contains a network of 56 stationary automatic air pollution monitoring stations, which allow continuous and round-the-clock monitoring of more than 20 atmospheric pollution parameters (Fig. 1). In addition, there is a high-altitude air pollution control station at the Ostankino television tower. These automated air pollution control stations are located throughout the city and cover all functional areas: areas under the influence of major roads, sleeping areas, areas located at a distance from emission sources (suitable for background monitoring), areas affected by emissions from large industrial facilities.

To analyze the contribution of meteorological factors, we used two datasets representing different patterns of city lifestyle. The first dataset contains the data for May-July 2020. The COVID restrictions had an impact on lifestyle during this period. The second dataset contains the data for May-July 2021. During this period, Moscow citizens came back to their usual lifestyle.

Each period was divided into a training sub-period (May-June) and a prediction sub-period (July). The training sub-period is used to determine the coefficients of the Eq. (1-4) and to evaluate how well the model fits the

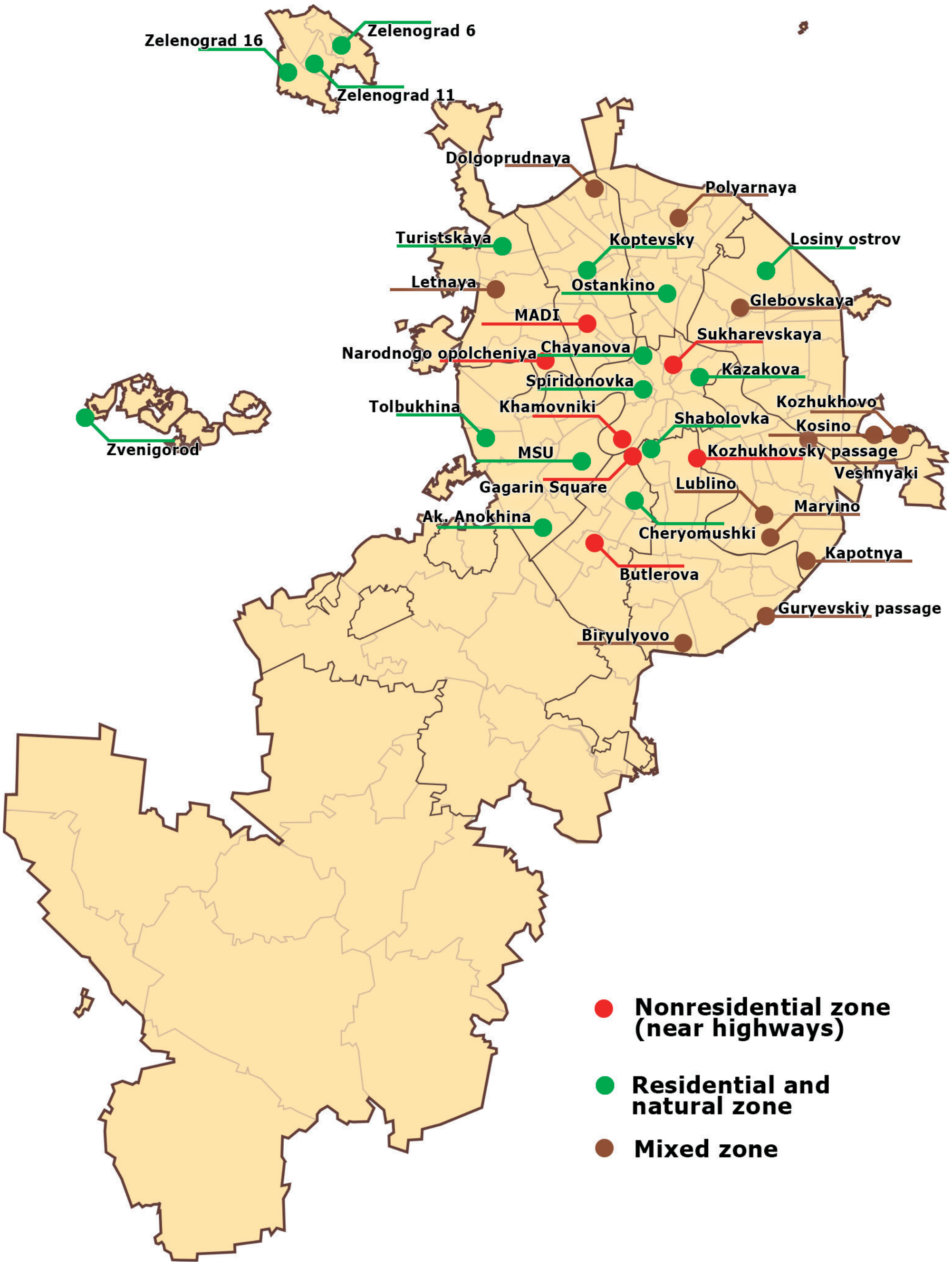

Fig. 1. Map of Automated air pollution control stations in Moscow
(map used as a source available by link https://commons.wikimedia.org/wiki/File:Msk_blank.svg?uselang=ru)

observations that were used for its training. The prediction sub-period is used to evaluate how well the model predicts observations that were not used for its training.

The meteorological data for the WMO station №27612 (VDNKh) which is usually considered a representative station for Moscow, and for the WMO station №27605 (Balchug), located in the city center, were taken from the RP5 website *(https://rp5.ru/)*. The code (R script) and primary data used in calculations are available upon request to the corresponding author.

RESULTS

The values of carbon monoxide concentration predicted with Eq. (1) correlate quite well with the observed ones (Table A.1). For example, at Zelenograd-6 station, the correlation coefficient is equal to 0.76, at MSU station, it is 0.85, at Chayanov, it is 0.78, and at half of the stations it exceeds 0.51.

One may slightly increase the correlation coefficient between the predicted and observed values of carbon monoxide concentrations by taking into account the factor of wind speed (Table A.1), Eq. (2). For example, at the MSU station, the correlation coefficient increases from 0.85 to 0.86, and at Chayanova, from 0.78 to 0.79. The exception is the Zvenigorod station, where the correlation coefficient increases from 0.03 to 0.43, and the Dolgoprudnaya station, where the correlation coefficient increases from 0.18 to 0.28.

If the air temperature (Table A.1) is also taken into account, Eq. (3) slightly improves the match between predicted and observed values compared to Eq. (2). The correlation coefficient increases by 0.15 at Dolgoprudnaya and by 0.12 at Sukharevskaya station; in most other cases, the increase does not exceed 0.02.

Considering additionally the factor of humidity (Table A.1), Eq. (4), has an even stronger effect: the correlation coefficient increases by 0.04 at most stations. The highest increase is achieved at the Lyublino station (by 0.17), the Dolgoprudnaya station (by 0.11) and the Glebovskaya station (by 0.10).

The Eq. (4), which includes wind speed, temperature, and relative humidity, reproduces well the concentrations observed at some stations (Fig. 2) and significantly increases the correlation between predicted and observed values compared to the Eq. (1), which does not include meteorological predictors: the correlation coefficient increases by 0.08 at most stations. In the case of Zvenigorod station, the correlation coefficient increases from 0.03 to 0.51, at the Dolgoprudnaya from 0.18 to 0.53, at the Lyublino from 0.24 to 0.50, at the Sukharevskaya from 0.50 to 0.71, at the station Spiridonovka from 0.39 to 0.55, and the median of the correlation coefficient increased to 0.59.

The results obtained using meteorological data from the Balchug station improved the average forecast results (July 2020 and 2021). For July 2020 with meteorological data from the VDNKh station (Table A.3), the maximum average correlation among all 4 types of models was 0.46 (Eq. (1)), but with meteorological data from the Balchug (Table A.5) it became 0.58 (Eq. (2)), exceeding the inertial forecast, which was 0.46, by 0.12 points.

For July 2021, we got almost the same results with meteorological data from the VDNKh station (Table A.4). The highest average correlation between all 4 types of models was 0.35 (Eq. (1)), but it rose to 0.56 (Eq. (2)) with meteorological data from the Balchug (Table A.6), which was 0.15 points higher than the inertial forecast of 0.41.

The observations show that the pattern of changes in carbon monoxide concentration varies from station to station. To find out if there was any connection between these patterns, we divided stations by administrative districts to see the correlation between stations. Stations were divided into 5 groups: northern districts (Table 1), Zelenograd district (Table 2), Eastern and Central administrative districts (Table 3) and Southern districts (Table 4). Carbon monoxide concentrations at the stations of the South-West Administrative District (Butlerova and Cheryomushki) correlate well with each other (Table 1). The South-Eastern Administrative District's stations (Veshnyaki, Lyublino, and Maryinsky Park) exhibit a similar correlation. As to the stations of the South Administrative District (Biryulyovo, Guryevskiy passage, Shabolovka), only Guryevskiy passage and Shabolovka correlate well with each other. The way that CO concentration changes over time at the Biryulyovo station is very different from how it changes at stations in the South Administrative District and in the southern parts of Moscow. As shown in Table 1, concentration changes at these stations (with the exception of Biryulyovo) are well correlated.

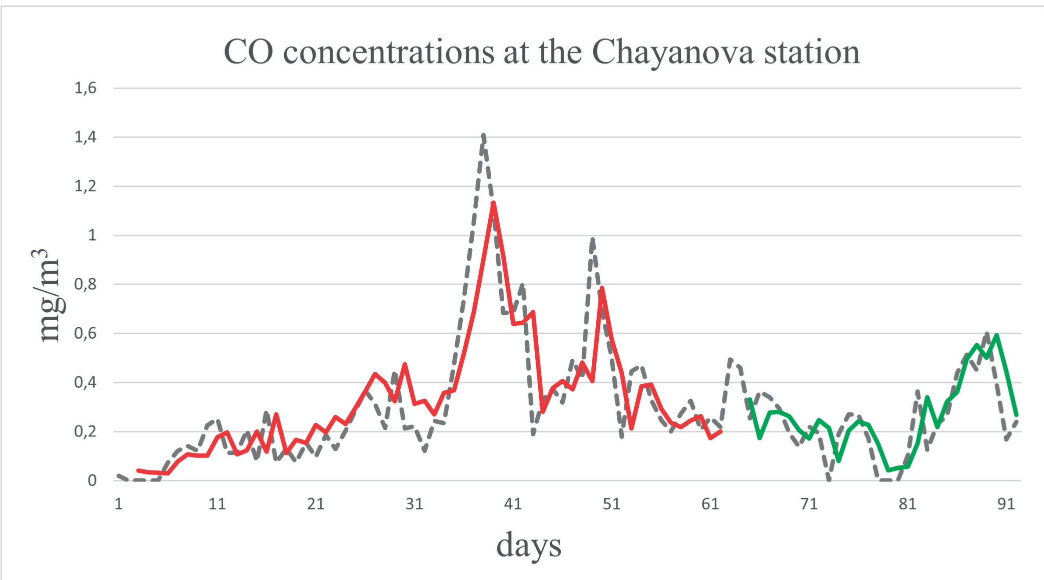

Fig. 2. CO concentrations at the Chayanova station in the period from May to July 2020: the gray dotted line is the observed values; the red line is the simulated values for the period from May to June; and the green line is the values for July (calculated with Eq. (4))

Table 1. Coefficients of pairwise correlation between changes in carbon monoxide concentration at the stations in the southern part of Moscow

Number and name of a station		1	2	3	4	5	6	7	8
1	Biryulyovo	1	0.53	0.41	0.25	0.45	0.44	0.50	0.34
2	Guryevskiy passage	0.53	1	0.71	0.76	0.77	0.67	0.63	0.68
3	Shabolovka	0.41	0.71	1	0.79	0.66	0.72	0.76	0.81
4	Veshnyaki	0.25	0.76	0.79	1	0.74	0.70	0.75	0.75
5	Lublino	0.45	0.77	0.66	0.74	1	0.81	0.59	0.72
6	Maryinsky park	0.44	0.67	0.72	0.70	0.81	1	0.59	0.74
7	Butlerova	0.50	0.63	0.76	0.75	0.59	0.59	1	0.74
8	Cheryomushki	0.34	0.68	0.81	0.75	0.72	0.74	0.74	1

The measurements at Zelenograd stations also correlate well with each other (Table 2).

However, the measurements at the stations of the Central Administrative District (Kazakova, Spiridonovka, Chayanova) do not correlate well with each other (Table 3a), as do the measurements at the stations of the Eastern Administrative District (Table 3b) and at the stations in the northern part of Moscow (Table 4).

The measurements at WAD stations (MSU and Tolbukhina) do not correlate well with each other (R=0.66). However, it is noteworthy that the MSU station's measurements exhibit a strong correlation with those from stations in other districts, specifically Ostankino (NEAD), R=0.77, Letnaya (NWAD), R=0.78, Kazakova (CAD), R=0.7, Shabolovka (SAD), R=0.77, Veshnyaki (SEAD), R=0.81, Cheryomushki (SWAD), R=0.77. In the worst scenario, the correlation coefficient between the measurements at the MSU station and the Kozhukhovo station is 0.25. However, measurements at the Kozhukhovo station generally correlate poorly with measurements at other stations in Moscow: the correlation coefficient does not exceed 0.49, and the median correlation coefficient is 0.3.

Another station where the measurements correlate poorly with those at other stations is the Biryulyovo station: the correlation coefficient does not exceed 0.51, and the median of the correlation coefficient is 0.25.

The measurements at the Losiny Ostrov station, located on a territory whose characteristics differ significantly from other observation zones, correlate better with measurements at other stations than measurements at Biryulyovo station: the median of the correlation coefficient is 0.53, and its maximum value is 0.7.

If we do not take into account the measurements at Biryulyovo, Kozhukhovo, Kosino, MADI, Polyarnaya,

Table 2. Pairwise correlation coefficients between changes in carbon monoxide concentration at Zelenograd stations

Number and name of a station		1	2	3
1	Zelenograd-mr 11	1	0.79	0.75
2	Zelenograd-mr 16	0.79	1	0.75
3	Zelenograd-mr 6	0.75	0.75	1

Table 3. Coefficients of pairwise correlation between changes in carbon monoxide concentration at the stations of the Central Administrative District (CAD) (a) and the Eastern Administrative District (EAD) (b)

Number and name of a EAD station (a)		1	2	3
1	Kozhukhovo	1	0.49	0.36
2	Kosino	0.49	1	0.40
3	Losiny Ostrov	0.36	0.40	1

Number and name of a CAD station (b)	1	2	3
Kazakova	1	0.55	0.28
Spiridonovka	0.55	1	0.32
Chayanova	0.28	0.32	1

Table 4. Coefficients of pairwise correlation between changes in carbon monoxide concentration at stations in the northern part of Moscow

Number and name of a station		1	2	3	4	5	6
1	Dolgoprudnaya	1	0.52	0.79	0.72	0.79	0.44
2	MADI	0.52	1	0.52	0.25	0.51	0.39
3	Ostankino	0.79	0.52	1	0.55	0.75	0.54
4	Polyarnaya	0.72	0.25	0.55	1	0.60	0.33
5	Letnaya	0.79	0.51	0.75	0.60	1	0.47
6	Turistskaya	0.44	0.39	0.54	0.33	0.47	1

Touristskaya, Chayanova stations, where the median of the correlation coefficient with measurements at other stations does not exceed 0.51, then we can say that the measurements at the remaining stations (Losiny Ostrov, Moscow State University, Tolbukhina, Dolgoprudny, Ostankino, Letnaya, Kazakova, Spiridonovka, Guryevskiy passage, Shabolovka, Lyublino, Maryinsky park, Butlerova, Cheryomushki) correlate well with each other: the medians of the correlation coefficient vary from 0.59, in the case of Losiny Ostrov station, to 0.74, in the case of the Veshnyaki station, and its smallest values vary from 0.47, in the case of the Spiridonovka station, to 0.64, in the case of the Veshnyaki station.

The absence of a pronounced spatial correlation between the stations supports the opinion (Dias-Robles et al. 2008, Gardner, Dorling 1998) that simplified onedimensional quasi-stationary statistical models are not less suitable than three-dimensional models for predicting the concentrations of pollutants for the day ahead. This means that each station can be analyzed and studied independently from the others.

We should keep in mind that the zones in which AAPMS is located determine its classification, given that changes in CO concentration by stations are independent. There are 3 types of zones: residential and natural, nonresidential (near highways) and mixed zones. Comparing predicted carbon monoxide concentrations for July 2020 and 2021 it is obvious that, in general, the correlation between the observed and predicted carbon monoxide concentrations for the prediction sub-period is stronger in the case of the station located in a residential and natural zone (Fig. 1) as can be seen from Tables 5 and 6.

DISCUSSION AND CONCLUSION

The application of the proposed statistical model with the account of different numbers of meteorological factors provides quite a complicated heterogeneous picture.

Table 5. Correlation between observed and predicted carbon monoxide concentrations for July 2020 (prediction sub-period) by zones

Station name	Correlation coefficient				
	Equation (1)	Equation (2) with v_i	Equation (3) with v, T	Equation (4) with v, T and u	Inertial
Residential and natural zone					
Shabolovka	0.44	0.56	0.56	0.58	0.46
Losiny Ostrov	0.65	0.70	0.70	0.60	0.62
Tolbukhina	0.50	0.56	0.59	0.60	0.52
Median	0.50	0.56	0.59	0.60	0.52
Average	0.53	0.61	0.62	0.59	0.53
Nonresidential zone (near highways)					
Sukharevskaya	0.5	0.57	-0.19	0.12	0.62
Kozhukhovsky passage	0.37	0.43	0.35	0.38	0.41
Zvenigorod	0.36	-0.02	-0.03	-0.04	0.36
Gagarin sq.	0.64	0.67	0.68	0.67	0.66
Median	0.44	0.50	0.16	0.25	0.52
Average	0.47	0.41	0.20	0.28	0.51
Mixed zone					
Maryino	0.21	0.01	0.2	-0.08	0,2
Glebovskaya	0.4	0.43	0.47	0.26	0.47
Lublino	0.18	0.2	0.22	0.02	0.18
Dolgoprudnaya	0.5	0.16	0.27	-0.06	0.42
Polyarnaya	0.65	0.64	0.66	0.62	0.64
Kozhukhovo	0.29	0.28	0.21	0.21	0.3
Median	0.35	0.24	0.25	0.12	0.36
Average	0.37	0.29	0.34	0.16	0.37

Table 6. Correlation between observed and predicted carbon monoxide concentrations for July 2021 (prediction sub-period) by zones

Station name	Correlation coefficient				
	Equation (1)	Equation (2) with v_i	Equation (3) with v, T	Equation (4) with v, T and u	Inertial
Residential zone					
Shabolovka	0.55	0.3	0.28	0.13	0.62
Losiny Ostrov	0.58	0.42	0.43	0.42	0.6
Tolbukhina	0.44	0.39	0.4	0.41	0.48
Median	0.55	0.39	0.40	0.41	0.60
Average	0.52	0.37	0.37	0.32	0.57
Nonresidential zone (near highways)					
Sukharevskaya	0.17	0.26	0.25	-0.05	0.3
Kozhukhovsky passage	0.53	0.5	0.5	0.46	0.6
Zvenigorod	0.23	0.31	0.32	0.28	0.32
Gagarin sq.	0.38	0.52	0.53	0.43	0.52
Median	0.31	0.41	0.41	0.36	0.42
Average	0.33	0.40	0.40	0.28	0.44
Mixed zone					
Maryino	0.18	0.16	0.12	0.13	0.2
Glebovskaya	0.2	0.27	0.27	0.25	0.29
Lublino	0.08	-0.04	-0.03	-0.01	0.13
Dolgoprudnaya	0.48	0.53	0.5	0.56	0.62
Polyarnaya	0.52	0.51	0.53	0.44	0.4
Kozhukhovo	0.02	0.08	0.07	0.11	0.16
Median	0.19	0.22	0.20	0.19	0.25
Average	0.25	0.25	0.24	0.25	0.30

Nevertheless. taking into account meteorological predictors such as wind speed. air temperature. and relative humidity increase the correlation between predicted and observed carbon monoxide concentrations. The addition of wind (Eq. (2)) increases the correlation coefficient between observed and modeled values by 0.0–0.4. adding temperature (Eq. (3)) increases the correlation coefficient by another 0.0–0.14. adding relative humidity (Eq. (4)) increases the correlation coefficient by another 0.0–0.17. It should be noted here that the effect of meteorological predictors is more pronounced at some stations than at others. For example. in the case of the station Sukharevskaya. the addition of meteorological predictors increases the correlation coefficient from 0.5 to 0.71 (Table A.1), and in the case of the MSU station, from 0.85 to 0.86 (Table A.1). To increase clarity, replace with: The effect of weather forecasters can change from year to year. For example, adding temperature raises the correlation coefficient between observed and modeled values in 2021 by 0.02–0.21; adding wind raises it by 0.00–0.07; and adding humidity raises it by 0.00–0.03. For example, in the case of the station Sukharevskaya, the correlation coefficient increases from 0.4 to 0.5 (Table A.2), and in the case of the MSU station, from 0.18 to 0.26 (Table A.2). Interannual variability in the intensity of economic activity might explain the interannual variability in the effect of meteorological predictors: in the period from May to June 2020, there were epidemiological restrictions on economic activity in Moscow (Ginzburg et al. 2020).

However, it is difficult to draw an unambiguous conclusion about the role of meteorological predictors for all stations when the equations were applied for periods that were not used in determining the coefficients. In some cases, adding relative humidity to the number of meteorological predictors reduces the correlation coefficient between predicted and observed values in July to negligible (and even negative) values. The addition of wind increases the correlation coefficient between observed and predicted values at 12 stations in July 2020 (Table A.3) by 0.0-0.12, and decreases by 0.01–0.38 at 6 stations; the addition of temperature increases the correlation coefficient by 0.0-0.19 at 13 stations and decreases by 0.01-0.76 at 5 stations; the addition of relative humidity increases the correlation coefficient by 0.0-0.31 at half of the stations and reduces by 0.01-0.33 the other half of the stations (Table A.3). In July 2021 (Table A.4) the addition of wind increases the correlation coefficient at 16 stations out of 28 stations by 0.0-0.14, and decreases by 0.01-0.25 at 12 stations; the addition of temperature increases the correlation coefficient by 0.0-0.04 at 18 stations and decreases by 0.01-0.05 at 10 stations; the addition of relative humidity increases the correlation coefficient by 0.0-0.09 at 13 stations and decreases by 0.01-0.3 at 15 stations (Table A.4). Almost the same result is obtained with RMSE (Table A.3, A.4), adding relative humidity (Eq. (4)) makes model worst then not adding any meteorological predictors (Eq.1). The correlation between the observed and predicted carbon monoxide concentrations for the training sub-periods of 2020 (Table A1) and 2021 (Table A.2) provided by the inertial forecast is weaker than that provided by any of the Eq. (1-4). As to the prediction sub-periods, at least one of Eq. (1-4) outperforms the inertial forecast at 15 out of 16 stations in 2020 (Table A.3) and at 10 out of 28 stations in 2021 (Table A.4). At all stations in 2020 (Table A.3) and at 23 of the 28 stations in 2021 (Table A.4), at least one of Eq. (1-4) does better than the inertial forecast in terms of RMSE. The correlation between the observed and predicted carbon monoxide concentrations for the prediction sub-periods provided by the Eq. (4) is weaker than that provided by any of the Eq. (1-3) at 8 out of 16 stations in 2020 (Table A.3) and at 14 out of 28 stations in 2021 (Table A.4). Hence, taking into account air humidity may reduce the prognostic value of a model. The RMSE provided by Eq. (4) is higher than that provided by any of Eq. (1-3) at the 4 out of 16 stations in 2020 (Table A.3) and at the 10 out of 28 stations in 2021 (Table A.4). This trend remains for meteorological data from Balchug, too. For 7 out of 16 stations, adding humidity worsened the correlation coefficient; for 5 out of 16 stations it improved, and for 4 stations, it remained unchanged. There were also exceptions at stations Shabolovka and Kozhukhovo. A gradual improvement was observed with the addition of meteorological parameters; the correlation coefficient increased from 0.44 to 0.68 and from 0.29 to 0.37, respectively. In the case of Dolgoprudnaya station, the correlation for Eq. (2) was 0.56, but when temperature and humidity were added, the correlation coefficient dropped to 0.29. This is also an isolated case, but the meteorological data from VDNKh showed a sharp drop in the correlation coefficient when adding meteorological parameters. The trend that adding humidity worsens the forecast also continues for 2021 and is revealed even more clearly. For 19 out of 27 stations, the addition of humidity led to a worsening of the forecast, and at 4 out of 27 to an improvement; at 4 stations there was no change. Stations Shabolovka and Kazakova, as in 2020, show a trend towards improving the forecast with the addition of meteorological parameters. At station Butlerova, with the addition of humidity, the correlation coefficient increased from 0.08 to 0.24, but this is rather an exception. For 2020 and 2021, we can conclude that changes in weather data led to a significant improvement in the forecast, but adding humidity is not recommended, since (in 70% of cases for the period in 2021), this leads to its deterioration. Hence, taking into account air humidity may reduce the prognostic value of a model.

Therefore, adding relative air humidity to the list of meteorological predictors doesn’t seem like a good way to improve a long-range forecast, since it makes the model less accurate most of the time. The inclusion of air temperature in the number of meteorological predictors increased the predictive value of the model at most stations, making it suitable for improving a long-range forecast of carbon monoxide concentration. Wind speed, similarly to air temperature, is shown to be a significant predictor of CO concentration in Moscow.

The wind speed, air temperature and relative humidity are not the only meteorological factors that may improve the accuracy of CO concentration forecast. There are some factors that describe weather conditions verbally (Kuznetsova 2021) that are hard to add to the model. For a more complete consideration of the influence of meteorological conditions on the predicted concentration of gaseous pollution, it is necessary to include in the statistical model wind direction, surface air pressure, and preferably temperature at a certain height (for example, on the Ostankino tower), verbal gradations of stratification types (unstable, stable, weakly stable) and mixing intensity (intense, moderate, weak, strong). However, it is difficult to consider all these factors within the framework of a single article. Further research is needed to understand why some meteorological factors may reduce the accuracy of CO concentration forecast provided by the statistical model. The results of this study suggest that the role of meteorological factors in explaining the observed variability of CO concentrations may fundamentally differ from their role in predicting the changes in CO concentrations for the day ahead: the comprehensive consideration of meteorological factors definitely improves the explanatory value of a model, but to improve the prognostic value of the model, it might be better to exclude some of the meteorological factors from consideration.

REFERENCES

Agirre-Basurko E., Ibarra-Berastedi G., Madariaga I. (2006). Regression and multilayer perception-based models to forecast O3 and NO2 levels in Bilbao area. Environmental Modelling & Software, 21(4), 430-446, DOI:10.1016/j.envsoft.2004.07.008.

Arya S.P. (1990). Air pollution meteorology and dispersion. Oxford: Oxford University Press.

Baklanov A., Hanninen O., Stordal L.H. et al. (2007). Integrated systems for forecasting urban meteorology, air pollution, and population exposure. Atmospheric Chemistry and Physics, 7(3), 855-874, DOI:/10.5194/acp-7-855-2007.

Benavides, J., Snyder, M., Guevara, M., Soret, A., Pérez García-Pando, C., Amato, F., & Jorba, O. (2019). CALIOPE-Urban v1. 0: coupling R-LINE with a mesoscale air quality modelling system for urban air quality forecasts over Barcelona city (Spain). Geoscientific Model Development, 12(7), 2811-2835, DOI:10.5194/gmd-12-2811-2019.

Berlyand M.E. (1985). Forecast and regulation of atmospheric pollution. Leningrad: Gidrometeoizdat.

Berlyand M.E. (1991). Statistical methods of air pollution forecasting. In: Prediction and Regulation of Air Pollution. Atmospheric Sciences Library, vol 14. Dordrecht: Springer, 159-201, DOI:10.1007/978-94-011-3768-3_6.

Bornstein R.D. and Johnson D.S. (1977). Urban – rural wind velocity differences. Atmospheric Environment, 11(7), 597-604, DOI:10.1016/0004-6981(77)90112-3.

Comrie A. C. and Diem J. E. (1999). Climatology and forecast modeling of ambient carbon monoxide in Phoenix, Arizona. Atmospheric Environment, 33(30), 5023-5036, DOI:10.1016/S1352-2310(99)00314-3.

Czerwińska J. and Wielgosiński G. (2020). The effect of selected meteorological factors on the process of» Polish smog» formation. Journal of Ecological Engineering, 21(1), 180-187, DOI:10.12911/22998993/112764.

Demchenko P.F., Ginzburg A.S., Aleksandrov G.G., Gorchakov G.I., Zavalishin N.N., Yudin N.I., Vereskov A.I., Zakharova P.V. and Lezina E.A. (2015). Statistical modeling of average daily concentration of pollutants in the atmosphere over Moscow megalopolis by the multiple regression method. Russian Meteorology and Hydrology, 40, 658-666, DOI:10.3103/S1068373915100039.

Dias-Robles L.A., Ortega J.C., Fu J.S., Reed G.D., Chow J.C., Watson J.G. and Moncada-Herrera J.A. (2008). A Hybrid ARIMA and artificial neural networks model to forecast particulate matter in urban areas: the case of Temuco, Chile. Atmospheric Environment, 42(35), 8331 – 8340, DOI:10.1016/j.atmosenv.2008.07.020.

Đurić M and Vujović D. (2020). Short-term forecasting of air pollution index in Belgrade, Serbia. Meteorological Applications, 27(5), 1946, DOI:10.1002/met.1946.

Elansky N.F., Belikov I.B., Skorokhod A.I., Lokoshchenko M.A. and Trifanova A.V. (2015). On contents of trace gases in the atmospheric surface layer over Moscow. Izvestiya, Atmospheric and Oceanic Physics, 51(1), 30-41, DOI:10.1134/S000143381501003X.

Gardner M.W and Dorling S.R. (1998). Artificial Neural Networks (the MaltilayerPrecepton) – a Review of applications in the atmospheric sciences. Atmospheric Environment, 32(14-15), 2627-2636, DOI:10.1016/S1352-2310(97)00447-0.

Ginzburg A.S., Semenov V.A., Semutnikova E.G., Aleshina M.A., Zakharova P.V. and Lezina E.A. (2020). Impact of COVID-19 Lockdown on Air Quality in Moscow. Doklady Earth Sciences, 495, 862–866, DOI:10.1134/S1028334X20110069.

Golitsyn G.S., Grechko E.I., Dzhola A.V., Emilenko A.S., Kopeikin V.M., Rakitin V.S., Safronov A.N., Fokeeva E.V., Wang G. and Wang P. (2015). Studying the pollution of Moscow and Beijing atmospheres with carbon monoxide and aerosol. Izvestiya, Atmospheric and Oceanic Physics, 51, 1-11, DOI:10.1134/S0001433815010041.

Gorchakov G.I., Zotkin E.V., Karpov A.V., Ul'yanenko A.V., Semutnikova E.G. and Lezina E.A. (2006). Variations in gaseous pollutants in the air basin of Moscow. Izvestiya, Atmospheric and Oceanic Physics, 42, 156-170, DOI:10.1134/S0001433806020046.

Gorchakov G.I., Karpov A.V., Kolesnikova A.B., Baikova E.S., Semutnikova E.G. and Zadorozhnaya O.S. (2010a). Weekly cycle of air pollution in Moscow: quantitative characteristics and refinement of the method of statistical forecasting of impurity concentrations. Optics of the atmosphere and the ocean, 23(9), 784-792, (in Russian with English summary).

Gorchakov G.I., Anoshin B.A., Karpov A.V., Kolesnikova A.B. and Semoutnikova E.G. (2010b). Statistical prediction of the pollution of the urban atmosphere. 1. Statistical regularities of the interdiurnal variations of the carbon monoxide and nitrogen oxide concentrations. Atmospheric and Oceanic Optics, 23(4), 309-316, DOI:10.1134/S102485601004010X.

Gorchakov G.I., Anoshin B.A., Karpov A.V., Kolesnikova A.B. and Semoutnikova E.G. (2010c). Statistical prediction of the urban atmosphere contamination. 2. Forecasting method of the interdiurinal and intradiurnal concentration variability of the carbon monoxide and nitrogen oxides. Atmospheric and Oceanic Optics, 23(5), 396-403, DOI:10.1134/S102485601005009X.

Grechko E.I., Dzhola A.V., Rakitin V.S., Fokeeva E.V.and Kuznetsov R.D. (2009). Variation of the carbon monoxide total column and atmospheric boundary layer parameters in the center of Moscow. Atmospheric and Oceanic Optics, 22(3), 203-208, DOI:10.1134/S1024856009020110.

Kuznetsova I.N. (2012). The effect of meteorology on air pollution in Moscow during the summer episodes of 2010. Izvestiya, Atmospheric and Oceanic Physics, 48(5), 504-515, DOI:10.1134/S0001433812050052.

Kuznetsova I.N., Tkacheva Yu.V, Shalygina I.Yu. and Nakhaev M.I. (2021). Forecasting a meteorological indicator of pollutant dispersion in surface air. Hydrometeorological Research and Forecasting, 3(381), 131-149, (in Russian with English summary), DOI:10.37162/2618-9631-2021-3-131-149.

Li R., Wang Z., Cui L., Fu H., Zhang L., Kong L. and Chen J. (2019). Air pollution characteristics in China during 2015–2016: Spatiotemporal variations and key meteorological factors. Science of the total environment, 648, 902-915, DOI:10.1016/j.scitotenv.2018.08.181.

Liu Y., Zhou Y. and Lu J. (2020). Exploring the relationship between air pollution and meteorological conditions in China under environmental governance. Scientific reports, 10(1), 14518, DOI:10.1038/s41598-020-71338-7.

Poggi J.M and Portier B. (2011). PM10 forecasting using clusterwise regression. Atmospheric Environment, 45(38), 7005-7014, DOI:10.1016/j.atmosenv.2011.09.016.

Rakitin V.S., Elansky N.F., Skorokhod A.I., Dzhola A.V., Rakitina A.V., Shilkin A.V., Kirillova N.S. and Kazakov A.V. (2021). Long-term tendencies of carbon monoxide in the atmosphere of the Moscow megapolis. Izvestiya, Atmospheric and Oceanic Physics, 57(1), 116-125, DOI:10.1134/S0001433821010102.

Revokatova, A. P., Surkova, G. V., Kirsanov A.A. and Rivin G.S. (2012). Forecast of air pollution in the Moscow region using the COSMO-ART model. Bulletin of Moscow University Series 5 Geography, 4, 25-32, (in Russian with English summary).

Ruan H. L., Deng W. S., Wang Y., Chen J. B., Hong W. L., Ye S. S. and Hu Z. J. (2021). Carbon monoxide poisoning: a prediction model using meteorological factors and air pollutant. BMC proceedings, 15, 1-9, DOI:10.1186/s12919-021-00206-7.

Vilfand R.M., Kuznetsova I.N., Shalygina I.Yu., Zvyagintsev A.M., Nakhaev M.I., Zakharova P.V. and Lapchenko V.A. (2014). Monitoring and forecasting of air quality in the Moscow region. Biosphere, 6(4), 339-351, (in Russian with English summary), DOI:10.24855/biosfera.v6i4.178.

Zavalishin N.N., Ginzburg A.S. and Alexandrov G.G. (2018). Statistical forecasting method for atmospheric air pollution in megapolises: Moscow case study. International conference and early career scientist's school on environmental observations, modeling and information systems: ENVIROMIS-2018, 302-305, (in Russian with English summary).

APPENDICES

Table A.1. Correlation and RMSE values between observed and predicted values of carbon monoxide concentrations for May-June 2020 (training sub-period) based on data from the VDHKh weather station.

Station name	Correlation coefficient / RMSE				
	Equation (1)	Equation (2) with v_i	Equation (3) with *v, T*	Equation (4) with *v, T and u*	Inertial
Sukharevskaya	0.50 / 0.119	0.51 / 0.110	0.63 / 0.099	0.71 / 0.089	0.50 / 0.127
Shabolovka	0.48 / 0.085	0.51 / 0.075	0.55 / 0.073	0.57 / 0.072	0.47 / 0.088
Kazakova	0.49 / 0.088	0.52 / 0.079	0.55 / 0.077	0.59 / 0.075	0.49 / 0.092
Maryino	0.29 / 0.084	0.35 / 0.075	0.36 / 0.075	0.42 / 0.073	0.30 / 0.097
Zelenograd 6	0.76 / 0.084	0.76 / 0.080	0.77 / 0.079	0.79 / 0.076	0.75 / 0.086
Zelenograd 11	0.51 / 0.065	0.51 / 0.061	0.51 / 0.060	0.55 / 0.059	0.50 / 0.071
MADI	0.22 / 0.182	0.27 / 0.156	0.28 / 0.155	0.29 / 0.155	0.26 / 0.199
Biryulyovo	0.65 / 0.143	0.68 / 0.131	0.70 / 0.127	0.72 / 0.124	0.65 / 0.152
Moscow State University (MSU)	0.85 / 0.090	0.86 / 0.084	0.86 / 0.082	0.86 / 0.077	0.82 / 0.090
Butlerova	0.63 / 0.052	0.64 / 0.048	0.66 / 0.048	0.71 / 0.045	0.61 / 0.053
Losiny Ostrov	0.64 / 0.124	0.65 / 0.113	0.65 / 0.112	0.71 / 0.105	0.66 / 0.135
Glebovskaya	0.43 / 0.172	0.44 / 0.146	0.46 / 0.145	0.56 / 0.133	0.42 / 0.184
Lublino	0.24 / 0.09	0.30 / 0.084	0.33 / 0.082	0.50 / 0.077	0.28 / 0.090
Chayanova	0.78 / 0.183	0.79 / 0.175	0.80 / 0.171	0.81 / 0.168	0.79 / 0.189
Tolbukhina	0.37 / 0.112	0.41 / 0.097	0.46 / 0.094	0.49 / 0.093	0.39 / 0.117
Dolgoprudnaya	0.18 / 0.093	0.28 / 0.081	0.42 / 0.076	0.53 / 0.071	0.21 / 0.106
Narodnogo opolcheniya	0.56 / 0.186	0.56 / 0.172	0.57 / 0.171	0.63 / 0.161	0.54 / 0.195
Polyarnaya	0.66 / 0.078	0.69 / 0.069	0.69 / 0.068	0.72 / 0.066	0.63 / 0.080
Spiridonovka	0.39 / 0.109	0.44 / 0.094	0.53 / 0.089	0.55 / 0.088	0.46 / 0.109
Kozhukhovsky passage	0.52 / 0.109	0.53 / 0.094	0.58 / 0.089	0.62 / 0.088	0.52 / 0.107
Ostankino	0.53 / 0.193	0.54 / 0.175	0.56 / 0.168	0.58 / 0.162	0.52 / 0.202
Zvenigorod	0.03 / 0.074	0.43 / 0.067	0.43 / 0.066	0.51 / 0.065	0.17 / 0.077
Kozhukhovo	0.41 / 0.127	0.47 / 0.094	0.50 / 0.094	0.51 / 0.089	0.43 / 0.150
Gagarin sq.	0.51 / 0.103	0.52 / 0.089	0.54 / 0.087	0.59 / 0.087	0.53 / 0.108
Median	0.51 / 0.109	0.52 / 0.094	0.55 / 0.089	0.59 / 0.088	0.50 / 0.108
Average	0.48 / 0.116	0.53 / 0.103	0.56 / 0.101	0.61 / 0.097	0.50 / 0.122

Table A.2. Correlation and RMSE values between observed and predicted carbon monoxide concentrations for May-June 2021 (training sub-period) based on data from the VDHKh weather station.

Station name	Correlation coefficient / RMSE value				
	Equation (1)	Equation (2) with v_i	Equation (3) with *v, T*	Equation (4) with *v, T and u*	Inertial
Sukharevskaya	0.40 / 0.147	0.47 / 0.127	0.49 / 0.126	0.50 / 0.125	0.38 / 0.161
Shabolovka	0.30 / 0.117	0.35 / 0.103	0.38 / 0.102	0.38 / 0.102	0.27 / 0.130
Kazakova	0.27 / 0.136	0.33 / 0.12	0.33 / 0.120	0.36 / 0.119	0.24 / 0.154
Maryino	0.40 / 0.144	0.45 / 0.129	0.47 / 0.128	0.47 / 0.127	0.37 / 0.165
Zelenograd 6	0.40 / 0.112	0.41 / 0.103	0.42 / 0.102	0.42 / 0.102	0.34 / 0.128
Zelenograd 11	0.51 / 0.112	0.52 / 0.104	0.52 / 0.103	0.52 / 0.103	0.50 / 0.123
Zelenograd 16	0.51 / 0.141	0.56 / 0.122	0.56 / 0.122	0.58 / 0.121	0.53 / 0.142
MADI	0.45 / 0.153	0.45 / 0.141	0.50 / 0.138	0.51 / 0.136	0.41 / 0.169
Biryulyovo	0.49 / 0.124	0.52 / 0.111	0.52 / 0.111	0.52 / 0.111	0.50 / 0.131
Moscow State University (MSU)	0.18 / 0.088	0.25 / 0.077	0.26 / 0.077	0.26 / 0.077	-0.12 / 0.118
Butlerova	0.08 / 0.147	0.24 / 0.119	0.31 / 0.117	0.32 / 0.116	0.17 / 0.156
Losiny Ostrov	0.35 / 0.082	0.40 / 0.073	0.40 / 0.073	0.40 / 0.073	0.32 / 0.089
Glebovskaya	0.46 / 0.104	0.47 / 0.096	0.47 / 0.096	0.47 / 0.096	0.47 / 0.112
Lublino	0.18 / 0.202	0.39 / 0.162	0.40 / 0.161	0.40 / 0.161	0.20 / 0.223
Ak. Anokhina	0.28 / 0.141	0.33 / 0.123	0.36 / 0.122	0.37 / 0.121	0.26 / 0.159
Chayanova	0.43 / 0.108	0.50 / 0.093	0.51 / 0.093	0.51 / 0.093	0.44 / 0.113
Tolbukhina	0.41 / 0.122	0.47 / 0.107	0.48 / 0.107	0.48 / 0.107	0.37 / 0.135
Veshnyaki	0.66 / 0.121	0.68 / 0.111	0.68 / 0.110	0.69 / 0.110	0.66 / 0.127
Dolgoprudnaya	0.31 / 0.119	0.46 / 0.102	0.47 / 0.102	0.47 / 0.101	0.32 / 0.135
Koptevsky	0.54 / 0.216	0.54 / 0.203	0.56 / 0.201	0.56 / 0.201	0.49 / 0.237
Polyarnaya	0.49 / 0.207	0.54 / 0.182	0.56 / 0.179	0.57 / 0.178	0.51 / 0.216
Cheryomushki	0.36 / 0.104	0.39 / 0.093	0.39 / 0.093	0.39 / 0.093	0.33 / 0.117
Touristskaya	0.27 / 0.113	0.31 / 0.099	0.31 / 0.099	0.31 / 0.099	0.25 / 0.129
Spiridonovka	0.40 / 0.097	0.44 / 0.086	0.44 / 0.086	0.44 / 0.086	0.39 / 0.105
Kozhukhovsky passage	0.67 / 0.128	0.68 / 0.12	0.68 / 0.120	0.68 / 0.120	0.64 / 0.140
Ostankino	0.28 / 0.095	0.32 / 0.084	0.33 / 0.083	0.34 / 0.083	0.18 / 0.104
Zvenigorod	0.30 / 0.162	0.40 / 0.138	0.41 / 0.138	0.41 / 0.137	0.33 / 0.173
Kozhukhovo	0.32 / 0.109	0.37 / 0.096	0.38 / 0.096	0.39 / 0.095	0.30 / 0.120
Gagarin sq.	0.34 / 0.196	0.40 / 0.169	0.40 / 0.169	0.41 / 0.169	0.36 / 0.207
Khamovniki	0.51 / 0.238	0.52 / 0.22	0.52 / 0.219	0.52 / 0.218	0.50 / 0.254
Kapotnya	0.69 / 0.101	0.71 / 0.093	0.72 / 0.091	0.72 / 0.091	0.69 / 0.106
Median	0.40 / 0.122	0.45 / 0.111	0.47 / 0.110	0.47 / 0.110	0.37 / 0.135
Average	0.39 / 0.135	0.45 / 0.120	0.46 / 0.119	0.46 / 0.118	0.37 / 0.148

Table A.3. Correlation and RMSE values between observed and predicted carbon monoxide concentrations for July 2020 (prediction sub-period) based on data from the VDHKh weather station.

Station name	Correlation coefficient / RMSE value				
	Equation (1)	Equation (2) with v_i	Equation (3) with *v, T*	Equation (4) with *v, T and u*	Inertial
Shabolovka	0.44 / 0.11	0.56 / 0.091	0.56 / 0.104	0.58 / 0.089	0.46 / 0.112
Maryino	0.21 / 0.065	0.01 / 0.062	0.20 / 0.059	-0.08 / 0.088	0.20 / 0.075
MADI	0.31 / 0.219	0.27 / 0.206	0.36 / 0.217	0.33 / 0.207	0.31 / 0.232
Losiny Ostrov	0.65 / 0.066	0.70 / 0.060	0.70 / 0.061	0.60 / 0.077	0.62 / 0.072
Glebovskaya	0.40 / 0.172	0.43 / 0.158	0.47 / 0.177	0.26 / 0.169	0.47 / 0.171
Lublino	0.18 / 0.185	0.20 / 0.175	0.22 / 0.213	0.02 / 0.190	0.18 / 0.203
Chayanova	0.62 / 0.129	0.65 / 0.127	0.67 / 0.154	0.69 / 0.119	0.61 / 0.140
Tolbukhina	0.50 / 0.117	0.56 / 0.105	0.59 / 0.133	0.60 / 0.107	0.52 / 0.118
Dolgoprudnaya	0.50 / 0.126	0.16 / 0.146	0.27 / 0.203	-0.06 / 0.171	0.42 / 0.146
Narodnogo opolcheniya	0.72 / 0.217	0.76 / 0.207	0.76 / 0.206	0.78 / 0.312	0.76 / 0.209
Polyarnaya	0.65 / 0.155	0.64 / 0.148	0.66 / 0.157	0.62 / 0.145	0.64 / 0.152
Spiridonovka	0.46 / 0.142	0.46 / 0.136	0.42 / 0.221	0.45 / 0.176	0.44 / 0.154
Kozhukhovsky passage	0.37 / 0.183	0.43 / 0.158	0.35 / 0.251	0.38 / 0.167	0.41 / 0.188
Zvenigorod	0.36 / 0.101	-0.02 / 0.119	-0.03 / 0.113	-0.04 / 0.183	0.36 / 0.114
Kozhukhovo	0.29 / 0.109	0.28 / 0.099	0.21 / 0.125	0.21 / 0.110	0.31 / 0.114
Gagarin sq.	0.64 / 0.135	0.67 / 0.126	0.68 / 0.138	0.67 / 0.131	0.66 / 0.137
Median	0.45 / 0.132	0.45 / 0.132	0.45 / 0.156	0.42 / 0.156	0.45 / 0.143
Average	0.46 / 0.139	0.42 / 0.133	0.44 / 0.158	0.38 / 0.153	0.46 / 0.146

Table A.4. Correlation and RMSE values between observed and predicted carbon monoxide concentrations for July 2021 (prediction sub-period) based on data from the VDHKh weather station.

Station name	Correlation coefficient / RMSE value				
	Equation (1)	Equation (2) with v_i	Equation (3) with *v, T*	Equation (4) with *v, T and u*	Inertial
Sukharevskaya	0.17 / 0.214	0.26 / 0.181	0.25 / 0.180	-0.05 / 0.241	0.30 / 0.211
Shabolovka	0.55 / 0.065	0.30 / 0.073	0.28 / 0.070	0.13 / 0.071	0.62 / 0.064
Kazakova	0.35 / 0.122	0.33 / 0.107	0.34 / 0.107	0.29 / 0.147	0.38 / 0.140
Maryino	0.18 / 0.153	0.16 / 0.133	0.12 / 0.135	0.13 / 0.145	0.20 / 0.169
Zelenograd 6	0.40 / 0.131	0.41 / 0.116	0.38 / 0.117	0.38 / 0.117	0.49 / 0.135
Zelenograd 11	0.35 / 0.093	0.35 / 0.085	0.35 / 0.086	0.33 / 0.093	0.35 / 0.099
Zelenograd 16	0.63 / 0.188	0.71 / 0.163	0.71 / 0.164	0.67 / 0.198	0.65 / 0.184
Biryulyovo	0.29 / 0.122	0.32 / 0.106	0.32 / 0.106	0.33 / 0.108	0.36 / 0.122
Moscow State University (MSU)	0.20 / 0.106	0.06 / 0.098	0.06 / 0.099	0.07 / 0.104	0.13 / 0.125
Butlerova	0.07 / 0.120	-0.16 / 0.115	-0.21 / 0.130	-0.12 / 0.111	0.04 / 0.136
Losiny Ostrov	0.58 / 0.047	0.42 / 0.064	0.43 / 0.063	0.42 / 0.061	0.60 / 0.048
Glebovskaya	0.20 / 0.150	0.27 / 0.136	0.27 / 0.135	0.25 / 0.138	0.29 / 0.153
Lublino	0.08 / 0.230	-0.04 / 0.199	-0.03 / 0.199	-0.01 / 0.198	0.13 / 0.246
Ak. Anokhina	0.39 / 0.127	0.47 / 0.116	0.46 / 0.125	0.34 / 0.113	0.54 / 0.120
Chayanova	0.52 / 0.114	0.56 / 0.105	0.56 / 0.103	0.56 / 0.106	0.56 / 0.117
Tolbukhina	0.44 / 0.134	0.39 / 0.124	0.40 / 0.124	0.41 / 0.123	0.48 / 0.139
Dolgoprudnaya	0.48 / 0.149	0.53 / 0.140	0.50 / 0.140	0.56 / 0.136	0.62 / 0.135
Koptevsky	0.12 / 0.193	0.15 / 0.176	0.13 / 0.184	0.17 / 0.199	0.24 / 0.210
Polyarnaya	0.52 / 0.191	0.51 / 0.166	0.53 / 0.164	0.44 / 0.229	0.40 / 0.195
Cheryomushki	0.37 / 0.092	0.39 / 0.092	0.39 / 0.092	0.34 / 0.092	0.71 / 0.079
Touristskaya	0.58 / 0.112	0.54 / 0.106	0.53 / 0.106	0.53 / 0.105	0.53 / 0.110
Kozhukhovsky passage	0.53 / 0.140	0.50 / 0.132	0.50 / 0.131	0.46 / 0.156	0.60 / 0.131
Ostankino	0.40 / 0.088	0.45 / 0.080	0.49 / 0.080	0.58 / 0.075	0.45 / 0.091
Zvenigorod	0.23 / 0.184	0.31 / 0.155	0.32 / 0.156	0.28 / 0.184	0.32 / 0.188
Kozhukhovo	0.02 / 0.119	0.08 / 0.107	0.07 / 0.104	0.11 / 0.145	0.16 / 0.123
Gagarin sq.	0.38 / 0.211	0.52 / 0.209	0.53 / 0.208	0.43 / 0.272	0.52 / 0.194
Khamovniki	0.42 / 0.167	0.43 / 0.148	0.45 / 0.150	0.32 / 0.211	0.47 / 0.169
Kapotnya	0.37 / 0.124	0.36 / 0.113	0.36 / 0.113	0.34 / 0.130	0.39 / 0.126
Median	0.38 / 0.129	0.38 / 0.116	0.37 / 0.124	0.34 / 0.133	0.43 / 0.135
Average	0.35 / 0.139	0.34 / 0.127	0.34 / 0.127	0.31 / 0.143	0.41 / 0.141

Table A.5. Correlation and RMSE values between observed and predicted carbon monoxide concentrations for July 2020 (prediction sub-period) based on data from the Balchug weather station.

Station name	Correlation coefficient / RMSE value				
	Equation (1)	Equation (2) with v_i	Equation (3) with *v, T*	Equation (4) with *v, T and u*	Inertial
Shabolovka	0.44 / 0.110	0.66 / 0.083	0.66 / 0.083	0.68 / 0.083	0.46 / 0.112
Maryino	0.21 / 0.065	0.48 / 0.054	0.50 / 0.061	0.54 / 0.057	0.20 / 0.075
MADI	0.31 / 0.219	0.44 / 0.193	0.40 / 0.193	0.33 / 0.195	0.31 / 0.232
Losiny Ostrov	0.65 / 0.066	0.74 / 0.056	0.75 / 0.056	0.74 / 0.057	0.62 / 0.072
Glebovskaya	0.4 / 0.172	0.64 / 0.135	0.66 / 0.135	0.66 / 0.135	0.47 / 0.171
Lublino	0.18 / 0.185	0.3 / 0.168	0.34 / 0.162	0.35 / 0.159	0.18 / 0.203
Chayanova	0.62 / 0.129	0.67 / 0.127	0.67 / 0.128	0.66 / 0.133	0.61 / 0.140
Tolbukhina	0.5 / 0.117	0.69 / 0.092	0.69 / 0.094	0.68 / 0.095	0.52 / 0.118
Dolgoprudnaya	0.5 / 0.126	0.56 / 0.130	0.29 / 0.137	0.29 / 0.137	0.42 / 0.146
Narodnogo opolcheniya	0.72 / 0.217	0.73 / 0.212	0.72 / 0.219	0.75 / 0.205	0.76 / 0.209
Polyarnaya	0.65 / 0.155	0.74 / 0.134	0.73 / 0.135	0.74 / 0.134	0.64 / 0.152
Spiridonovka	0.46 / 0.142	0.46 / 0.138	0.46 / 0.138	0.46 / 0.138	0.44 / 0.154
Kozhukhovsky passage	0.37 / 0.183	0.6 / 0.141	0.63 / 0.137	0.64 / 0.137	0.41 / 0.188
Zvenigorod	0.36 / 0.101	0.43 / 0.113	0.38 / 0.149	0.42 / 0.144	0.36 / 0.114
Kozhukhovo	0.29 / 0.109	0.35 / 0.096	0.37 / 0.093	0.37 / 0.094	0.31 / 0.114
Gagarin sq.	0.64 / 0.135	0.75 / 0.112	0.75 / 0.117	0.74 / 0.122	0.66 / 0.137
Median	0.45 / 0.132	0.62 / 0.128	0.64 / 0.135	0.65 / 0.135	0.45 / 0.143
Average	0.46 / 0.139	0.58 / 0.124	0.56 / 0.127	0.56 / 0.127	0.46 / 0.146

Table A.6. Correlation and RMSE values between observed and predicted carbon monoxide concentrations for July 2021 (prediction sub-period) based on data from the Balchug weather station.

Station name	Correlation coefficient / RMSE value				
	Equation (1)	Equation (2) with v_i	Equation (3) with v, T	Equation (4) with v, T and u	Inertial
Sukharevskaya	0.17 / 0.214	0.30 / 0.177	0.26 / 0.182	0.32 / 0.180	0.30 / 0.211
Shabolovka	0.55 / 0.065	0.75 / 0.049	0.74 / 0.062	0.75 / 0.066	0.62 / 0.064
Kazakova	0.35 / 0.122	0.51 / 0.102	0.49 / 0.100	0.47 / 0.102	0.38 / 0.140
Maryino	0.18 / 0.153	0.39 / 0.128	0.40 / 0.123	0.40 / 0.123	0.20 / 0.169
Zelenograd 6	0.40 / 0.131	0.64 / 0.100	0.64 / 0.099	0.69 / 0.094	0.49 / 0.135
Zelenograd 11	0.35 / 0.093	0.47 / 0.084	0.37 / 0.088	0.36 / 0.089	0.35 / 0.099
Zelenograd 16	0.63 / 0.188	0.67 / 0.171	0.43 / 0.207	0.45 / 0.205	0.65 / 0.184
Biryulyovo	0.29 / 0.122	0.63 / 0.092	0.58 / 0.090	0.58 / 0.089	0.36 / 0.122
Moscow State University (MSU)	0.20 / 0.106	0.47 / 0.090	0.39 / 0.086	0.40 / 0.086	0.13 / 0.125
Butlerova	0.07 / 0.120	0.08 / 0.118	0.08 / 0.120	0.24 / 0.112	0.04 / 0.136
Losiny Ostrov	0.58 / 0.047	0.77 / 0.046	0.81 / 0.057	0.80 / 0.056	0.60 / 0.048
Glebovskaya	0.20 / 0.150	0.37 / 0.130	0.37 / 0.130	0.35 / 0.131	0.29 / 0.153
Lublino	0.08 / 0.230	0.61 / 0.170	0.44 / 0.173	0.44 / 0.173	0.13 / 0.246
Ak. Anokhina	0.39 / 0.127	0.65 / 0.116	0.46 / 0.113	0.45 / 0.113	0.54 / 0.120
Chayanova	0.52 / 0.114	0.65 / 0.093	0.38 / 0.130	0.36 / 0.134	0.56 / 0.117
Tolbukhina	0.44 / 0.134	0.74 / 0.100	0.67 / 0.104	0.67 / 0.104	0.48 / 0.139
Dolgoprudnaya	0.48 / 0.149	0.67 / 0.133	0.59 / 0.136	0.54 / 0.138	0.62 / 0.135
Koptevsky	0.12 / 0.193	0.17 / 0.172	0.03 / 0.199	0.05 / 0.196	0.24 / 0.210
Polyarnaya	0.37 / 0.191	0.78 / 0.114	0.56 / 0.170	0.52 / 0.180	0.40 / 0.195
Cheryomushki	0.58 / 0.092	0.81 / 0.076	0.78 / 0.072	0.70 / 0.079	0.71 / 0.079
Touristskaya	0.43 / 0.112	0.81 / 0.088	0.61 / 0.092	0.62 / 0.090	0.53 / 0.110
Kozhukhovsky passage	0.53 / 0.140	0.70 / 0.110	0.74 / 0.108	0.74 / 0.108	0.60 / 0.131
Ostankino	0.40 / 0.088	0.57 / 0.073	0.57 / 0.073	0.64 / 0.069	0.45 / 0.091
Zvenigorod	0.23 / 0.184	0.30 / 0.162	0.34 / 0.155	0.34 / 0.155	0.32 / 0.188
Kozhukhovo	0.02 / 0.119	0.47 / 0.089	0.47 / 0.094	0.48 / 0.094	0.16 / 0.123
Gagarin sq.	0.38 / 0.211	0.54 / 0.193	0.49 / 0.261	0.51 / 0.261	0.52 / 0.194
Kapotnya	0.37 / 0.124	0.68 / 0.091	0.64 / 0.090	0.62 / 0.093	0.39 / 0.126
Median	0.37 / 0.127	0.63 / 0.102	0.49 / 0.108	0.48 / 0.108	0.43 / 0.135
Average	0.35 / 0.138	0.56 / 0.114	0.49 / 0.123	0.50 / 0.123	0.41 / 0.141