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INFLUENCE OF METEOROLOGICAL PARAMETERS ON $PM_{2.5}$ AND ASSOCIATED AIR POLLUTION EPISODES IN KARAGANDA, CENTRAL KAZAKHSTAN (2017–2024)

Karaganda, one of the most heavily polluted industrial cities worldwide, experiences severe air quality challenges due to emissions from coal mining, metallurgical industry and coal-fired power plants. This study investigates the influence of meteorological parameters on $PM_{2.5}$ concentrations and associated air pollution episodes in Karaganda, Central Kazakhstan, using a monthly dataset spanning 2017–2024. The meteorological parameters including temperature (°C), relative humidity (%), atmospheric pressure (hPa), wind speed (m/s) and pollutant concentrations including suspended particulate matter (dust, mg/m³), $PM_{2.5}$ (mg/m³), PM_{10} (mg/m³), sulfur dioxide (SO_2, mg/m³), carbon monoxide (CO, mg/m³), nitrogen dioxide (NO_2, mg/m³), ozone (O_3, mg/m³), ammonia (NH_3, mg/m³), and formaldehyde (HCHO, mg/m³) were analyzed to explore meteorology-driven variability in air pollution. Time series analyses and correlation assessments were conducted, and three complementary regression approaches, Multiple Linear Regression (MLR), Random Forest Regression, and Gradient Boosting via LightGBM were applied to robustly characterize the relationships between meteorological conditions and $PM_{2.5}$ levels. Results indicate persistently high pollution levels, with exceedances of daily average concentrations observed for $PM_{2.5}$, PM_{10}, dust, phenol, formaldehyde, and ozone, with $PM_{2.5}$ showing the most pronounced exceedances. Air pollution episodes were particularly severe during the cold season, driven by emissions from thermal power plants and residential heating. Multi-year trends revealed increasing occurrences of high-concentration events, primarily due to $PM_{2.5}$, PM_{10}, SO_2, and CO, highlighting the significant contribution of industrial and energy-related emissions to the urban atmosphere. Meteorological conditions, particularly calm or low-wind periods (0–3 m/s), further exacerbated pollutant accumulation during episode periods, with 106 such days recorded in 2024 alone. These findings underscore the critical role of both emission sources and weather conditions in shaping air quality in Karaganda and provide a basis for targeted mitigation strategies.

Keywords: Karaganda, $PM_{2.5}$, meteorological parameters, air pollution episodes.

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Қарағанды, Орталық Қазақстандағы $PM_{2.5}$ концентрациясына және онымен байланысты ауаның ластану эпизодтарына метеорологиялық параметрлердің әсері (2017–2024)

Әлемдегі ең ластанған өнеркәсіптік қалалардың бірі Қарағанды көмір өнеркәсібінен, болат өндірісінен және көмірмен жұмыс істейтін электр станцияларынан шығатын зиянды заттарға байланысты ауа сапасының күрделі мәселелеріне тап болып отыр. Бұл зерттеуде 2017 жылдан

2024 жылға дейінгі айлық деректерді пайдалана отырып, Орталық Қазақстандағы Қарағанды қаласындағы PM_{25} концентрациясына және онымен байланысты ауаның ластану эпизодтарына метеорологиялық параметрлердің әсері зерттеледі. Метеорологиялық жағдайларға байланысты ауаның ластануының өзгергіштігін зерттеу үшін температура (°C), салыстырмалы ылғалдылық (%), атмосфералық қысым (hPa), жел жылдамдығы (м/с) және аспалы бөлшектер (шаң, мг/м³), $PM_{2.0}$ (мг/м³), PM_{10} (мг/м³), күкірт диоксиді (SO_2, мг/м³), көміртегі тотығы (CO, мг/м³), азот диоксиді (NO_2, мг/м³), озон (O_3, мг/м³), аммиак (NH_3, мг/м³) және формальдегид (HCHO, мг/м³) сияқты ластаушы заттардың концентрациясы сияқты метеорологиялық параметрлер талданды. Уақыт қатарларын талдау және корреляциялық бағалау жүргізілді, сондай-ақ үш толықтырушы регрессия тәсілі қолданылды: көптік сызықтық регрессия (MLR), кездейсоқ орман регрессиясы және метеорологиялық жағдайлар мен $PM_{2.5}$ деңгейлері арасындағы байланысты сенімді түрде сипаттау үшін LightGBM көмегімен градиентті күшейту. Нәтижелер $PM_{2.5}$, PM_{10}, шаң, фенол, формальдегид және озонның тәуліктік орташа концентрациясынан асып түсетін ластану деңгейінің тұрақты жоғары екенін көрсетеді, ең айқын асып кетулер $PM_{2.5}$ үшін байқалады. Ауаның ластану эпизодтары әсіресе суық мезгілде жылу электр станциялары мен тұрғын үй жылыту жүйелерінен шығатын шығарындыларға байланысты болды. Ұзақ мерзімді үрдістер негізінен $PM_{2.0}$, PM_{10}, SO_2 және CO салдарынан жоғары концентрациялы оқиғалар санының артуын көрсетті, бұл қала атмосферасына өнеркәсіптік және энергетикалық шығарындылардың айтарлықтай үлесін көрсетеді. Метеорологиялық жағдайлар, әсіресе тыныш немесе әлсіз жел кезеңдері (0-3 м/с), мұндай оқиғалар кезінде ластаушы заттардың жиналуын одан әрі күшейтті, тек 2024 жылы осындай 106 күн тіркелді. Бұл деректер Қарағандыдағы ауа сапасын қалыптастырудағы шығарындылар көздерінің де, ауа райы жағдайларының да маңызды рөлін көрсетеді және мақсатты азайту стратегияларының негізін қалайды.

Түйін сөздер: Қарағанды, $PM_{2.5}$, метеорологиялық параметрлер, ауаның ластану эпизодтары.

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Влияние метеорологических параметров на концентрации $PM_{2.5}$ и связанные эпизоды загрязнения атмосферного воздуха в г. Караганда, Центральный Казахстан (2017–2024 гг.)

Караганда, один из самых загрязненных промышленных городов мира, сталкивается с серьезными проблемами качества воздуха из-за выбросов от угольной промышленности, металлургического производства и угольных электростанций. В данном исследовании изучается влияние метеорологических параметров на концентрацию $PM_{2.5}$ и связанные с этим эпизоды загрязнения воздуха в Караганде, Центральный Казахстан, с использованием ежемесячных данных за период 2017–2024 годов. Для изучения изменчивости загрязнения воздуха, обусловленной метеорологическими условиями, были проанализированы метеорологические параметры, включая температуру (°C), относительную влажность (%), атмосферное давление (гПа), скорость ветра (м/с) и концентрации загрязняющих веществ, в том числе взвешенных частиц (пыль, мг/м³), $PM_{2.5}$ (мг/м³), PM_{10} (мг/м³), диоксида серы (SO_2, мг/м³), монооксида углерода (CO, мг/м³), диоксида азота (NO_2, мг/м³), озона (O_3, мг/м³), аммиака (NH_3, мг/м³) и формальдегида (HCHO, мг/м³). Были проведены анализ временных рядов и корреляционные оценки, а также применены три взаимодополняющих регрессионных подхода: множественная линейная регрессия (MLR), регрессия случайного леса и градиентный бустинг с использованием LightGBM для надежной характеристики взаимосвязей между метеорологическими условиями и уровнями $PM_{2.5}$. Результаты указывают на постоянно высокий уровень загрязнения, с превышением среднесуточных концентраций $PM_{2.5}$, PM_{10}, пыли, фенола, формальдегида и озона, причем наиболее выраженные превышения наблюдались для $PM_{2.5}$. Эпизоды загрязнения воздуха были особенно сильными в холодное время года, что было вызвано выбросами тепловых электростанций и систем отопления жилых домов. Многолетние тенденции выявили увеличение числа случаев высоких концентраций, в основном из-за $PM_{2.5}$, PM_{10}, SO_2 и CO, что подчеркивает значительный вклад промышленных и энергетических выбросов в городскую атмосферу. Метеорологические условия, особенно периоды штиля или слабого ветра (0–3 м/с), еще больше усугубляли накопление загрязняющих веществ в периоды таких явлений, причем только в 2024 году было зафиксировано 106 таких дней. Эти данные подчеркивают решающую роль как источников выбросов, так и погодных условий в формировании качества воздуха в Караганде и служат основой для целенаправленных стратегий по смягчению последствий.

Ключевые слова: Караганда, $PM_{2.5}$, метеорологические параметры, эпизоды загрязнения воздуха.

Introduction

Kazakhstan is among the world's top ten countries in terms of proven coal reserves, most of which are located in Central Kazakhstan. The Karaganda coal basin represents one of the country's largest and most strategically important coal-bearing regions (Kopobayeva et al., 2024; Kopobayeva et al., 2024; Safaei-Farouji et al., 2025). Major metallurgical companies in the region play a significant role in industrial activity and are key sources of atmospheric pollutant emissions due to their large-scale production processes. As a result, the region hosts extensive coal mining, processing, and coal-fired power generation activities, which significantly contribute to atmospheric emissions and make it one of the most polluted industrial areas in the country (Safaei-Farouji et al., 2025; U.S. Environmental Protection Agency, 2013; Junussov& Mustapayeva, 2024). In particular, these activities are major sources of primary $PM_{2.5}$ and gaseous precursors such as SO_2 and NO_x, which promote secondary aerosol formation, leading to elevated fine particulate matter concentrations, frequent air pollution episodes, and contributing to global warming (Asif et al., 2025).

In Karaganda, urban air quality is influenced not only by pollutant emissions but also by meteorological and climatic factors. Periods of calm weather, characterized by low wind speeds, promote the accumulation of pollutants, leading to the formation of air pollution episodes. Temperature, wind, and precipitation directly affect pollutant dispersion and removal, while broader climate patterns such as shifts in prevailing winds, reduced overall wind activity, and increased frequency of calm periods can further contribute to the buildup of suspended particles in the urban atmosphere.

$PM_{2.5}$ originates from both primary sources–direct emissions like coal combustion, industrial processes, and vehicle exhaust–and secondary formation, which occurs in the atmosphere through chemical reactions involving gaseous precursors such as SO_2, NO_x, and Volatile Organic Compounds (VOCs) (Jiang et al., 2025; Hsu et al., 2025; Ormanova et al., 2025). Many studies have investigated the influence of meteorological parameters on $PM_{2.5}$ concentrations and associated air pollution episodes (Martinez-Soto et al., 2025; Wei & Sobrino, 2025; Rakhimberdina et al., 2025). For example, analyses of meteorological factors such as wind speed, temperature, humidity, and atmospheric pressure have been used to quantify their correlations with $PM_{2.5}$ levels in urban environments, demonstrating how weather conditions modulate pollutant accumulation and dispersion (Wabinyai et al., 2026; Wang et al., 2025). Research across China has shown that temperature, humidity, and wind exert strong influences on $PM_{2.5}$ variability, with significant spatial and seasonal heterogeneity (Gao et al., 2023; Chen et al., 2020). In addition, studies focusing on high pollution episodes in regional basins have identified key meteorological factors such as atmospheric boundary layer height, temperature inversions, and wind patterns that contribute to the onset and persistence of $PM_{2.5}$ pollution episodes (Shi et al., 2020; Zhang et al., 2020). $PM_{2.5}$ pollution episodes are defined as multi-day events during which fine particulate matter concentrations substantially exceed daily air quality standards, frequently associated with enhanced emissions, secondary particle formation, and unfavorable dispersion conditions (Wang et al., 2018).

However, before this study, there has been a significant knowledge gap in understanding the influence of meteorological parameters on $PM_{2.5}$ concentrations and associated air pollution episodes in Karaganda region. Addressing this gap is essential for characterizing the city's air quality dynamics and for providing a scientific basis for the development of targeted mitigation strategies.

This study aims to quantitatively assess the influence of meteorological parameters on $PM_{2.5}$ concentrations and associated air pollution episodes in Karaganda from 2017 to 2024.

Materials and methods

Study area. Karaganda, located in Central Kazakhstan, originated in 1857 with the establishment of the Ivanovsky coal mine, marking the beginning of the city's development around coal mining. The region hosts large industrial enterprises involved in coal mining, machinery manufacturing, metal processing, and the food industry. Currently, Karaganda experiences some of the most severe environmental conditions in the region. According to data from the Department of Ecology of the Karaganda Region, in 2024 there are 332 enterprises in the region that emit pollutants into the environment. The total annual emissions from stationary sources amount to 585,000 tons. The major sources of air pollution include motor vehicles, solid waste landfills, combined heat and power plants (CHPs), a foundry and mechanical plant, railway enterprises, and motor transport companies. The main sources of pollution include the enterprises "Kazakhmys" Corporation LLC, "ArcelorMittal Temirtau" JSC, and "TEMK" (KhMZ) JSC which are among the major mining and metallurgical enterprises operating in the area as well as road transport, municipal solid waste landfills, the combined heat and power plant, the foundry and mechanical plant, railway transport facilities, and other vehicle-related enterprises (Environmental Status Bulletin of the Karaganda Region, 2017–2024).

The residential sector also contributes significantly to urban air pollution, particularly in areas affected by emissions from household stoves and small boilers. The highest contributions are observed in the districts of Maikuduk, Prishakhtinsk, and Kirzavod-1 and -2, where low chimney heights in private households limit pollutant dispersion. In contrast, industrial facilities, schools, hospitals, and combined heat and power (CHP) plants are equipped with taller stacks, allowing pollutants to disperse at higher altitudes. Another concern is the lack of control over fuel quality; many residents use low-grade coal that does not meet certified standards, and some rely on 'Nedelka' stoves, which are believed to emit more soot than conventional household stoves.

The climate in Karaganda is sharply continental, characterized by harsh winters, hot summers, and relatively low annual precipitation, with snowstorms and blizzards common during winter.

Data collection and assessment. In this study, monthly meteorological and air quality data for Karaganda for the period 2017–2024 were obtained from RSE "Kazhydromet" (Republican State Enterprise "Kazakhstan Hydrometeorological Service") https://www.kazhydromet.kz/en/. The meteorological parameters included temperature (°C), relative humidity (%), atmospheric pressure (hPa), and wind speed (m/s). Air quality measurements comprised suspended particulate matter (dust, mg/m³), $PM_{2.5}$ (mg/m³), PM_{10} (mg/m³), sulfur dioxide (SO_2, mg/m³), carbon monoxide (CO, mg/m³), nitrogen dioxide (NO_2, mg/m³), ozone (O_3, mg/m³), ammonia (NH_3, mg/m³), and formaldehyde (HCHO, mg/m³). Air quality monitoring in Karaganda is conducted at 7 observation stations, including 4 manual sampling posts and 3 automatic monitoring stations [19]. The dataset provided monthly observations over this eight-year period, which were used to assess temporal trends, seasonal variations, and relationships between meteorological conditions and pollutant concentrations. These data allowed for a comprehensive analysis of air pollution patterns in Karaganda and the identification of factors influencing atmospheric quality in both industrial and residential areas.

Modelling framework. Prior to modelling, the dataset underwent systematic preprocessing to ensure numerical consistency and temporal coherence. Numeric formatting was standardized by converting decimal commas into decimal points, followed by type casting of all predictor variables to continuous numeric form. A unified temporal index was reconstructed by combining month and year fields into a single datetime variable, enabling chronological ordering and time-series operations. To capture cyclical seasonal behavior, temporal features were encoded using trigonometric transformations:

$$month_{sin} = sin\left(\frac{2\pi m}{12}\right), \quad month_{cos} = cos\left(\frac{2\pi m}{12}\right) \tag{1}$$

This representation preserves continuity between calendar boundaries and avoids artificial discontinuities inherent in categorical encoding. Because particulate matter exhibits temporal persistence, autoregressive predictors were introduced to account for carryover effects, including a one-month lag of $PM_{2.5}$ to capture short-term memory and a twelve-month lag to represent seasonal recurrence patterns. Observations with undefined lag values were excluded to maintain modelling integrity.

To robustly characterize relationships between meteorological conditions and particulate concentrations, three complementary regression approaches were implemented. The selection reflects a balance between interpretability, nonlinear modelling capacity, and predictive performance. The modelling task was formulated as a supervised regression problem where $PM_{2.5}$ concentration (mg/m³) serves as the response variable. Meteorological predictors were selected based on established atmospheric transport and dispersion theory and include air temperature (°C), relative humidity (%), atmospheric pressure (hPa), wind speed (m/s). These variables represent key mechanisms governing pollutant accumulation, vertical mixing, hygroscopic growth of aerosols, and horizontal transport.

Multiple Linear Regression. A standardized multiple linear regression model was adopted as a transparent baseline. After feature scaling, the model estimates relationships of the form:

$$PM_{2.5} = \beta_0 + \sum_{i=1}^{p}(\beta_i X_i + \varepsilon) \tag{2}$$

where:

$PM_{2.5}$ – observed concentration of fine particulate matter (mg/m³) at a given time step;

β_0 – intercept term, representing the baseline $PM_{2.5}$ concentration when all predictors are equal to zero;

$\sum_{i=1}^{p}$ – summation operator indicating that the model aggregates contributions from all predictors, where ppp denotes the total number of independent variables;

β_i – regression coefficient associated with the iii-th predictor, quantifying the magnitude and direction of its influence on $PM_{2.5}$ concentration;

X_i – the i-th predictor variable (e.g., temperature, relative humidity, atmospheric pressure, wind speed);

p – total number of predictors included in the model;

ε – stochastic error term capturing unexplained variability, measurement noise, and the influence of omitted factors.

This approach enables direct interpretation of coefficient magnitudes and directional influence of predictors. Although limited in capturing nonlinear interactions, it provides an essential reference for assessing added value of more complex algorithms.

Random Forest Regression. A Random Forest ensemble was employed to model nonlinear relationships and feature interactions without imposing parametric assumptions. This method constructs multiple decision trees via bootstrap resampling of observations, randomised feature selection, and ensemble averaging. Such an architecture effectively captures threshold behavior and multivariate dependencies commonly observed in atmospheric systems.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \overline{y})^2} \tag{3}$$

where:

y_i – observed $PM_{2.5}$ concentration;

$\hat{y}_i$ – predicted concentration;

$\overline{y}$ – mean of the observed concentration;

n – number of observations.

Gradient Boosting via LightGBM. To achieve high predictive accuracy, a gradient boosting model based on LightGBM was implemented. This algorithm iteratively minimizes residual error by sequentially fitting weak learners to gradient updates:

$$F_{t+1}(x) = F_t(x) + \gamma_t h_t(x) \tag{4}$$

where:

$F_t(x)$ – the current ensemble prediction function at iteration ttt; it represents the aggregated output of all previously constructed weak learners;

$F_{t+1}(x)$ – the updated ensemble function after incorporating the new weak learner at iteration t+1t+1t+1;

x – the vector of input features (meteorological variables, seasonal encodings, and lagged $PM_{2.5}$ values);

$h_t(x)$ – the weak learner fitted at iteration ttt, typically a decision tree trained to approximate the negative gradient of the loss function (i.e., the residuals);

γ_t – the learning rate (or step size) applied to the weak learner, controlling the magnitude of its contribution to the ensemble model.

LightGBM's histogram-based optimization and leaf-wise growth strategy provide computational efficiency and enhanced modelling capacity for structured environmental datasets. Within the modelling hierarchy, this approach functions as the primary performance-oriented learner.

Forecasting methodology. Model assessment followed a temporally consistent validation protocol to reflect real-world forecasting deployment. Data were split along the time axis, reserving the final twelve months for testing. This approach prevents information leakage and evaluates model generalization under forward-prediction conditions. To further assess robustness, expanding-window cross-validation was applied using TimeSeriesSplit. In each fold, the training horizon grows while validation advances chronologically, providing stability estimates across temporal regimes.

Model accuracy and explanatory strength were evaluated using complementary measures, including Root Mean Square Error (RMSE), which emphasizes large deviations; Mean Absolute Error (MAE), which measures the average magnitude of error; the coefficient of determination (R^2), which captures explained variance; and Mean Absolute Percentage Error (MAPE). Together, these metrics quantify predictive precision, stability, and descriptive adequacy.

Future $PM_{2.5}$ concentrations for 2025–2026 were estimated using recursive multi-step prediction. Since meteorological observations for future periods are unavailable, a climatological scenario was adopted whereby monthly mean meteorological values derived from historical records were assigned to corresponding forecast months. This procedure approximates expected seasonal atmospheric conditions without reliance on external climate projections. Lagged pollutant features were updated iteratively using model-generated predictions, allowing dynamic propagation of temporal dependencies throughout the forecast horizon.

Uncertainty quantification. To account for predictive uncertainty, interval estimates were constructed using the cross-validated RMSE of the best-performing model. Assuming approximate normality of residuals, bounds were computed as: $\hat{y}_i \pm 1.96 * RMSE$. While ensemble models do not inherently produce probabilistic outputs, this pragmatic approximation provides interpretable confidence envelopes suitable for applied environmental forecasting contexts. Interpretation of model behavior was conducted through complementary analyses. Feature importance rankings derived from ensemble methods identify dominant meteorological drivers, while standardized linear coefficients reveal directional relationships between predictors and pollutant levels. Together these perspectives enhance transparency and support environmental inference beyond predictive accuracy alone.

Results and discussion

Between 2017 and 2024, pollution levels in Karaganda have remained consistently high. The descriptive statistics indicate clear seasonal variability in both meteorological parameters and air pollutant concentrations across the sampling period (Table-1). The mean air temperature was 4.44 ± 12.33 °C, ranging from −18.1 to 23.9 °C, reflecting strong seasonal contrast between winter and summer months. Lower temperatures were observed during the winter months (approximately December–February), accompanied by higher relative humidity (63.54 ± 11.41%, range: 41–82%) and reduced atmospheric mixing conditions. The mean wind speed was 2.68 ± 0.41 m/s (1.9–4.2 m/s), and the mean atmospheric pressure was 954.12 ± 5.53 hPa (942.4–966.0 hPa), indicating relatively stable synoptic conditions during certain periods (Figure 1). These meteorological factors favor pollutant accumulation near the surface due to temperature inversions, a shallow planetary boundary layer, and limited dispersion.

Elevated concentrations of particulate matter and combustion-related pollutants were primarily associated with the cold season. The mean concentration of $PM_{2.5}$ was 0.136 ± 0.136 mg/m³ (0.000–1.200 mg/m³), while PM_{10} averaged 0.132 ± 0.107 mg/m³ (0.000–0.790 mg/m³). Suspended particulate matter (dust) showed a mean of 0.125 ± 0.063 mg/m³ (0.010–0.330 mg/m³). The relatively high maximum values suggest episodic pollution events, most likely occurring during winter. Combustion-related gaseous pollutants also showed substantial variability: CO averaged 1.25 ± 0.60 mg/m³ (0.03–4.00 mg/m³), SO_2 averaged 0.024 ± 0.006 mg/m³ (0.010–0.046 mg/m³), and NO_2 averaged 0.041 ± 0.019 mg/m³ (0.014–0.150 mg/m³). These elevated concentrations during colder months are consistent with increased coal-based heating, thermal power generation, and residential solid fuel combustion, combined with unfavorable dispersion conditions.

Table 1
Descriptive statistics for parameters (N=96)

Variable	Mean	Std	Min	25%	Median	75%	Max
Date	6.702	3.47	1.202	3.952	6.702	9.452	12.202
Temperature (°C)	4.441	12.331	-18.1	-7.125	6.05	16.95	23.9
Relative Humidity (%)	63.542	11.407	41.0	54.0	64.5	73.0	82.0
Atmospheric Pressure (hPa)	954.119	5.533	942.4	950.575	954.9	958.325	966.0
Wind Speed (m/s)	2.683	0.412	1.9	2.4	2.6	2.9	4.2
Suspended particulate matter (dust), mg/m³	0.125	0.063	0.01	0.087	0.122	0.153	0.33
$PM_{2.5}$, mg/m³	0.136	0.136	0.0	0.05	0.12	0.187	1.2
PM_{10}, mg/m³	0.132	0.107	0.0	0.048	0.12	0.18	0.79
Sulfur dioxide (SO_2), mg/m³	0.024	0.006	0.01	0.02	0.021	0.027	0.046
Carbon monoxide (CO), mg/m³	1.249	0.602	0.03	0.915	1.155	1.411	4.0
Nitrogen dioxide (NO_2), mg/m³	0.041	0.019	0.014	0.03	0.038	0.042	0.15
Ozone (O_3), mg/m³	0.035	0.068	0.0	0.018	0.03	0.041	0.68
Ammonia (NH_3), mg/m³	0.009	0.008	0.0	0.005	0.01	0.01	0.057
Formaldehyde (HCHO), mg/m³	0.013	0.01	0.0	0.01	0.01	0.013	0.1

In contrast, warmer months (approximately May–September) were characterized by higher temperatures and improved atmospheric mixing, resulting in generally lower concentrations of primary combustion pollutants such as $PM_{2.5}$, PM_{10}, CO, and SO_2. However, O_3 exhibited a mean concentration of 0.035 ± 0.068 mg/m³ (0.000–0.680 mg/m³), with higher levels expected during warmer periods due to enhanced photochemical activity driven by stronger solar radiation and elevated temperatures. Photochemical reactions involving NO_x and VOCs promote secondary ozone formation under these conditions. Additional reactive pollutants included NH_3 with a mean of 0.009 ± 0.008 mg/m³ (0.000–0.057 mg/m³) and HCHO at 0.013 ± 0.010 mg/m³ (0.000–0.100 mg/m³), which may contribute to secondary aerosol and photochemical processes.

Figures 1 and 2 present a time series analysis of meteorological parameters alongside pollutant concentrations, providing a comprehensive understandding of temporal variations in air quality in Karaganda.

The correlation matrix reveals structured relationships between meteorological conditions and pollutant concentrations, indicating that atmospheric variability plays a measurable role in shaping air quality patterns (Figure-3).

Temperature shows moderate negative correlations with particulate matter fractions ($PM_{2.5}$ and PM_{10}) and several gaseous pollutants, suggesting that lower temperature regimes are associated with increased pollutant accumulation. This behavior is consistent with reduced atmospheric mixing and more stable boundary layer conditions that limit dispersion.

Relative humidity demonstrates moderate positive correlations with particulate matter ($r \approx 0.29$–0.33) and several gaseous species, while showing inverse association with temperature. These relationships may reflect the contribution of moisture-driven processes such as hygroscopic particle growth or secondary aerosol formation, which can influence measured concentrations under humid conditions.

Atmospheric pressure exhibits one of the more consistent associations across pollutant groups, with positive correlations observed for $PM_{2.5}$ ($r \approx 0.41$), PM_{10} ($r \approx 0.45$), SO_2 ($r \approx 0.48$), and CO ($r \approx 0.46$). Such patterns suggest that stable pressure systems may favor pollutant retention by limiting vertical air exchange, thereby increasing concentration persistence near the surface.

Figure 1
Time series of meteorological parameters

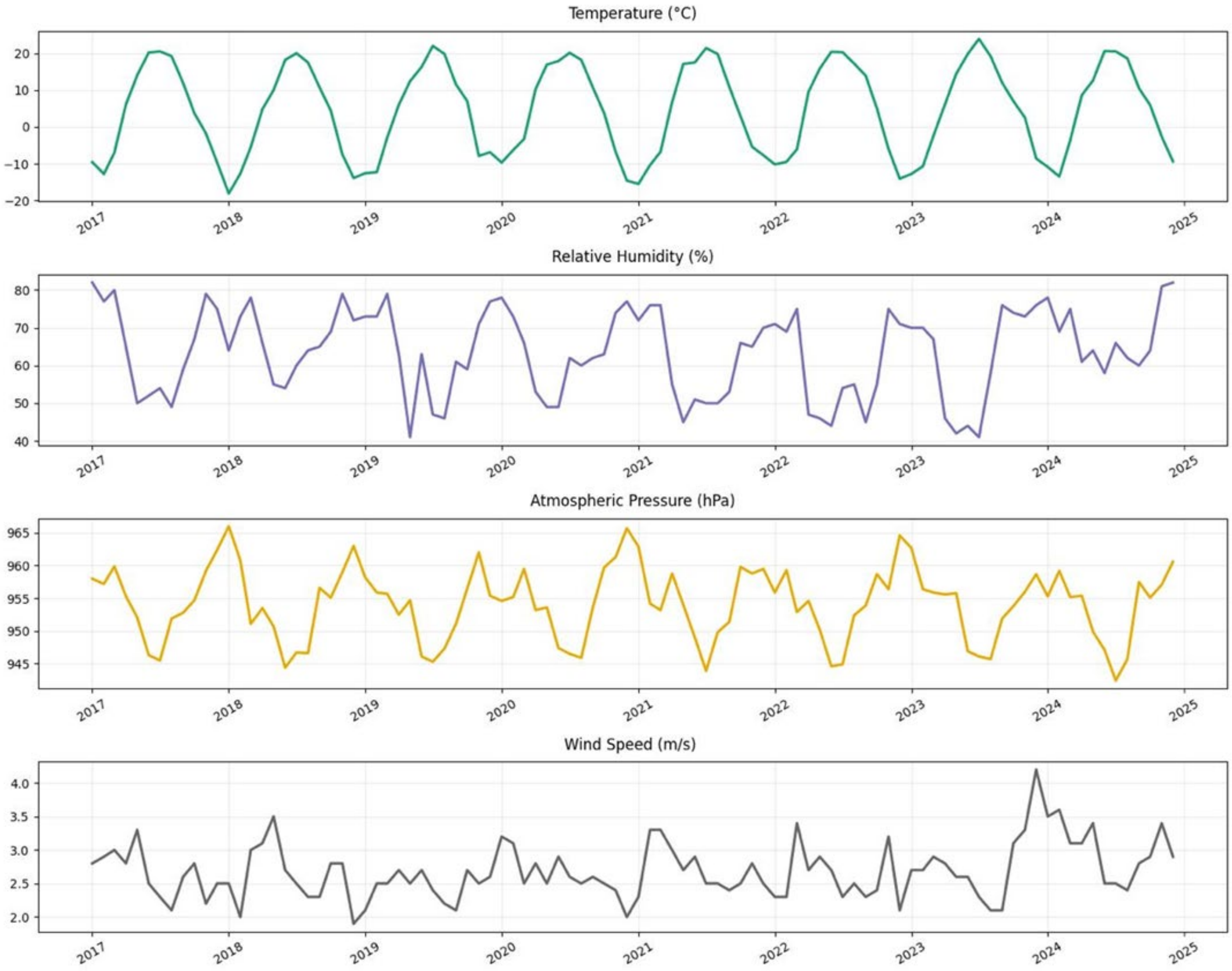


Figure 2
Time series of pollutant concentrations ($PM_{2.5}$, PM_{10}, SO_2, NO_x, and CO)

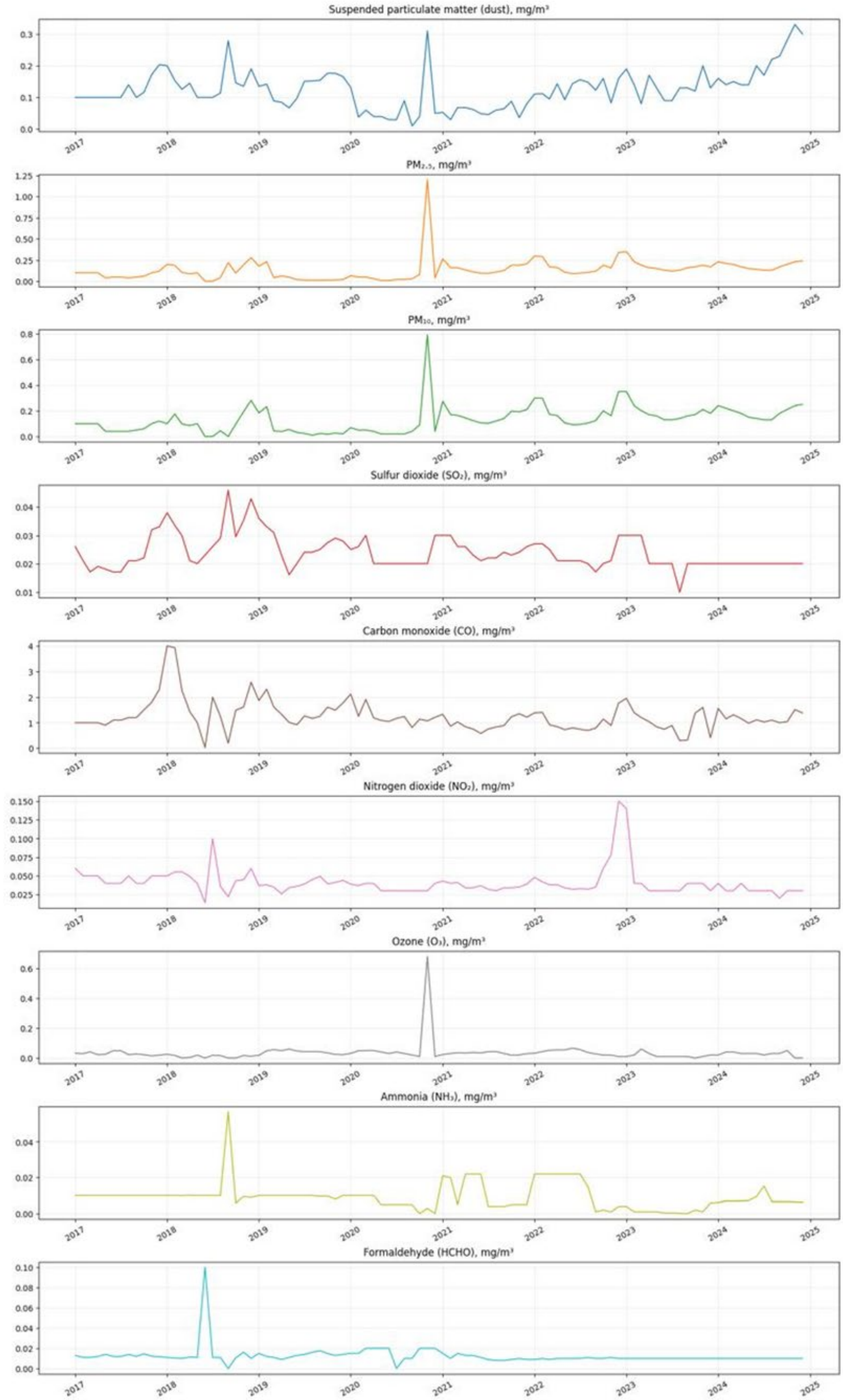
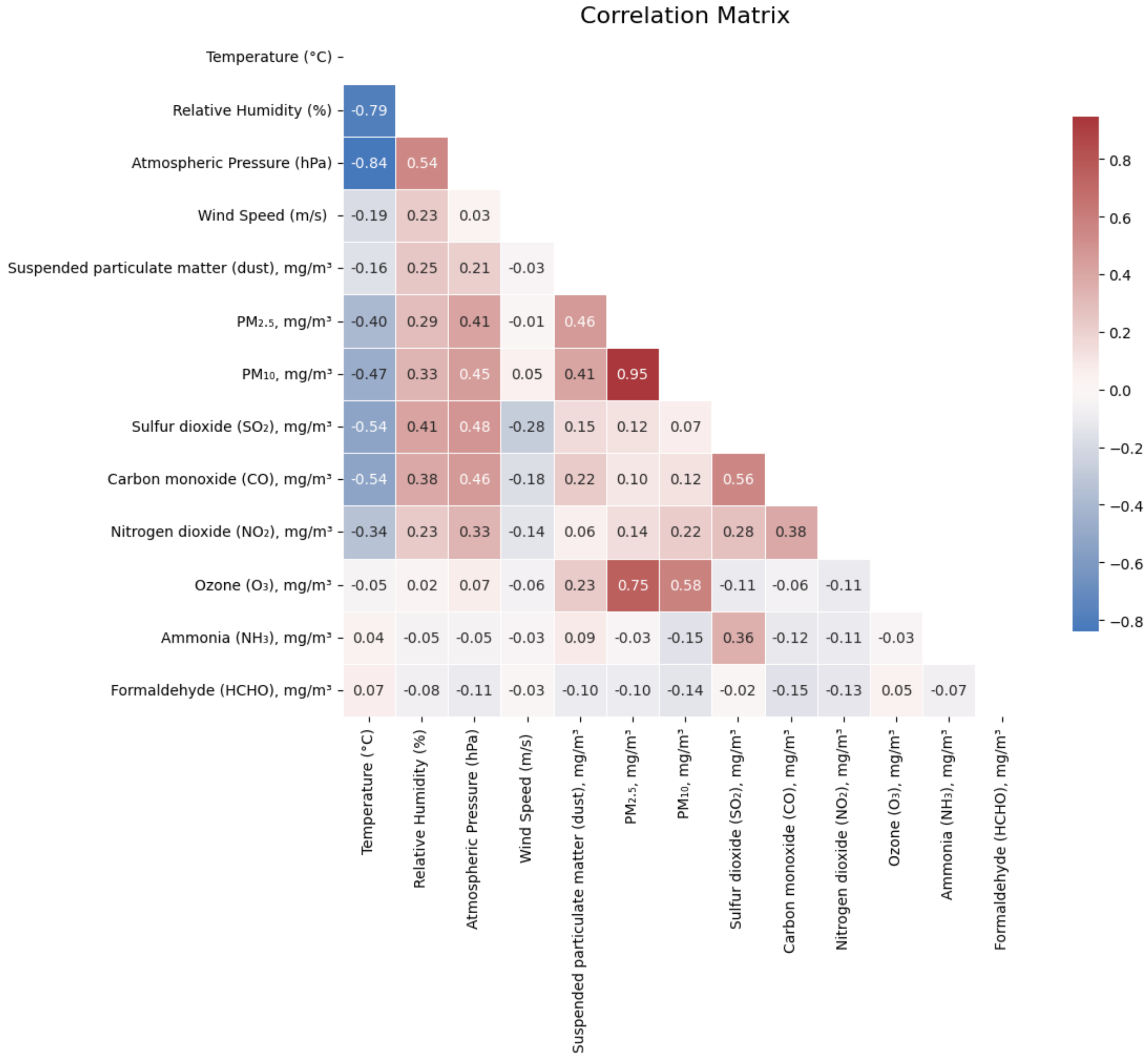


Figure 3
The Pearson correlation of all parameters



Wind speed generally shows weak to moderate negative relationships with several pollutants, particularly SO_2 and CO, supporting its role as a dispersion mechanism. However, the overall magnitude of these correlations remains limited, indicating that wind-driven transport effects may be episodic or nonlinear rather than strongly reflected through simple linear dependence.

Collectively, these findings confirm that meteorological variables are not merely background descriptors but active drivers influencing pollutant variability. Their inclusion in predictive modeling frameworks is therefore justified, as they capture environmental dynamics directly linked to pollutant transport, transformation, and accumulation processes.

Model Performance Evaluation (MAE). The predictive performance of the evaluated models was assessed using walk-forward cross-validation, with the results summarized in Table 2.

Table 2
Predictive performance comparison of regression models evaluated using walk-forward cross-validation

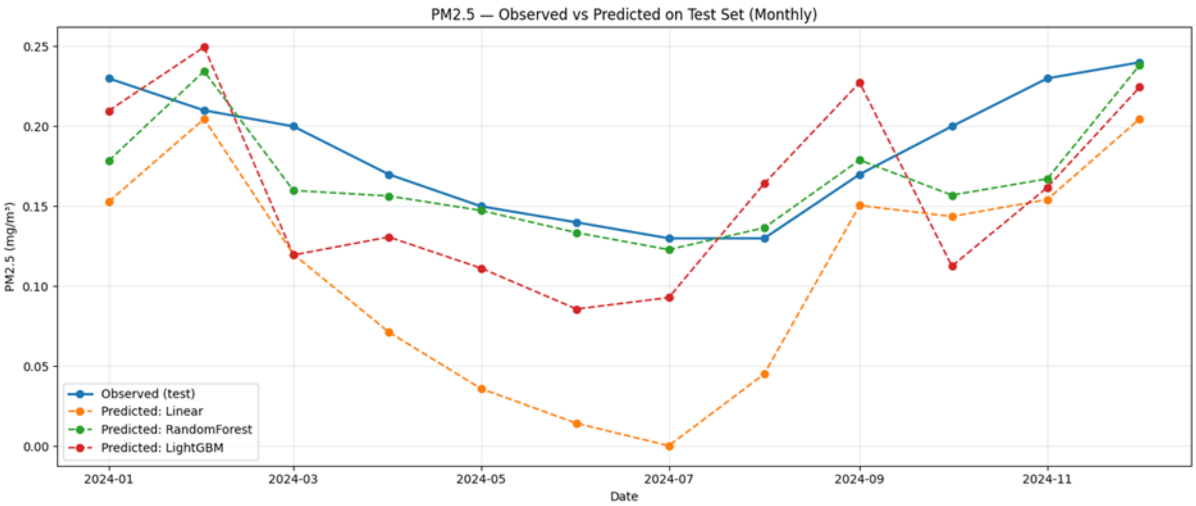
Model	RMSE (mean ± std)	MAE (mean ± std)	R^2 (mean ± std)	MAPE % (mean ± std)
Random Forest	0.107 ± 0.116	0.062 ± 0.041	0.185 ± 0.468	110.94 ± 132.15
LightGBM	0.132 ± 0.109	0.087 ± 0.035	−0.563 ± 0.416	168.91 ± 193.41
Linear Regression	0.239 ± 0.179	0.141 ± 0.058	−22.30 ± 46.71	193.04 ± 181.55

Among the three approaches, the Random Forest model demonstrated the strongest overall performance. It achieved the lowest mean RMSE of 0.107 mg/m³, indicating the smallest average deviation between predicted and observed $PM_{2.5}$ concentrations. This model also produced the lowest mean MAE (0.062 mg/m³) and the most favorable coefficient of determination (R^2 = 0.185 ± 0.468), reflecting limited but positive explanatory capacity. In contrast, the LightGBM model exhibited higher prediction error, with a mean RMSE of 0.132 mg/m³, and reduced explanatory capability (R^2 = −0.563 ± 0.416), suggesting inconsistent alignment with observed variance patterns. The linear regression model showed substantially weaker performance, yielding a mean RMSE of 0.239 mg/m³ and strongly negative R^2 values (−22.30 ± 46.71), indicating an inability to capture the underlying data structure. Additionally, elevated MAPE values for both the linear and boosting models (193% and 169%, respectively) highlight instability in relative error magnitude.

Overall, these quantitative comparisons suggest that the relationship between meteorological variables and $PM_{2.5}$ concentrations cannot be adequately described using linear assumptions. Instead, nonlinear ensemble methods appear more suitable for capturing threshold effects and complex multivariate interactions inherent in the data.

Test-Period Prediction Behavior. Figure 4 illustrates the comparison between observed $PM_{2.5}$ concentrations and model predictions for the 2024 hold-out period. Observed values ranged approximately between 0.13 and 0.24 mg/m³, reflecting moderate seasonal variability.

Figure 4
Observed versus predicted $PM_{2.5}$ concentrations during the test period (monthly resolution)

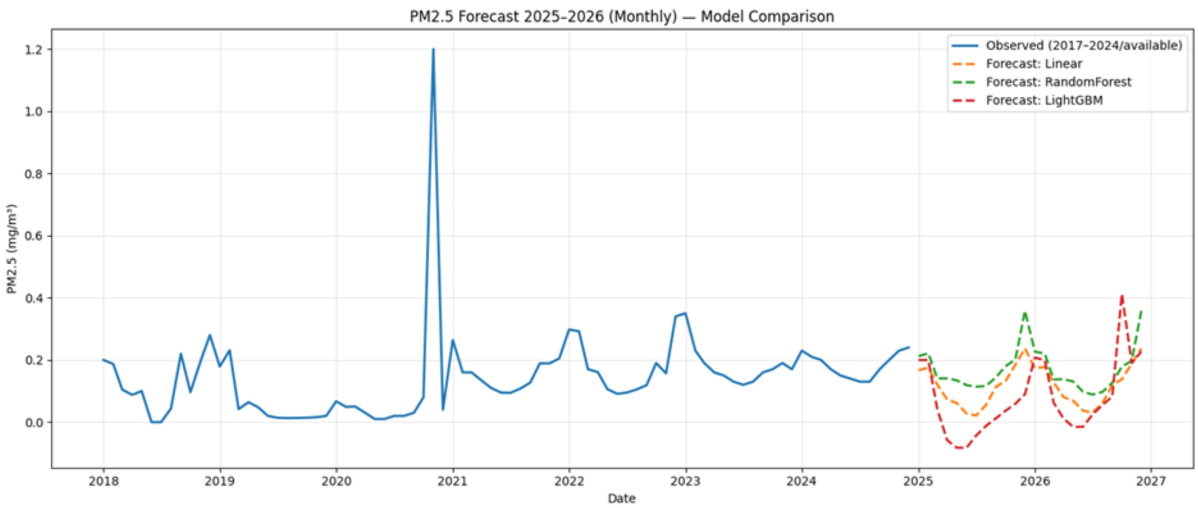


The Random Forest model tracked seasonal dynamics closely, particularly reproducing the late-year increase toward ~0.24 mg/m³. Linear regression consistently underestimated concentrations, producing values near 0.00–0.15 mg/m³, including unrealistic near-zero predictions during mid-year months. LightGBM showed greater responsiveness but also generated oscillatory behaviour and local overestimations (e.g., exceeding 0.22 mg/m³ during transitional periods). These observations visually reinforce the numerical performance metrics and demonstrate the superior temporal stability of the Random Forest approach.

Forecasting Analysis $PM_{2.5}$ concentrations for 2025–2026. Based on the validated models, $PM_{2.5}$ concentrations were projected for 2025–2026 under climatological meteorological conditions. The forecast trajectories are presented in Figure 5.

Figure 5

Multi-model $PM_{2.5}$ forecast for 2025–2026 using climatological meteorological inputs

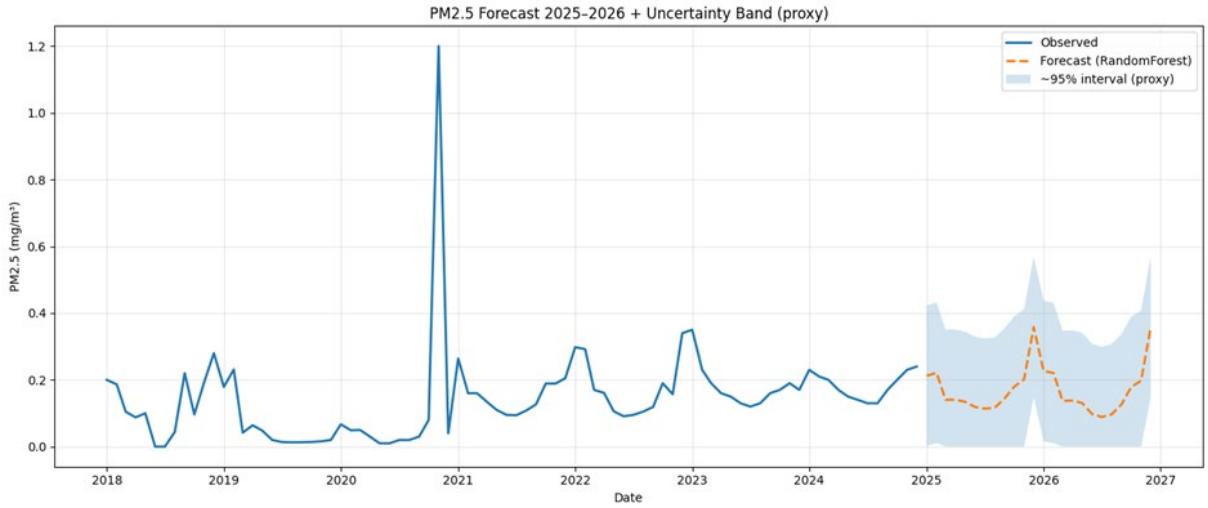


The Random Forest forecast suggests seasonal oscillations within a range of approximately 0.10–0.35 mg/m³, maintaining amplitude comparable to historical behavior. Linear model projections remain smoother and confined to a narrower interval (~0.03–0.22 mg/m³), reflecting their limited dynamic sensitivity. LightGBM produces the largest variability, including transient spikes approaching 0.40 mg/m³, consistent with its higher variance observed during validation. Despite differences in magnitude, all models preserve the annual periodic pattern, indicating that cyclical encoding and lag features successfully propagate seasonal structure into forward predictions.

It should be emphasized that forecasts are scenario-based and assume average meteorological conditions. Consequently, they represent expected seasonal tendencies rather than deterministic future pollution events.

Uncertainty quantification. Prediction uncertainty was evaluated for the best-performing model (Random Forest) using cross-validated RMSE as an error proxy. The mean RMSE of 0.107 mg/m³ was used to construct approximate 95% confidence bounds: $\hat{y}_i \pm 1.96 * RMSE$ resulting in an uncertainty width of roughly ±0.21 mg/m³ (Figure-6).

Figure 6
Random Forest forecast with approximate 95% uncertainty envelope



The uncertainty band indicates that projected concentrations near 0.20 mg/m³ may realistically vary between approximately 0.0 and 0.41 mg/m³, reflecting inherent atmospheric variability and modelling limitations. While this interval does not represent a fully probabilistic estimate, it provides valuable contextual interpretation of forecast reliability. The comparative modelling results provide insight into atmospheric processes governing particulate variability. The inability of linear regression to represent observed dynamics supports the hypothesis that $PM_{2.5}$ concentrations respond nonlinearly to meteorological drivers. Ensemble methods capture interaction effects between humidity, temperature, and transport mechanisms more effectively, consistent with established aerosol formation theory.

Conclusion

This study demonstrated pronounced seasonal variability in both meteorological parameters and air pollutant concentrations during the sampling period, indicating that air quality dynamics in Karaganda are strongly influenced by seasonal changes in temperature, atmospheric stability, and dispersion conditions.

Winter conditions, characterized by low air temperatures, elevated relative humidity, and limited atmospheric mixing, promoted the accumulation of primary pollutants. Elevated concentrations of $PM_{2.5}$, PM_{10}, suspended particulate matter, CO, SO_2, and NO_2 were observed during the cold season, reflecting the dominant contribution of combustion-related sources such as coal-based heating, thermal power plants, and residential solid fuel use. Reduced wind speeds and stable synoptic conditions further enhanced pollutant buildup near the surface, leading to frequent air pollution episodes.

In contrast, warmer months were associated with improved dispersion conditions and generally lower levels of primary combustion pollutants. However, O_3 concentrations increased during this period, highlighting the enhanced role of photochemical processes driven by higher temperatures and stronger solar radiation. This seasonal shift underscores the transition from primary emission dominance in winter to secondary pollutant formation in summer.

Exceedances of daily average concentration standards were observed for suspended particles ($PM_{2.5}$, PM_{10}, dust), phenol, formaldehyde, and ozone, with the most pronounced exceedances noted for $PM_{2.5}$. Such pollution is typical during the cold season, associated primarily with emissions from thermal power plants and residential heating. Over the years, increases in the "highest frequency" indicator have been largely attributed to $PM_{2.5}$, PM_{10}, hydrogen sulfide, and carbon monoxide, reflecting the significant contribution of industrial and thermal power plant emissions to urban air pollution and the persistent accumulation of these pollutants in the city's atmosphere.

Furthermore, the persistence of seasonal oscillations in particulate concentrations across forecast horizons using Multiple Linear Regression, Random Forest Regression, and Gradient Boosting via LightGBM indicates that climatic forcing remains a dominant regulator of particulate behavior in the region.

Overall, the findings confirm that winter air pollution in coal-mining regions is primarily governed by anthropogenic combustion emissions, including those from residential heating and coal-fired power plants, combined with unfavorable meteorological conditions. In contrast, summer air quality is more strongly influenced by atmospheric chemistry and photochemical reactions. These results emphasize the need for season-specific air quality management strategies, such as reducing emissions from coal combustion and residential heating during winter, and controlling ozone precursors and secondary pollutants during warmer months. These findings underscore the importance of implementing seasonally adaptive mitigation strategies, rather than applying uniform air quality policies throughout the year.

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Gulden Ormanova: Writing – original draft, Writing – review & editing, Methodology, Investigation, Formal analysis, Funding acquisition, Resources. Aruzhan Rakhimberdina: Data curation, Software, Visualization. Alexey Alexeyev: Data curation. Kyran Kassym: Formal analysis. Dhawal Shah: Validation, Supervision. Nurxat Nuraje: Validation, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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