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O. Butenko[*1],
orcid.org/0000-0001-6045-3106,
K. Vasiutynska[1],
orcid.org/0000-0001-9800-1033,
A. Karamushko[1],
orcid.org/0000-0002-5748-9746,
S. Melnyk[1],
orcid.org/0009-0002-5144-1212,
A. Nedova[2],
orcid.org/0009-0005-1884-226X

1 – Odesa Polytechnic National University, Odesa, Ukraine
2 – LTD Ecosmartlab, Odesa, Ukraine
[*] Corresponding author e-mail: butenko@op.edu.ua

ASSESSMENT OF THE IMPACT OF NATURAL AND ANTHROPOGENIC FACTORS ON THE AIR QUALITY OF URBANISED AREAS

Purpose. To determine the patterns of distribution and accumulation of pollutants in the air of large urban areas of Ukraine and the impact of natural and anthropogenic factors on these processes.

Methodology. The aim of the study was realised by collecting, systematising, mathematically processing and analysing the results of observation of air pollution indicators in the right-bank part of Kyiv.

Findings. The regularities were identified and the influence of natural (meteorological) and anthropogenic factors on the concentrations of particulate matter, carbon monoxide and sulphur dioxide in the air of an urbanised environment was assessed.

Originality. The nature of the dependence or lack of dependence of the concentration of the main pollutants in the atmospheric air of the right-bank territory of the city of Kyiv on basic meteorological indicators has been established. A negative correlation between the content of solid particles in the air and wind speed and wind gust speed has been revealed. Moreover, wind gust speed has a greater impact on dustiness than wind speed, and its direction is irrelevant for the city of Kyiv. A strong negative correlation between air dustiness and rainfall has been recorded. A correlation in particulate matter content has been established between all areas of the city, even those far apart from each other. This makes it possible to predict, with a calculable probability, the nature of changes in air dustiness in areas where monitoring is temporarily not being carried out. A clear daily cycle of carbon monoxide concentration in the atmospheric air and a correlation between different areas of the city for this indicator have been established, as well as a correlation between carbon monoxide concentration and solid particles. There is no daily cycle in the concentration of sulphur dioxide in the atmospheric air of the city of Kyiv. The correlation between CO and SO_2 and precipitation is moderately negative.

Practical value. The use of the obtained results makes it possible to make quick and informed decisions in the field of air quality management in large urban areas.

Keywords: *environmental safety, air quality index, meteorological factors, urbanised area, correlation coefficient*

Introduction. One of the main challenges for modern humanity is to ensure an adequate level of global environmental safety. This task is being addressed both at the international and domestic levels. Thus, according to the Law of Ukraine 'On Environmental Protection', environmental safety is a state of the environment that ensures prevention of environmental degradation and the emergence of a danger to human health. A similar interpretation of environmental safety is used in most developed countries. In Ukraine, it is guaranteed by a wide range of interrelated political, economic, technical, organisational, state and legal, and other measures. An important component of overall environmental safety is maintaining a safe state of atmospheric air, i.e., regulating and controlling the content of pollutants in it. In Ukraine, in accordance with the Hygienic Regulations approved by the Ministry of Health, there are maximum permissible concentrations of chemical and biological substances in the air of populated areas. In total, more than five hundred pollutants are regulated, but in reality, only some of them are monitored regularly within settlements. These include dust particles, ozone, sulphur dioxide, carbon monoxide, nitrogen dioxide, and formaldehyde. This state of affairs is typical for virtually all countries in the world where air quality is monitored. The World Health Organisation provides recommendations on the content of particulate matter ($PM_{2.5}$ and PM_{10}), ozone, nitrogen dioxide, sulphur dioxide and carbon monoxide [1]. The choice of the above pollutants is due to their widespread distribution and negative impact on ecosystem biocenoses and human health. Residents of large cities and industrial agglomerations are most adversely affected. Since the level of urbanisation of the population has a steady upward trend, it is predicted that by the middle of this century, approximately 68 % of the total population will live in cities [2, 3]. This process will take place at the expense of Asian and African countries, and 80 % of the largest megacities (especially in Asia) are currently experiencing a steady trend towards even greater population growth [4]. Thus, the problem of atmospheric air quality in urbanised areas is of great importance, and studying the patterns of dynamics of pollution indicators and determining the role osf natural and anthropogenic factors influencing these processes is an urgent task.

Literature review. Numerous studies conducted by scientists around the world over the past decades have generally made it possible to assess the risks to people caused by air pollution. The mechanisms and consequences of the main pollutants' impact on human health have also been largely understood.

There is reason to believe that dust (particulate) particles are 'universal' pollutants of the atmosphere. This definition is justified by the fact that they are found in greater or lesser concentrations in the air of any area. Even if there are no artificial sources of dust in a particular area, natural sources of dust in that area or transboundary transfer of dust masses from other areas can play a negative role. However, if we consider urbanised areas, the main source of air pollutants is anthropogenic objects. Anthropogenic air pollution is one of the most serious threats to public health worldwide, as it causes about 9 million deaths per year [5].

According to the Council of the European Union, the main anthropogenic source of dust particles is energy (58 % for $PM_{2.5}$ and 44 % for PM_{10}), agricultural production (7 % for $PM_{2.5}$ and 19 % for PM_{10}), industrial production and mining (14 % for $PM_{2.5}$ and 19 % for PM_{10}), transport (9 % for $PM_{2.5}$ and for PM_{10}), and waste (8 % for $PM_{2.5}$ and 5 % for PM_{10}) [6]. According to the WHO, particulate matter is the most dangerous pollutant because, among other things, it can carry chemicals and bacteria [7, 8].

The problem of the negative impact of air pollution is increasing due to overpopulation and uncontrolled urbanisation [9]. This is especially true in poor countries, where wood and coal are widely used as the main fuel in the home. Three billion people live in such conditions [10].

PM_{10}, NO_2, CO, and SO_2 have been found to be significantly associated with out-of-hospital cardiac arrests among Seoul residents, and a 10 μg/m^3 increase in $PM_{2.5}$ concentration with a delay of 1 to 2 days increases the risk of such events by 1.3 % [11]. It has also been shown that male gender, old age, hypertension, diabetes, heart disease, and stroke in combination are risk factors. Similar studies in Japan have shown similar results: an increase in $PM_{2.5}$ concentration by 10 μg/m^3 on the first day increases the likelihood of a case of the disease by 1.6 %, and over the next three days – up to 2.3 % [12]. Elderly people were also more susceptible to the effects of dust particles, but no gender differences were found in this study. Studies [13, 14] examined the impact of low concentrations of $PM_{2.5}$ in the air on mortality in North America. It was shown that there is a positive correlation between the concentration of $PM_{2.5}$, even at a value of about 2.5 μg/m^3, and non-accidental mortality. Moreover, it was found that the correlation becomes weaker with the increase of ozone in the air.

$PM_{2.5}$ is more harmful than PM_{10} because it has a better ability to penetrate the lungs and stay there [8, 15]. A study of air pollution in Pakistan (Faisalabad) found a significant excess of PM_{10} over $PM_{2.5}$ and a significant impact of particles on the growth of chronic respiratory diseases in the elderly and the rapid development of lung failure in newborns [16]. Studies in Taiwan have shown that there is a causal relationship between $PM_{2.5}$ and PM_{10} and pulmonary dysfunction and pneumonia in the warm season [17]. A study in Vietnam [18] showed a positive correlation between the number of hospital admissions of young children with acute lower respiratory tract infections in Ho Chi Minh City and PM_{10}, NO_2 and SO_2 levels in the air for the dry season and no correlation for the rainy season.

The authors of [19] proved that PM_{10} has a negative effect on lung cells, causing an inflammatory reaction, which can contribute to epithelial damage and thus the development and exacerbation of respiratory diseases, such as viral diseases. The harmfulness of particulate matter can increase depending on the amount and properties of the chemicals associated with it [20].

In [21], which studied air pollution in 22 cities in India during the COVID-19 pandemic, it is noted that weather conditions are important for the concentration of particulate matter. However, this impact has not been studied in detail.

In [22], qualitative and quantitative assessments of anthropogenic and natural impacts on air pollution in Dhaka city and neighbouring agglomerations (Bangladesh) were considered. It was shown that various meteorological factors, such as precipitation, wind speed, wind direction, air temperature, and solar radiation, play an important role in fluctuations in pollutant concentrations, although the main sources of air pollution with particulate matter were fossil fuel combustion, vehicles, construction activities, and brick production, especially in the dry season. Statistical analysis showed that the concentration of particulate matter was negatively related to air temperature (Pearson correlation coefficient $r = -0.84$) and positively related to atmospheric pressure ($r = 0.8$). The strong correlation ($r = 0.85$) between $PM_{2.5}$ and PM_{10} was explained by the similarity of pollution sources, which include emissions from various anthropogenic activities such as vehicle emissions, road dust, construction activities and brick production in kilns. The average ratio of $PM_{2.5}$ to PM_{10} varies significantly (from 0.05 to 0.85) at different monitoring stations in different seasons. $PM_{2.5}$ demonstrates a positive correlation with NO_x, indicating the same type of pollution sources. Similar results for this area were obtained by the authors [23]. A significant seasonal variation was also noted, which, according to the authors, is associated with wet deposition of particles due to precipitation and seasonality of anthropogenic pollution sources. The number of rainy days per month during the wet season has a strong negative correlation with monthly average particulate matter concentrations with correlation coefficients of $r = -0.85$ for $PM_{2.5}$ and $r = -0.94$ for PM_{10}. This is explained by the fact that brick kilns are closed during the rainy season. However, daily precipitation during the wet period does not seem to have any effect on daily particulate matter concentrations, as PM_{10} showed a very small negative correlation ($r = -0.15$), while $PM_{2.5}$ showed virtually no correlation ($r = 0.06$). This suggests that although precipitation in general can contribute to wet deposition of particulate matter, daily precipitation alone does not significantly affect PM concentrations and therefore cannot be an important indicator of potential air pollution. A contrary conclusion can be drawn from studies conducted for the German state of Baden-Württemberg [24]. Pearson's correlation coefficient between the concentration of particulate matter and precipitation, depending on the season, varied within the range of r = –0.32––0.57 for $PM_{2.5}$ and r = –0.35––0.54 for PM_{10}, which indicates a moderate statistical dependence. Here, as in [22], a strong correlation between $PM_{2.5}$ and PM_{10} concentrations and temperature was found. However, for Germany, this correlation was negative in the cold season (r = –0.61 for $PM_{2.5}$ and r = –0.63 for PM_{10}) and positive in the warm season (r = 0.65 for $PM_{2.5}$ and r = 0.69 for PM_{10}). In spring and autumn, there was virtually no correlation. A strong correlation was also found between $PM_{2.5}$ and PM_{10} (r = 0.92–0.97), which almost did not change depending on the season and on the population density in the study area.

In [25], a statistical correlation was conducted between meteorological factors such as temperature, relative humidity, precipitation and the Air Quality Index (AQI) for the state of West Bengal, India. Precipitation showed a strong negative correlation (r = –0.821) with AQI. This indicates that precipitation has a significant impact on improving air quality. Temperature and relative humidity showed a weaker relationship (r = –0.605 for temperature and r = –0.647 for humidity).

The results of processing data from 896 monitoring stations show that for China, the concentrations of most pollutants in the air are correlated with wind speed, precipitation, relative humidity and atmospheric pressure [26]. At constant precipitation, relative humidity and wind speed were significantly negatively correlated with the concentrations of most pollutants in the air, but positively correlated with atmospheric pressure.

In general, the analysis shows that air quality forecasting is a complex task due to the limited information on emission sources and the complexity of the processes of direct and indirect impact of weather factors on air quality. At present, forecasting methods can be divided into two main classes: traditional forecasting methods and the latest deep learning methods. The former include numerical modelling methods, statistical methods and traditional machine learning methods. The latter involve the use of a spatio-temporal hybrid deep learning model, which consists in the appropriate (automatic) processing of statistical data for a given area for a given period of time [27].

Unsolved aspects of the problem. The analysis of previous studies shows that the quality of atmospheric air has a significant impact on human health, especially in areas with high density. It has been proven that natural, including meteorological, factors affect the concentration of pollutants. However, this influence has different magnitudes and sometimes the opposite direction in different areas. Therefore, a study of the qualitative and quantitative characteristics of the impact of meteorological factors on air quality in Ukrainian cities requires a separate study and analysis.

Purpose. The aim of the study is to determine the patterns of distribution and accumulation of pollutants in the atmospheric air in the territories of large cities of Ukraine on the example of the right-bank part of Kyiv. The goal was achieved by implementing the following tasks: critical analysis of common indicators of atmospheric air quality; establishing a correlation between the concentrations of the main pollutants in the city air and weather indicators, cycles of anthropogenic activity, and the territorial location of control sites; establishing a correlation between the concentrations of individual pollutants.

Methods. The study was conducted by collecting, mathematically processing and analysing data on actual air pollution and weather indicators in Kyiv from open sources, such as SaveEcoBot (accessed by the non-governmental organisation Save Dnipro) and EcoThreat (official resource of the Ministry of Environmental Protection and Natural Resources of Ukraine).

In view of the proven harmful effects of air pollution on human health, developed countries have organised air quality monitoring networks that cover mainly the territory of cities and agglomerations. The combination of individual efforts has resulted in the creation of an international network of air quality data, presented, for example, on the "World's Air Pollution: Real-time Air Quality Index". The US Environmental Protection Agency standard is used to classify air quality [28]

$$I_p = \frac{I_{Hi} - I_{Lo}}{BP_{Hi} - BP_{Lo}}\left(C_p - BP_{Lo}\right) + I_{Lo},$$

where I_p is the index for pollutant p; C_p is the truncated concentration of pollutant p (for particulate matter – the average value for the last 24 hours, for carbon monoxide or ozone – for the last 8 hours, for sulphur dioxide or nitrogen dioxide – for the last hour), μg/m^3; BP_{Hi} is the concentration breakpoint that is greater than or equal to C_p, μg/m^3; BP_{Lo} is the concentration breakpoint that is less than or equal to C_p, μg/m^3; I_{Hi} is the AQI value corresponding to BP_{Hi}; I_{Lo} is the AQI value corresponding to BP_{Lo}.

The main purposes of using the AQI are 1) to quantify air pollution in order to make informed, effective management and technical decisions in certain areas and to compare different areas in terms of pollution levels; 2) to divide pollution levels into categories, each of which has its own characteristics of the pollutant's impact on human health. The methodology calculates the AQI value for PM based on the latest 24 hours of observation data. For the first objective, this approach is acceptable, as it does not contradict the purpose of using the index. But averaging daily results for the second purpose is at least illogical. Recommendations for certain (vulnerable) groups of the population regarding the risks of being outdoors at a given time should not be based on calculations based on data from previous hours. A person is exposed to pollutants "here and now". The state of pollution in the previous hours of the day does not affect the risk at the moment. Therefore, we can agree with the authors of the resource [29] that calculating AQI based on the average daily concentration of dust particles is a "very bad idea". A certain step in overcoming this contradiction is the application of the Now Cast principle.

The formula for AQI Now Cast

$$NowCast = \frac{\sum_{i=1}^{12} w^{i-1} C_i}{\sum_{i=1}^{12} w^{i-1}},$$

where

$$w = \begin{cases} w^* \text{ if } w^* > 0.5 \\ 0.5 \text{ if } w^* \le 0.5 \end{cases};$$

$$w^* = \frac{C_{\min}}{C_{\max}},$$

where $C_{\min}$ and $C_{\max}$ are minimum and maximum hourly concentration of the pollutant for a 12-hour period, μg/m^3.

The advantage of the Now Cast principle is that only the last 12 hours are taken into account and that the impact of each i^{th} hour on the final result is smaller, the further away it is from the reference hour. However, this approach only partially resolves the above contradiction. In addition, despite the commonality of the approach and the same calculation formula, and sometimes the same abbreviation (AQI), the division of AQI values into categories differs significantly in different countries. For example, in the United States, there are six such categories (good, moderate, unhealthy for sensitive groups, unhealthy, very unhealthy, hazardous), while in South Korea there are four (good, moderate, unhealthy, very unhealthy). Moreover, South Korea has stricter requirements for the same index categories. The air quality index in China, like in the United States, has six categories (excellent, good, light pollution, moderate pollution, significant pollution, severe pollution). However, the values of pollutant concentrations permissible for these levels are significantly higher. For example, the US Environmental Protection Agency's "good" category (AQI = 0–50, $PM_{2.5}$ = 0–12 μg/m^3) corresponds to the "excellent" category (China AQI = 0–50, $PM_{2.5}$ = 0–35 μg/m^3) according to Chinese standards.

In Ukraine, the Composite Air Pollution Index (CAPI) is used to assess the quality of atmospheric air in settlements. Its calculation usually takes into account the concentrations of sulphur and nitrogen dioxides, carbon monoxide, ground-level ozone and particulate matter. These concentrations are measured in ambient air using stationary observation posts of the hydrometeorological service, as well as mobile laboratories. In determining the CAPI, it is believed that at the level of the maximum permissible concentration, all pollutants have the same negative impact on humans, and with increasing concentrations, the level of harmfulness increases with the intensity determined by the hazard class of a given pollutant. This approach, as well as the complexity of the CAPI indicator, makes its use in the present study impossible.

Thus, the use of AQI or CAPI to analyse the factors influencing the state of atmospheric air in urban areas is inappropriate. In this study, primary data from monitoring stations were used, expressed in terms of the mass of pollutant per unit volume of air.

The choice of Kyiv as the city under study is mainly due to the fact that there are about one hundred monitoring stations (MS) on its territory. Not all of them are characterised by stable operation over time and the required list of measured values. However, it was easy to choose ten stations as control stations, which are relatively evenly distributed across the right-bank part of the city and provide data on the necessary pollutants and weather indicators. Most of them belong to the Kyiv City State Administration (Fig. 1).

Fig. 1. Map of monitoring stations location:

MS-1 – 64g Pravdy Ave.; MS-2 – 7 k1 Obolonska Naberezhna St.; MS-3 – 33 Syretska St.; MS-4 – 97 Peremohy St.; MS-5 – 28 Turivska St.; MS-6 – 11 Karla Chapeka St.; MS-7 – 3 Heroiv Sevastopol St.; MS-8 – 10 Yakutska St.; MS-9 – 2 Kakha Bendukidze St.; MS-10 – 39a Knyaziv Ostrozkykh St.

Results. Since anthropogenic factors can influence the concentration of pollutants in the city's atmospheric air, data collection was carried out from midnight on Monday to midnight on Sunday – the observation cycle coincided with the weekly cycle of human activity [30]. Data from monitoring stations were recorded at 1-hour intervals. A total of 169 values for each parameter were recorded during the observation cycle. This observation cycle was carried out monthly over the course of one year.

Particulate matter concentrations were recorded at all ten monitoring stations. In addition, carbon monoxide and sulphur dioxide concentrations were also recorded at MS-1, MS-4 and MS-5 at one-hour intervals. The weather factors considered were air temperature t (°C), humidity H (%), atmospheric pressure P (mmHg), wind speed v (m/s), wind gust speed w (m/s), cloud cover Cl (points), and precipitation R (mm).

Fig. 2 shows graphs of the dynamics of the concentration of particulate matter for the control week of March 2025; Fig. 3 – graphs of changes in weather conditions in the area of 39a Kniaziv Ostrozkykh Street.

The graphs in Fig. 2 shows that there is no clear daily cyclicality for the concentration of particulate matter. There is also no clear dependence on weather conditions. In this case, it is advisable to use the methods of statistical processing of the database – calculation of the correlation coefficient between the concentration of pollutants in the air and the values of weather factors. For this purpose, Pearson's coefficient was used, which makes it possible to establish the existence of a correlation between databases of two values [31].

$$r = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2}\sqrt{\sum_{i=1}^{n}(y_i - \bar{y})^2}},$$

where n is sample size (for each cycle $n = 169$) [30]; x_i, y_i are individual sample points; $\bar{x}$, $\bar{y}$ are average values.

It was considered that the interval $0.9 < r < 1.0$ corresponds to a strong positive correlation (close to perfect), at $0.7 < r < 0.9$ – a very high correlation, at $0.5 < r < 0.7$ – a high correlation, at $0.3 < r < 0.5$ – a moderate correlation, at $0 < r < 0.3$ – a weak or absent correlation. Such an interpretation is rather arbitrary, since the same value of the r coefficient for different types of tasks may indicate a different degree of relationship between x and y. In addition, the detected correlation does not always guarantee that one value really depends on the other – in some cases, a relatively large value of r may indicate that both parameters, without having a mutual influence, simultaneously depend on some third value.

In order to be sure that the value of Pearson's coefficient is not the result of a random coincidence, its critical (threshold) value r_{cr} was determined for a significance level of 0.05. Since the sample size for all pairs of values is the same ($n = 169$), the degree of freedom $df = n - 2 = 167$. Using the Python library, we can get that for $df = 167$, $r_{cr} = 0.151$. Therefore, with a 95 % probability, the value $|r| > 0.151$ is not the result of chance, but indicates the presence of a statistically significant relationship.

Table 1 shows the results for Pearson's coefficient calculated for the MS-10 indicators. For each season of the year, the pairs of physical quantities in the table correspond to three r values (one for each month). Consideration of the obtained results allows us to state a strong positive correlation between $RM_{2.5}$ and RM_{10}, which is in line with the results of other authors [22, 24] and is expected, given that $RM_{2.5}$ is a component of RM_{10}.

As in [24] for the state of Baden-Württemberg (Germany), no reliable and unambiguous dependence of $PM_{2.5}$ and PM_{10} concentrations on air temperature was found. At the same time, in [25] for West Bengal, such a dependence was recorded with $r = -0.605$. Obviously, this discrepancy may be due to the indirect influence of weather conditions. In India, when the temperature decreases, the use of firewood increases, which is a source of particulate matter when burned, while in European cities there is no such causal relationship. Similarly, a significant decrease in pressure in the subtropical monsoon climate of Bangladesh [22] and parts of China [26] leads to an increase in the likelihood of precipitation and, accordingly, a likely decrease in the amount of pollutants in the air. In temperate climates, atmospheric pressure fluctuations are much smaller and do not always lead to precipitation, so its correlation with pollution is not clearly established (Table 1).

Similar conclusions can be drawn about the impact of atmospheric pressure and humidity. Single rather high values of the r module cannot be the basis for an unambiguous conclusion about the dependence of air dustiness on these meteorological indicators – rather, we can talk about the influence of certain unaccounted-for factors, such as fires caused by the shelling of the city or the effects of massive dust inflows from North Africa.

The effect of wind speed is characterised by a predominantly moderate to weak negative correlation. Wind gusts have a moderate to strong negative correlation. The wind direction (at least for the right-bank part of Kyiv) does not matter. Neither does cloud cover.

Table 1 does not show data on the correlation between dustiness and precipitation. This is due to the fact that either no precipitation was observed at all during a particular control week, or it was so weak and short-lived that it was not possible to collect a sufficient sample for a reasonable determination of r. The March control week (Figs. 2, 3) was favourable for determining the role of precipitation, when rain was observed three times and one of them was quite long. The graphs of the dependence $C = f(\tau)$ clearly show a sharp decrease in the concentration of $PM_{2.5}$ and PM_{10} as a reaction to precipitation in the form of rain. For these three time intervals, the correlation of PM_{10} with precipitation R (mm) was calculated, with coefficients $r = -0.789$; -0.703; -0.811, which is expected to indicate a very strong negative dependence. It was unexpected that the $PM_{2.5}/PM_{10}$ ratio, which under normal conditions ranges from 0.3 to 0.8, was approximately 0.9 to 0.92 during rainy weather. A rational explanation for this effect could not be found, and the highest value of this ratio in the literature reviewed was 0.85 [22].

The analysis of the observation results showed that at the same time in different parts of the city, air dust content can differ by several times. This is mainly due to differences in the levels of anthropogenic impact. At the

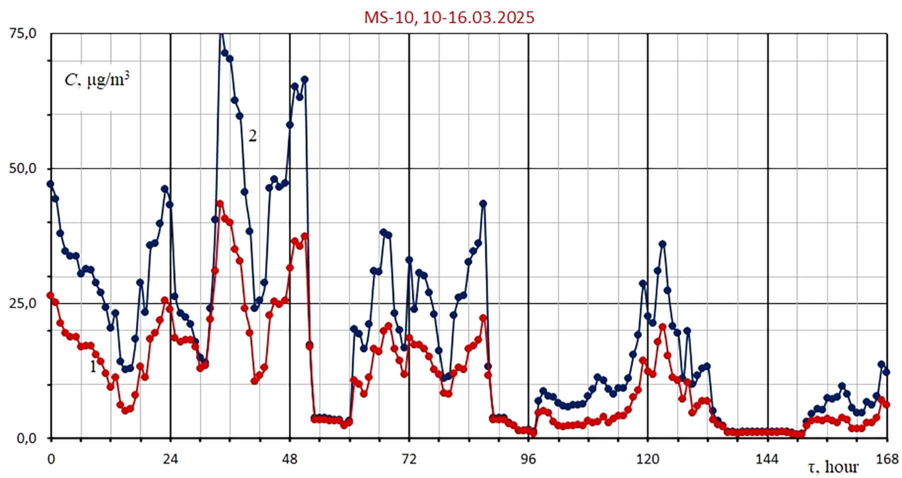

Fig. 2. Concentrations of dust particles $PM_{2.5}$ (1) and PM_{10} (2) in the period 10.03.25–16.03.25 at MS-10

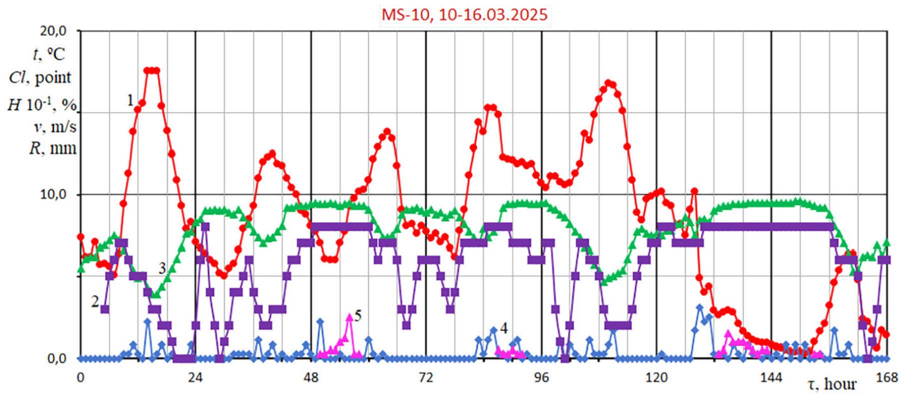

Fig. 3. Some meteorological parameters for the period 10.03.25–16.03.25 at MS-10:
1 – temperature t, °C; 2 – cloud cover Cl; 3 – humidity H, %; 4 – wind speed v, m/s; 5 – precipitation R, mm

Table 1

Pearson's correlation coefficients for MS-10 by $RM_{2.5}$ and RM_{10} with weather indicators

	PM_{10}	$PM_{2,5}$	Temperature	Humidity	Pressure	Wind speed	Wind gusts	Wind direction	Cloud cover
03.06–09.06.2024/08.07–14.07.2024/12.08–18.08.2024									
PM_{10}	–	0.932	–0.103	0.084	0.364	–0.012	–0.483	0.260	–0.108
	–	0.943	–0.086	0.179	–0.477	0.370	0.067	0.067	–0.009
	–	0.959	–0.113	–0.137	–0.543	–0.254	–0.466	0.050	0.089
$PM_{2,5}$	0.932	–	–0.249	0.255	0.348	0.056	–0.523	0.206	–0.202
	0.943	–	–0.106	0.275	–0.427	0.374	0.153	–0.166	–0.039
	0.959	–	–0.283	0.042	–0.607	–0.354	–0.602	0.051	–0.011
09.09–15.09.2024/14.10–20.10.2024/04.11–10.11.2024									
PM_{10}	–	0.838	–0.119	0.151	–0.124	–0.092	–0.106	0.002	0.236
	–	0.951	–0.732	0.693	–0.007	–0.412	–0.619	0.120	0.336
	–	0.980	0.424	0.018	0.112	–0.175	–0.175	–0.078	–0.351
$PM_{2,5}$	0.838	–	–0.209	0.339	–0.249	–0.251	–0.282	–0.085	0.296
	0.951	–	–0.848	0.839	–0.123	–0.474	–0.754	0.079	0.321
	0.980	–	0.416	0.131	0.156	–0.209	–0.210	–0.056	–0.387
16.12–22.12.2024/13.01–19.01.2025/10.02–16.02.2025									
PM_{10}	–	0.963	–0.326	–0.380	0.356	–0.246	–0.486	–0.078	0.163
	–	0.959	–0.099	–0.651	–0.264	–0.028	–0.062	–0.013	–0.012
	–	0.939	0.334	–0.137	0.138	–0.046	–0.146	–0.061	0.169
$PM_{2,5}$	0.963	–	–0.408	–0.189	0.281	–0.309	–0.567	–0.093	0.172
	0.959	–	–0.071	–0.503	–0.265	–0.020	–0.102	–0.041	0.019
	0.939	–	0.172	0.106	0.249	–0.067	–0.218	–0.117	0.232
10.03–16.03.2025/14.04–20.04.2025/12.05–18.05.2025									
PM_{10}	–	0.978	0.278	–0.321	0.025	–0.094	–0.263	0.024	–0.215
	–	0.942	–0.124	0.341	–0.305	–0.245	–0.440	0.053	–0.285
	–	0.893	0.432	–0.601	0.023	0.114	0.360	–0.009	–0.463
$PM_{2,5}$	0.978	–	0.209	–0.201	0.002	–0.135	–0.313	0.017	–0.197
	0.942	–	–0.325	0.533	–0.178	–0.248	–0.456	0.038	–0.208
	0.893	–	0.227	–0.326	–0.034	0.059	0.239	–0.006	–0.352

same time, the processing of measurements from twelve weekly observation cycles allowed us to reasonably assert the existence of a correlation in $PM_{2.5}$ and PM_{10} between all ten monitoring stations. As an example, Table 2 shows the following data for MS-10. The top line is the maximum value out of twelve possible, the bottom line is the lowest, and the middle line is the arithmetic mean. The data for other MS do not differ qualitatively from the example above. The value of the average r value does not depend on the distance between the monitoring stations.

One of the main technical problems during the year of observation was the instability of some stations, which could be due to the lack of stable power supply, Internet connection, etc. People who are sensitive to air quality may face the same problem. The correlation of $PM_{2.5}$ and PM_{10} between all ten monitoring stations, in case of temporary absence of data from any one station, allows us to predict the dynamics of changes in air dustiness based on data from neighbouring stations.

For this type of task, a correlation criterion may be convenient and useful – one that takes into account the direction of change of a controlled parameter in two data samples and is defined as the ratio of the number of similarly directed changes in parameter pairs (k) to the total number of changes observed during the control period (n – 1)

Table 2

Pearson's correlation coefficients of MS-10 with other MS for $RM_{2.5}$ and RM_{10}
(highest/average/lowest out of 12 possible)

	MS-1	MS-2	MS-3	MS-4	MS-5	MS-6	MS-7	MS-8	MS-9
PM_{10}	0.783 0.645 0.313	0.642 0.538 0.417	0.814 0.596 0.366	0.833 0.535 0.321	0.828 0.550 0.373	0.797 0.568 0.440	0.698 0.545 0.442	0.667 0.557 0.501	0.830 0.616 0.304
$PM_{2,5}$	0.863 0.643 0.324	0.784 0.650 0.418	0.797 0.600 0.439	0.903 0.684 0.425	0.920 0.645 0.359	0.787 0.633 0.409	0.793 0.611 0.442	0.711 0.583 0.422	0.877 0.680 0.327

$$V = \frac{k}{(n-1)}.$$

It can be called a vector correlation coefficient because it does not take into account the absolute value of the change in the parameter, but is based only on the direction of change (increase or decrease in the value of the parameter). Unlike Pearson's correlation coefficient, the V coefficient has a clear physical meaning – it is the probability that, for example, the growth of a parameter in a given time period of the first sample will be accompanied by the same growth in the same time period in the second sample. In conditions when the operation of monitoring stations is not stable, the direction of change of a parameter in one sample can be predicted with probability $K = V$ based on the data of another sample.

The reliability of such a prediction can be increased if the out-of-service monitoring station is matched with several neighbouring stations rather than just one. Then, considering the events of parameter change to be independent, the probability of the expected direction of parameter change at the out-of-service station is

$$K(1 \mid 2 \cap 3 \cap \ldots m) = 1 - (1 - K(1 \mid 2)) \times$$
$$\times (1 - K(1 \mid 3) \times \ldots \times (1 - K(1 \mid m)),$$

where $K(1 \mid 2 \cap 3 \cap \ldots m)$ is probability of an event of unidirectional change in the monitored parameter at monitoring station "1" due to the combined effect of $2 \ldots m$ factors; $K(1 \mid m)$ is probability of unidirectional change in the parameter at stations "1" and "m" [32].

A case in which no change in the parameter is observed in either of the two samples over a given time interval is considered a similarly directed change and is included in the value of k. If the parameter remains unchanged in one sample but changes in the other (regardless of the direction), the case is considered a differently directed change. This approach can be applied to any pollutants, provided there is a sufficient database to determine k, and thus V.

Carbon monoxide (CO) and sulphur dioxide (SO_2) are among the hazardous gaseous air pollutants in urban environments that are subject to regulation. Fig. 4 illustrates, as an example, the graphs of relative carbon monoxide concentration over the monitoring week of April 14.04–20.04.25, at stations MS-1, MS-4, and MS-5. The current CO concentration was normalized to the weekly average concentration (C_m). For different districts of Kyiv, the graphs clearly demonstrate a diurnal cycle: CO concentrations decrease at night and around midday, and increase in the morning and evening. This pattern can be explained by the fact that the primary source of carbon monoxide in urban areas is the internal combustion engines of motor vehicles, whose usage peaks during morning and evening hours. The observed daily cyclicality of concentration changes is typical for all 12 weeks, corrected for sharp outbreaks that coincided in time with the fires caused by the shelling of Kyiv. The cyclical nature is typical for both monitoring stations located in the middle of residential areas (MS-1, MS-5) and those located near the road (MS-4). The Pearson's coefficient values between MS-1, MS-4 and MS-5 are shown in Table 3. They confirm the conclusions drawn from the visual analysis of the graphs and show a very high correlation.

The graphs of relative sulphur dioxide concentrations for the period 14.04–20.04.25 for MS-1, MS-4 and MS-5 are shown in Fig. 5. They show the absence of a clear daily cycle and are characterised by sharp and unsystematic concentration spikes. It is noteworthy that these outbreaks occur simultaneously for different monitoring stations (city districts), which indicates the possibility of a common source of SO_2. The Pearson's coefficient values between MS-1, MS-4 and MS-5 are shown in Table 4. The correlation is moderate to very high.

Table 5 shows the correlation coefficients for MS-1, MS-4 and MS-5 between the different pollutants. These data show no or weak correlation between SO_2 and CO, SO_2 and PM_{10}, and moderate to very high correlation

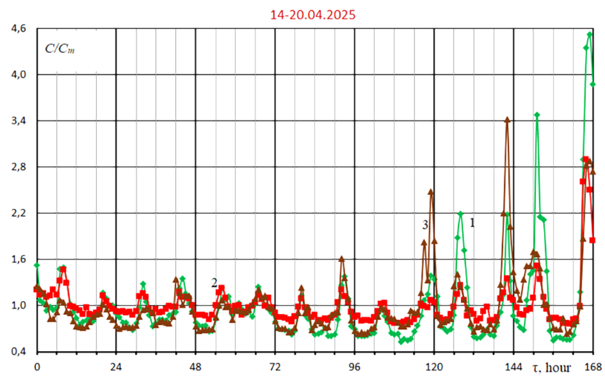

Fig. 4. Relative concentrations of carbon monoxide in the period 14.04–20.04.25 at MS-1 (1), MS-4 (2) and MS-5 (3)

Table 3

Pearson's correlation coefficients for carbon monoxide for the control week 14.04–20.04.25

	MS-1	MS-4	MS-5
MS-1	–	0.897	0.778
MS-4	0.897	–	0.713
MS-5	0.778	0.713	–

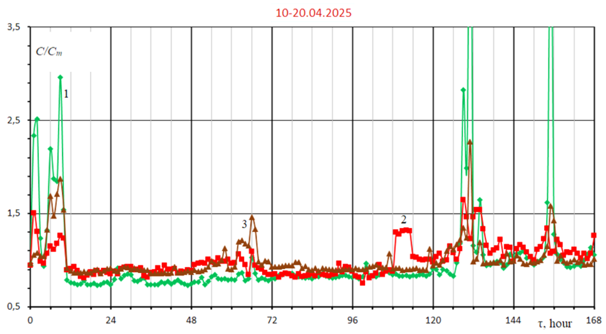

Fig. 5. Relative concentrations of sulphur dioxide in the period 14.04–20.04.25 at MS-1 (1), MS-4 (2) and MS-5 (3)

Table 4

Pearson's correlation coefficients for sulphur dioxide for the control week 14.04–20.04.25

	MS-1	MS-4	MS-5
MS-1	–	0.381	0.736
MS-4	0.381	–	0.396
MS-5	0.736	0.396	–

Table 5

Correlation coefficients between different pollutants for the control week 14.04–20.04.25

	MS-1	MS-4	MS-5
SO_2/CO	0.041	0.108	0.059
SO_2/PM_{10}	0.137	0.209	0.148
CO/PM_{10}	0.642	0.302	0.750

Table 6

Correlation coefficients between CO and SO_2 with precipitation for the control week 10.03–16.03.2025

	MS-1	MS-4	MS-5
CO/*R*	–0.323	–0.487	–0.487
SO_2/R	–0.844	–0.415	–0.802

between CO and PM_{10}. This result indicates the existence of at least one common source of carbon monoxide and particulate matter (e.g., motor vehicles), although it does not exclude the presence of separate (individual) sources (e.g., soil dust for PM_{10}).

Table 6 shows the correlation coefficients for MS-1, MS-4 and MS-5 between CO and SO_2 and precipitation. The correlation of carbon monoxide concentration with precipitation is moderate, and that of sulphur dioxide is moderate to very high.

The results of calculations of the correlation of carbon monoxide and sulphur dioxide concentrations with weather indicators for the March control week (10.03–16.03.2025) are shown in Table 7. According to these data, only a moderate negative correlation between the concentration of carbon monoxide and the speed of wind gusts can be stated. No other patterns were found.

The CO and SO_2 data and their processing for the remaining eleven weekly observation cycles qualitatively coincide with the above examples.

Conclusions. The following conclusions can be drawn as a result of the study.

1. The air quality index, which is used in international practice to characterise the state of atmospheric air, has shortcomings related to the methodology of its calculation. These shortcomings call into question its optimality in making quick management decisions on air quality and in responding in a timely manner to changes in air quality of sensitive populations.

2. Mathematical processing of the collected data allowed us to conclude the following:

- a weak to moderate negative correlation between air dust concentration and wind speed, and a moderate to strong negative correlation with wind gust speed, as well as no correlation with wind direction;

- no identifiable correlation between air dust concentration and atmospheric pressure, humidity, cloud cover, or temperature;

- a very strong negative correlation between air dust concentration and the amount of precipitation in the form of rain.

3. Despite the fact that air pollution can vary by several times in different parts of the city at the same time, there is a correlation for $PM_{2.5}$ and PM_{10} between all, even remote, districts. This fact makes it possible to predict, with a calculable probability, the nature of changes in air pollution in some areas where monitoring is temporarily not carried out, based on data from other areas.

4. A clear daily cyclicity of carbon monoxide concentration in the atmospheric air and a very high correlation between different, even remote, areas of the city in terms of this indicator, as well as a correlation (from moderate to very high) of carbon monoxide concentration with air dustiness, were established. This result indicates the existence of common anthropogenic sources

Table 7

Correlation coefficients of CO and SO_2 concentrations with weather indicators for the period 10.03–16.03.2025

	Temperature	Humidity	Pressure	Wind speed	Wind gusts	Wind direction	Cloud cover
MS-1							
Carbon monoxide	0.019	–0.052	0.033	–0.200	–0.468	0.119	–0.127
Sulphur dioxide	0.219	–0.029	–0.201	0.009	0.058	0.027	0.095
MS-4							
Carbon monoxide	–0.124	–0.058	0.059	–0.161	–0.416	–0.015	–0.088
Sulphur dioxide	–0.084	–0.167	0.171	0.015	–0.152	–0.145	0.138
MS-5							
Carbon monoxide	–0.041	0.034	–0.066	–0.175	–0.440	0.183	–0.068
Sulphur dioxide	0.231	–0.007	–0.260	0.123	0.119	–0.046	0.126

of carbon monoxide and particulate matter. Correlation with precipitation negative moderate.

5. The absence of daily cyclicality of sulphur dioxide concentrations in the air was established. A correlation (from moderate to very high) was found between different districts of the city for this indicator, as well as the absence of correlation between sulphur dioxide concentrations and carbon monoxide and dust. The correlation with precipitation is negative (moderate to very high).

6. Comparison of the results obtained with similar data for other urbanised areas of the world shows that changes in the same meteorological factor in different regions can have not only different quantitative but also different qualitative impacts on environmental air safety. This is due to the fact that the impact can be both direct and indirect, when weather changes lead to an increase or decrease in anthropogenic load. Therefore, it is unacceptable to automatically extend the patterns identified for megacities in some countries (regions) to megacities in other countries (regions)

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Оцінка впливу природних й антропогенних факторів на якість атмосферного повітря урбанізованих територій

О. Г. Бутенко[*1], *К. А. Васютинська*[1], *А. В. Карамушко*[1], *С. В. Мельник*[1], *А. О. Нєдова*[2]

1 – Національний університет “Одеська політехніка”, м. Одеса, Україна

2 – ТОВ Екосмартлаб, м. Одеса, Україна

[*] Автор-кореспондент e-mail: butenko@op.edu.ua

Мета. Визначення закономірностей поширення й накопичення забруднюючих речовин у атмосферному повітрі великих урбанізованих територій України та впливу на ці процеси природних й антропогенних факторів.

Методика. Мета дослідження реалізовувалася шляхом збору, систематизації, математичної обробки та аналізу результатів спостереження за показниками забруднення атмосферного повітря у правобережній частині м. Київ.

Результати. Виявлені закономірності та оцінено вплив природних (метеорологічних) й антропогенних факторів на концентрації твердих частинок, чадного газу й діоксиду сірки в атмосферному повітрі урбанізованого середовища.

Наукова новизна. Встановлено характер залежності або відсутність залежності концентрації основних полютантів атмосферного повітря правобережної території міста Київ від базових метеорологічних показників. Виявлена негативна кореляція вмісту у повітрі твердих частинок зі швидкістю вітру та швидкістю поривів вітру. Причому, швидкість поривів вітру має більший вплив на запиленість ніж швидкість вітру, а його напрямок для міста Київ значення не має. Зафіксована велика негативна кореляція запиленості повітря з опадами у вигляді дощу. Встановлена кореляція по вмісту твердих частинок між усіма, навіть віддаленими один від одного, районами міста. Це дає можливість з імовірністю, що може бути розрахована, прогнозувати характер зміни запиленості повітря районів, де моніторинг тимчасово не ведеться. Встановлена чітка добова циклічність концентрації чадного газу в атмосферному повітрі й кореляція за цим показником між різними районами міста, а також кореляція концентрації чадного газу із твердими частинками. Добова циклічність концентрації діоксиду сірки в атмосферному повітрі міста Київ відсутня. Кореляція CO і SO_2 з величиною опадів помірно негативна.

Практична значимість. Використання отриманих результатів дає можливість прийняття швидких та обґрунтованих рішень у сфері управління якістю атмосферного повітря великих урбанізованих територій.

Ключові слова: *екологічна безпека, індекс якості повітря, метеорологічні фактори, урбанізована територія, коефіцієнт кореляції*

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