

Comparative evaluation of CHIMERE and ENSEMBLE model estimates versus in-situ measurements of particulate matter in the Iași urban area, Romania

Liliana Drăgoi (Oniu)^{1*}, Pavel Ichim¹, Marius-Mihai Cazacu²

¹ Faculty of Geography and Geology, Doctoral School of Geosciences, "Alexandru Ioan Cuza" University of Iasi, Carol I Boulevard, No. 11, 700506 Iasi, Romania;

² Department of Physics, "Gheorghe Asachi" Technical University of Iasi, 700050 Iasi, Romania

*Corresponding author: liliana.dragoi@student.uaic.ro

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Abstract: This research investigates the air quality in Iași in 2024 by comparing estimations of particulate matter (PM_{2.5} and PM₁₀) from the European Copernicus Atmosphere Monitoring Service (CAMS) with measurements obtained from an urban background air quality monitoring station within Romania's national network. The analysis compared the Ensemble CAMS output, representing an average of many models, to the individual CHIMERE model. Both provide a spatial resolution of 0.1° × 0.1°. The expected yearly mean for PM_{2.5} was 13.56 µg/m³ with CHIMERE and 13.15 µg/m³ with the Ensemble multi-model, compared to an observed value of 15.52 µg/m³. CHIMERE estimated PM₁₀ at 21.2 µg/m³, whereas the Ensemble calculated it at 16.31 µg/m³, while the measured value was 27.57 µg/m³. The monthly average bias was negative for both models, indicating underestimation (December being an exception). The monthly root mean squared error (RMSE) varied from 3.8 to 21.7 µg/m³, depending on the model and pollutant. Optimal correlations for PM_{2.5} were observed in November, with both models exhibiting values of 0.9. Strong correlations were noted for PM₁₀ in November and April for both CHIMERE and Ensemble, indicating enhanced model performance throughout seasonal transitions. Of the 25 exceedances of the daily PM₁₀ limit value documented in 2024 at the urban background station, the CHIMERE model validated seven, while the Ensemble model validated none. The conclusions highlight that, while CAMS products are effective for delineating spatial pollution patterns, rigorous local validation is necessary, especially in urban environments, where local factors and weather patterns may influence the accuracy of simulate predictions.

1. Introduction

Air pollution is one of the greatest environmental threats to human health. It is the fourth leading cause of death globally, responsible for almost 7 million deaths each year. (Health Effects Institute, 2022).

Of all air pollutants, fine particulate matter (PM) is considered to be among the most harmful to human health, alongside nitrogen oxides (NO_x) and ozone (O₃) (European Environment Agency, 2019; Sicard et al., 2023). Exposure to these particles over a long period of time can lead to premature death and worsen existing respiratory and cardiovascular diseases (Dai et al., 2014; Delfino et al., 2009; González Ortiz et al., 2021; Hvidtfeldt et al., 2021; World Health Organization, 2021). The PM also plays an important role in climate change (Fuller et al., 2022).

In southeastern Europe, including Romania, exposure to PM is significantly higher than the European average. The European Commission estimates that approximately 17900 people in Romania died prematurely in 2022 due to exposure to PM_{2.5},

corresponding to 185100 years of life lost (Directorate-General for Environment, 2025). Tanasa et al. (2023) identified Iași as the city with the highest PM_{2.5} concentrations among the four Romanian cities investigated, highlighting the importance of particulate matter as a major air-quality and public-health concern (Tanasa et al., 2023).

In Romania, ambient air quality is regulated by Law No. 104/2011, which transposes Directive 2008/50/EC on ambient air quality and cleaner air for Europe into national legislation. [Click or tap here to enter text.](#) According to Law No. 104/2011, air quality assessment can be conducted under three assessment regimes: Regime A (measurements at fixed monitoring stations), Regime B (a combination of measurements at fixed points, modelling techniques, and/or indicative measurements), or Regime C (emission modelling techniques, objective estimation techniques, or both) [Click or tap here to enter text.](#) According to Order No. 1956/2021 of the Ministry of Environment, Water and Forests the municipality of Iași, is classified under Regime A for PM₁₀ and PM_{2.5}, requiring these pollutants to be monitored through fixed monitoring stations (Ministry of Environment, Water and Forests, 2021).

In 2024, measurements at the IS-2 urban background station indicated that PM remained a significant air-quality concern in Iași, with exceedances of the daily PM₁₀ limit value recorded during the study period. Although the annual mean concentrations of PM₁₀ and PM_{2.5} remained below the current annual limit values established under Law No. 104/2011, they exceeded the more stringent annual limit values established by Directive (EU) 2024/2881 (Drăgoi et al., 2025a). The Directive which is to be transposed into national law by 11 December 2026, introduces stricter air-quality standards, underscoring the importance of reliable forecasting of PM₁₀ and PM_{2.5} concentrations to anticipate potential exceedances and support authorities in achieving compliance with the forthcoming limit values. In this context, the present study compares observations data from the IS-2 urban background station in 2024 with regional air-quality forecasts from the CHIMERE model and the CAMS regional Ensemble model to assess their consistency and potential for forecasting PM₁₀ and PM_{2.5} concentrations.

Chemistry-transport models of the atmosphere, including CHIMERE, are frequently used (Bessagnet et al., 2017; Cholakian et al., 2023; De Meij et al., 2009; Gama et al., 2019; Menut et al., 2013; Terrenoire et al., 2015; Thunis et al., 2017) to generate maps of pollutant concentrations over time and space and to assess the effectiveness of emission reduction strategies. Validations have shown that CHIMERE reproduces temporal variability at urban background stations but tends to underestimate PM₁₀, except during some summer months (De Meij et al., 2009). Analyses conducted in Melpitz, Germany, indicated that simulated concentrations were lower than observed values, with PM_{2.5} concentrations of 13.2 and 17.8 µg/m³, respectively, and PM₁₀ concentrations of 15.7 and 22.1 µg/m³, respectively. Maximum summer standard deviations ranged from 10 to 15 µg/m³ (Couvidat et al., 2018).

This underestimation is associated with an incomplete representation of the coarse fraction, which includes secondary organic aerosols, mineral dust, and sea salt. This explains why PM_{2.5} performs better than PM₁₀ (Terrenoire et al., 2015).

Multi-model studies have confirmed the difficulty of reproducing episodes with high concentrations. For instance, Stern et al. (2008), Sartelet et al. (2007) demonstrated that all European models, including CHIMERE, consistently underestimate primary and secondary aerosols as observed PM₁₀ concentrations increase. Within the CAMS service, the ensemble indicated negative biases of approximately -4.5 µg/m³ during the winter of 2013-2014 (Marécal et al., 2015).

Global assessments of PM_{2.5} reported the same pattern: negative biases in Europe and the United States due to underestimation of ammonium nitrates and missing wood-burning emissions in the used inventories. In contrast, the models reproduced the observed levels well in Beijing, where concentrations are dominated by dust (Bessagnet et al., 2017).

Research conducted by Terrenoire et al. (2015) confirms these trends. For PM_{10} , a negative percentage bias of -14% was found. For $PM_{2.5}$, a slight overestimation of 4.9% was found, which is very close to the observed values. Forecasts for the cold season of 2022–2023 in the Padana Plain indicated superior performance of the CHIMERE model for $PM_{2.5}$, while the Ensemble model showed higher correlations but overestimations. The average positive bias was $8.1 \mu\text{g}/\text{m}^3$ for $PM_{2.5}$ and $4.0 \mu\text{g}/\text{m}^3$ for PM_{10} (Gualtieri et al., 2025).

These results suggest that CAMS model limitations arise from the incomplete representation of local sources and the inadequate description of regional atmospheric processes. Spatial resolution is key to the performance of chemical transport models. In a European intercomparison exercise involving five regional air quality models, CHIMERE demonstrated significant improvements when the resolution increased from 56 km to 14–7 km, especially regarding urban concentrations of NO_2 and PM_{10} . However, the authors emphasize that finer resolution alone is insufficient without more detailed emission inventories and meteorological data (Schaap et al., 2015).

CHIMERE is widely used to forecast particulate matter concentrations and evaluate the effectiveness of emission reduction plans. De Meij et al. (2009) demonstrated that reducing emissions from the residential sector and road traffic in the Padana Plain leads to significant decreases in $PM_{2.5}$ concentrations. However, approximately 40% of pollution originates from regional contributions and background conditions. At the European level, Thunis et al. (2017), showed that the effectiveness of measures varies between regions. In Eastern Europe, for instance, the greatest benefits are achieved through interventions in the residential and transport sectors, while the industrial contribution remains low.

Gualtieri et al. (2025) found that, among models used by the Copernicus Atmosphere Monitoring Service (CAMS), CHIMERE showed the best performance in reproducing observed $PM_{2.5}$ concentrations. However, further efforts are needed to improve CAMS models' performance in estimating particle concentrations. The CAMS ensemble showed the highest correlations but not the best bias values.

Despite these advances, there is a lack of studies directly comparing the daily PM estimates of the CHIMERE and Ensemble models with in-situ observations from urban background stations in southeastern Europe, especially Romania and the municipality of Iași.

Thus, this study aims to analyze daily PM_{10} and $PM_{2.5}$ estimates obtained with CHIMERE and a multi-model ensemble, comparing them with observations from an urban background station in Iași and evaluating the performance of the two models based on statistical indicators.

2. Materials and Methods

2.1. Modelled data

This study used data provided by CAMS. The data is available online at the Atmosphere Data Store: <https://ads.atmosphere.copernicus.eu/>.

The analysis focused on PM_{10} and $PM_{2.5}$ concentration data obtained from the CHIMERE and Ensemble multi-model from January to December of 2024.

CHIMERE is a chemistry-transport model designed to simulate atmospheric composition on a regional scale. Mailler et al. (2017) describe it in detail. The model and related documentation are available at <http://www.lmd.polytechnique.fr/chimere/>.

CHIMERE runs operationally within CAMS with an approximate spatial resolution of $0.1^\circ \times 0.1^\circ$ (approximately 10 km) and an hourly temporal resolution. The model considers emission, transport, and chemical transformation processes.

The ensemble is a CAMS multi-model median product. For each time step of the daily forecasts, the individual model fields are interpolated onto a regular grid with a resolution of $0.1^\circ \times 0.1^\circ$. This grid covers the European domain (25°W – 45°E , 30°N – 72°N) and is

used for CAMS regional production. At each point on this grid, the ensemble value is defined as the median of all participating models (CHIMERE, DEHM, EMEP, EURAD-IM, GEM-AQ, LOTOS-EUROS, MATCH, and MOCAGE). This approach reduces uncertainty associated with individual models, generally leading to more robust statistical performance (Marécal et al., 2015).

2.2. Observation data and Study area

The daily concentrations of PM₁₀ and PM_{2.5} were obtained using the reference gravimetric method at the IS-2 urban background station, which is part of the Romanian National Air Quality Network. The station's coordinates are: 47.150951° N, 27.581920° E. The station is located at an altitude of approximately 42 meters (<https://calitateaer.ro/>).

To ensure comparability, both observational and modeled data were aggregated to a daily temporal resolution.

The modeled data were extracted for the period from January to December 2024 for the grid point closest to the IS-2 station's location.

The IS-2 urban background station is located in Iași, a large city in northeastern Romania with 389895 inhabitants in 2024 (National Institute of Statistics, 2026). It lies at an altitude of 100 meters above sea level at the coordinates 47.1200°N, 27.1600°E.

The region's climate is cold in winter and hot in summer, transitional between temperate and continental, with precipitation distributed uniformly throughout the year (Sfîcă et al., 2018).

There is very little industrial activity, which is mainly situated about 10–15 km southwest of Iași. During the winter, traffic and domestic heating appear to be the most significant local sources of emissions. The Integrated Air Quality Plan for Nitrogen Dioxide/Nitrogen Oxides (NO₂/NO_x) and PM₁₀ and PM_{2.5} in the municipality of Iași states that, in 2018, the main source of PM₁₀ emissions was the production of asphalt mixtures for road paving (32.09%), followed by residential heating (25.92%). However, road paving does not occur during the cold season, when most daily limit value exceedances were recorded. Residential heating was the main source of PM_{2.5} emissions in Iași Municipality in 2018 (49.7%), followed by road transport (28.9%) and road paving (15.9%) (Iași Municipality, 2018).

In addition to these local emission sources, previous aerosol observations in Iași have identified a mixture of urban/industrial aerosols, biomass-burning aerosols, and Saharan dust, highlighting the influence of both local emissions and long-range transported aerosols on the city's atmospheric composition (Unga et al., 2013).

2.3. Methods of analysis

The performance of the models was evaluated based on standard statistical indicators: Pearson correlation coefficient (R), Root Mean Square Error (RMSE), Mean Bias Error (Mean bias), Mean Absolute Error (MAE), Root Mean Square Error Normalised (NRMSE), centered Root Mean Square Deviation (cRMSD) defined as follows:

$$R = \frac{\sum_{i=1}^n (M_i - \bar{M})(O_i - \bar{O})}{\sqrt{\sum_{i=1}^n (M_i - \bar{M})^2} \sqrt{\sum_{i=1}^n (O_i - \bar{O})^2}} \quad (1)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (M_i - O_i)^2}{n}} \quad (2)$$

$$Mean\ bias = \frac{1}{n} \sum_{i=1}^n (M_i - O_i) \quad (3)$$

$$MAE = \frac{1}{n} \sum_{i=1}^n |Mi - Oi| \quad (4)$$

$$NRMSE = \frac{RMSE}{O_{max} - O_{min}} \quad (5)$$

$$cRMSD^2 = \sigma_M^2 + \sigma_O^2 - 2\sigma_M\sigma_OR \quad (\text{Taylor})$$

$$\sigma_M = \sqrt{\sum_{i=1}^n (Mi - \bar{M})^2} \quad \sigma_O = \sqrt{\sum_{i=1}^n (Oi - \bar{O})^2} \quad (6)$$

$$RMSE^2 = \text{Mean bias}^2 + cRMSD^2$$

Where

Mi = estimated model values (CHIMERE, Ensemble)

Oi = observed values (IS-2)

$\bar{M}$, $\bar{O}$ = the means of the two series

n = total number of observations compared

σ_O = standard deviation of observed values

σ_M = standard deviation of modeled values

O_{max} = maximum daily concentration observed

O_{min} = minimum daily concentration observed

A visual evaluation was performed using daily and monthly charts.

To assess each model's ability to capture daily variability, Taylor diagrams (Taylor, 2001) were generated.

To investigate how the models reproduce pollution events and the spatial distribution of particles, a representative day was selected: April 1, 2024. On this day, the daily limit value for PM₁₀ was exceeded due to the transport of Saharan dust. This event was confirmed by observations and CHIMERE simulations. A concentration map was created for this day to analyze how the model captures the phenomenon's spread on a regional scale.

3. Results

3.1. Observed and Modeled PM₁₀ Concentrations

Data from the IS-2 air quality monitoring station showed that the daily limit value for PM₁₀ protection of human health (50 µg/m³, not to be exceeded more than 35 times in a calendar year) was exceeded 25 times in 2024. Most of these exceedances occurred in the autumn months, particularly in October (6 exceedances) and November (5 exceedances). There were three exceedances in January, March, and September, and two in February and April. There was only one exceedance during the summer, in August (Figure 1). The highest daily concentrations were associated with thermal inversion episodes, low temperatures, and combustion from residential and energy facilities. (Drăgoi et al., 2025b).

Of the 25 exceedances of the daily limit value recorded in 2024 at the IS-2 urban background station, the CHIMERE model validated seven, while the Ensemble model did not validate any. The models reproduced the general trend of daily concentration variation, but they underestimated the peaks observed at the IS-2 station. For instance, CHIMERE estimated the maximum observed value of 101.63 µg/m³ in April at 78.80 µg/m³ (Figure 2), while Ensemble estimated it at 36.87 µg/m³. Similarly, Ensemble estimated the November peak of 101.45 µg/m³ at 48.11 µg/m³, while CHIMERE

estimated it at $58.42 \mu\text{g}/\text{m}^3$. An exception for both models was in December when they both overestimated daily PM_{10} concentrations.

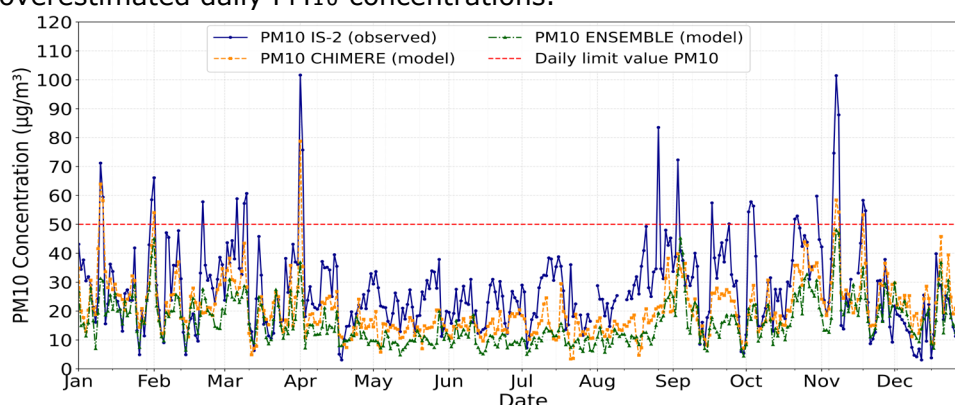


Figure 1. Daily PM_{10} concentrations, Observed vs Models (2024)

On April 1, 2024, the daily PM_{10} concentration recorded at IS-2 was $101.63 \mu\text{g}/\text{m}^3$, which was higher than the $78.8 \mu\text{g}/\text{m}^3$ predicted by CHIMERE. This increase may have been partly due to the long-range transport of Saharan dust (Environmental Protection Agency Iaşi, 2024). The modeled PM_{10} concentrations in northeastern Romania by CHIMERE were predominantly in the range of $50\text{--}80 \mu\text{g}/\text{m}^3$, which is above the daily limit value of $50 \mu\text{g}/\text{m}^3$ established by Law 104/2011 (Figure 2).

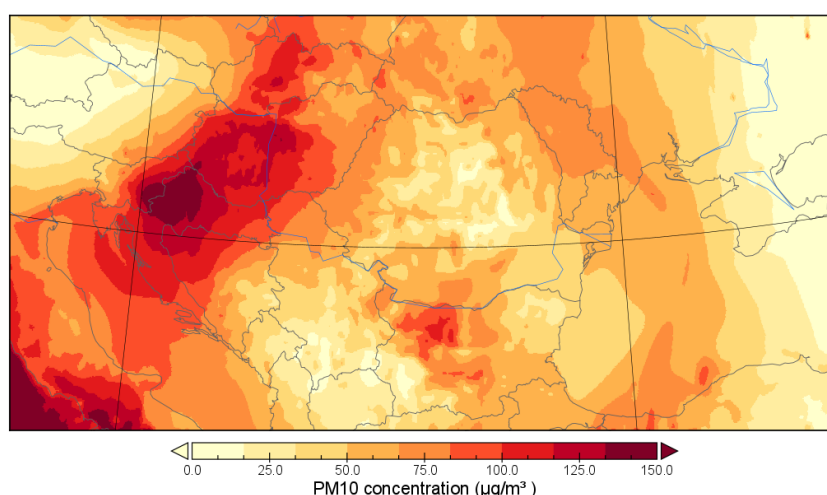


Figure 2. Spatial distribution of PM_{10} concentrations ($\mu\text{g}/\text{m}^3$) over Romania and surrounding regions on April 1, 2024, as simulated by the CHIMERE model.

The monthly mean PM_{10} concentrations measured at the IS-2 were highest in October ($34.30 \mu\text{g}/\text{m}^3$) and November ($33.16 \mu\text{g}/\text{m}^3$), followed by January ($29.99 \mu\text{g}/\text{m}^3$). The lowest monthly mean PM_{10} concentrations were recorded between May and July. Both Ensemble and CHIMERE followed the monthly trend but underestimated PM_{10} concentrations, except in December (Figure 3).

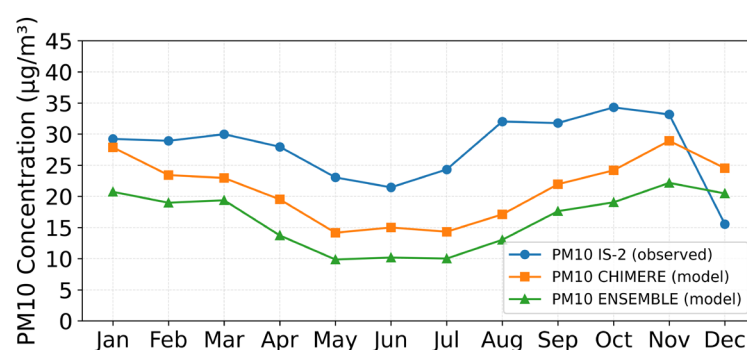


Figure 3. Monthly PM₁₀ concentrations, Observed vs Models (2024)

In general, the Ensemble multi-model underestimated daily PM₁₀ data from station IS-2. The highest correlations were recorded in November ($R = 0.90$) and April ($R = 0.87$). The weakest correlations were recorded in May ($R = 0.16$) and December ($R = 0.38$), indicating the model's reduced ability to reproduce PM₁₀ concentrations in these months.

The average bias was negative in most months, ranging from $-19.0 \mu\text{g}/\text{m}^3$ to $-8.5 \mu\text{g}/\text{m}^3$, which confirms the model's tendency to underestimate observed concentrations. December was the only exception, with a positive bias of $4.9 \mu\text{g}/\text{m}^3$, indicating an overestimation of the observed concentrations.

Average absolute errors ranged from 8.1 to $19.0 \mu\text{g}/\text{m}^3$, and RMSE values varied from 11.4 to $21.7 \mu\text{g}/\text{m}^3$, with maximums recorded in August. This indicates higher deviations during this period.

The NRMSE ranged from 0.2 to 0.3 during the cold months, suggesting a good fit between the model and observations. However, the high values in May (0.6) and June (0.7) indicate poor model performance during these months (Table 1).

Table 1. Monthly Statistical Performance Indicators of the ENSEMBLE Model for PM₁₀(2024)

Month	Mean IS-2 µg/m ³	Pearson coef.	Mean Bias µg/m ³	MAE µg/m ³	RMSE µg/m ³	NRMSE
Between PM ₁₀ Observed (IS-2) and PM ₁₀ Ensemble Model						
January	29.23	0.74	-8.5	9.5	13.4	0.2
February	28.92	0.77	-9.9	11.4	14.4	0.2
March	29.99	0.73	-10.6	11.3	15.1	0.3
April	27.54	0.87	-13.8	14.3	19.8	0.2
May	23.05	0.16	-13.2	13.4	14.9	0.6
June	21.40	0.49	-11.3	11.4	12.3	0.7
July	24.33	0.77	-14.3	14.3	16.2	0.5
August	32.02	0.64	-19.0	19.0	21.7	0.3
September	32.22	0.58	-14.2	14.7	18.6	0.3
October	34.30	0.75	-15.3	15.3	18.5	0.4
November	33.16	0.90	-11.0	13.3	18.8	0.2
December	15.55	0.38	4.9	8.1	11.4	0.3

A statistical analysis of the CHIMERE model in relation to IS-2 station observations for 2024 revealed optimal results during the cold and transitional seasons (spring and fall) and suboptimal results during the summer.

The strongest correlations between observed and modeled PM₁₀ concentrations were recorded in April (0.92), November (0.89), and September (0.82). This suggests that the model effectively reproduces daily variability during these periods. The weakest correlations were recorded in July (0.26) and May (0.30).

The model's tendency to underestimate observed concentrations was confirmed by the average negative bias, ranging from -1.4 to $-14.9 \mu\text{g}/\text{m}^3$ from January to November.

An exception was December, when a positive bias of $9.0 \mu\text{g}/\text{m}^3$ was recorded, indicating overestimation.

The MAE ranged from $6.7 \mu\text{g}/\text{m}^3$ in June to $14.9 \mu\text{g}/\text{m}^3$ in August, and the RMSE ranged from $8.1 \mu\text{g}/\text{m}^3$ in June to $18.8 \mu\text{g}/\text{m}^3$ in August. These results indicate better performance in spring, autumn, and winter, and poorer performance in summer.

NRMSE values (0.1–0.2 in winter and 0.4 in May–July) highlight the model's satisfactory ability to reproduce observations in the cold season but also its difficulties in the summer (Table 2).

Table 2. Monthly Statistical Performance Indicators of the CHIMERE Model for PM_{10} (2024)

Month	Mean IS-2 $\mu\text{g}/\text{m}^3$	Pearson coef. Between PM_{10} Observed (IS-2) and PM_{10} Chimere Model	Mean Bias $\mu\text{g}/\text{m}^3$	MAE $\mu\text{g}/\text{m}^3$	RMSE $\mu\text{g}/\text{m}^3$	NRMSE
January	29.23	0.75	-1.4	7.8	9.7	0.1
February	28.92	0.63	-5.5	9.7	12.8	0.2
March	29.99	0.62	-7.0	9.9	13.5	0.2
April	27.54	0.92	-8.5	9.6	12.2	0.1
May	23.05	0.30	-8.9	9.3	11.1	0.4
June	21.40	0.54	-6.4	6.7	8.1	0.4
July	24.33	0.26	-10.0	10.8	13.8	0.4
August	32.02	0.49	-14.9	14.9	18.8	0.3
September	32.22	0.82	-9.8	11.0	13.6	0.2
October	34.30	0.72	-10.1	10.7	14.4	0.3
November	33.16	0.89	-4.2	10.4	14.6	0.2
December	15.55	0.48	9.0	10.4	12.7	0.3

3.2. Observed and Modeled Daily $\text{PM}_{2.5}$ Concentrations .

Current legislation (Law 104/2011) does not provide daily limit values for $\text{PM}_{2.5}$ for human health protection. Similar to PM_{10} , daily $\text{PM}_{2.5}$ concentrations showed seasonal variability, with higher values in January, February, October, and November, and lower values during the warm season.

While the CHIMERE and Ensemble models followed this general trend, they underestimated the maximum observed value of $71.74 \mu\text{g}/\text{m}^3$ in November (Figure 4).

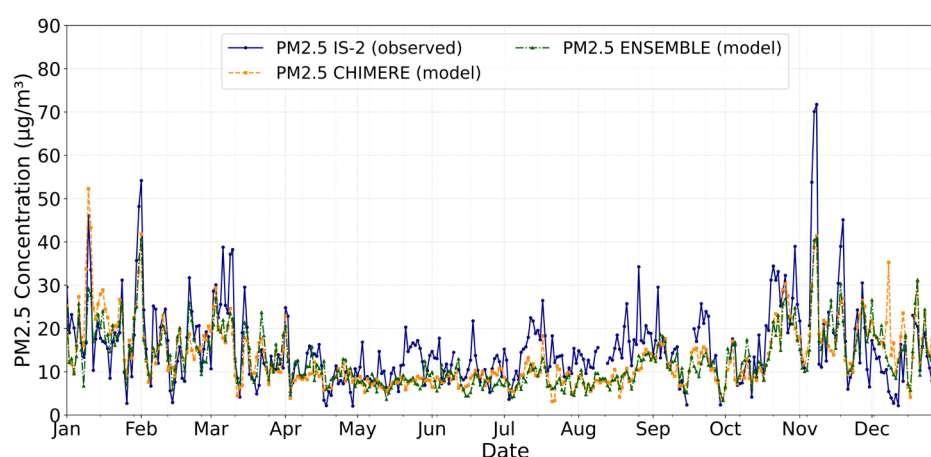


Figure 4. Daily $\text{PM}_{2.5}$ concentrations, Observed vs Models (2024)

At the IS-2 station, the mean monthly $PM_{2.5}$ concentrations ranged from 10.21 $\mu g/m^3$ in April to 23.51 $\mu g/m^3$ in November. While the CHIMERE and Ensemble models reproduced the seasonal trend, higher values in the cold months and lower values in the summer, they underestimated the observed concentrations, particularly in winter. CHIMERE slightly overestimated concentrations in January, while Ensemble provided estimates close to the observed values in April (Figure 5).

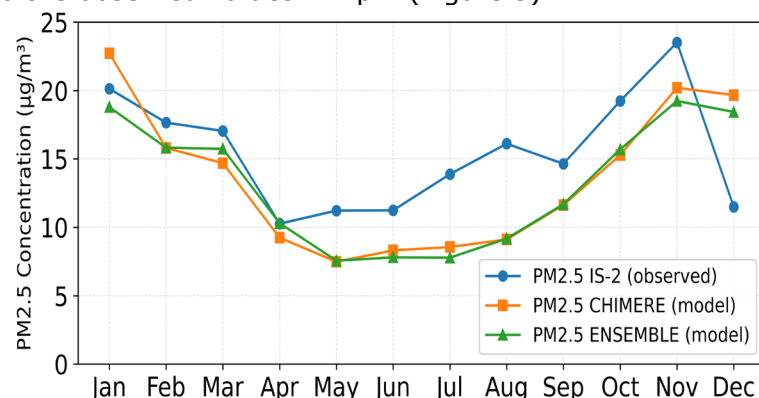


Figure 5. Monthly $PM_{2.5}$ concentrations, Observed vs Models (2024)

A statistical analysis of the Ensembles model for $PM_{2.5}$ compared to observations from the IS-2 station showed better performance than that of the PM_{10} model, with high correlations and moderate errors. The highest correlations were recorded during the cold season ($R = 0.91$ in November, 0.88 in February, and 0.82 in October), which confirms the model's ability to reproduce temporal variability. In contrast, the low values in May, June, and December indicated an absence of correlation between the model values and the observations at the IS-2 station.

The average negative bias ranged from -1.3 to $-6.9 \mu g/m^3$, indicating a tendency to underestimate observed concentrations. Exceptions were in April, when the bias was close to zero ($0.1 \mu g/m^3$), and in December, when the model overestimated the observations ($6.9 \mu g/m^3$).

The MAE ranged from $3.2 \mu g/m^3$ in April to $7.7 \mu g/m^3$ in December, and the RMSE ranged from 4.1 to $11.4 \mu g/m^3$. These values are significantly lower than those for PM_{10} . The NRMSE remained low in the cold months (0.1 – 0.2), indicating a satisfactory fit. However, it reached high levels (0.4 – 0.5) in May, June, and December, indicating poor performance.

The Ensemble model reproduces the seasonal trends and variability of $PM_{2.5}$, performing better in winter. Lower errors and reduced bias compared to PM_{10} indicate better estimation, though there are some limitations (Table 3).

Table 3. Monthly Statistical Performance Indicators of the Ensemble Model for $PM_{2.5}$ (2024)

Month	Mean IS-2 $\mu g/m^3$	Pearson coef.	Mean Bias $\mu g/m^3$	MAE $\mu g/m^3$	RMSE $\mu g/m^3$	NRMSE
Between $PM_{2.5}$ Observed (IS-2) and $PM_{2.5}$ Ensemble Model						
January	20.13	0.80	-1.3	4.9	6.3	0.1
February	17.65	0.88	-1.8	4.5	5.4	0.1
March	17.04	0.79	-1.3	5.1	6.7	0.2
April	10.21	0.62	0.1	3.2	4.1	0.2
May	11.22	0.12	-3.7	4.4	5.4	0.4
June	11.33	-0.10	-3.4	4.4	5.3	0.3
July	13.88	0.72	-6.1	6.3	7.2	0.3

August	16.11	0.69	-6.9	6.9	7.9	0.3
September	14.79	0.62	-2.9	4.4	6.1	0.2
October	19.23	0.82	-3.5	5.1	6.8	0.2
November	23.51	0.91	-4.3	7.6	11.4	0.2
December	11.49	0.40	6.9	7.7	10.7	0.5

The CHIMERE model's performance in relation to daily PM_{2.5} data from the IS-2 station showed good correlation during the cold months. The highest correlations were recorded in November (R=0.88), February (R=0.82), and October (R=0.80). However, no correlations were recorded in May, June, and December (R=0.2), suggesting that the model had a reduced ability to reproduce PM_{2.5} concentrations during these months.

The average bias was negative in most months, ranging from $-1 \mu\text{g}/\text{m}^3$ to $-7 \mu\text{g}/\text{m}^3$, which confirms the model's tendency to underestimate the observed concentrations. The exceptions were January and December, when the bias was positive, indicating overestimation of the observed concentrations.

Average absolute errors ranged from $3.1 \mu\text{g}/\text{m}^3$ in April to $8.8 \mu\text{g}/\text{m}^3$ in December, and RMSE values varied from 3.8 to $11.6 \mu\text{g}/\text{m}^3$, with maximums recorded in August, indicating higher deviations during this period.

The NRMSE ranged from 0.1 to 0.2 during the cold months, suggesting a good fit between the model and observations. However, high values in May (0.4) and December (0.6) indicated poor model performance during these periods.

The results showed that CHIMERE underestimated PM_{2.5} concentrations, particularly in May, June, and December (Table 4), though it was more accurate than for PM₁₀.

Table 4. Monthly Statistical Performance Indicators of the CHIMERE Model for PM_{2.5} (2024)

Month	Mean IS-2 $\mu\text{g}/\text{m}^3$	Coef. Pearson Between PM _{2.5}	Mean Bias $\mu\text{g}/\text{m}^3$ Observed (IS-2)	MAE $\mu\text{g}/\text{m}^3$ and PM _{2.5}	RMSE $\mu\text{g}/\text{m}^3$ CHIMERE	NRMSE Model
January	20.13	0.68	2.6	6.8	8.1	0.2
February	17.65	0.82	-1.8	5.3	6.2	0.1
March	17.04	0.71	-2.3	5.5	7.6	0.2
April	10.21	0.74	-1.0	3.1	3.8	0.2
May	11.22	0.21	-3.7	4.0	5.3	0.4
June	11.33	0.20	-2.9	3.5	4.5	0.3
July	13.88	0.62	-5.3	5.5	6.6	0.3
August	16.11	0.52	-7.0	7.0	8.2	0.3
September	14.79	0.77	-3.0	4.1	5.5	0.2
October	19.23	0.80	-3.9	5.2	7.1	0.2
November	23.51	0.88	-3.3	8.2	11.6	0.2
December	11.49	0.17	8.2	8.8	11.6	0.6

In 2024, the analysis shows that the annual average values simulated by Ensemble ($16.31 \mu\text{g}/\text{m}^3$) and CHIMERE ($21.2 \mu\text{g}/\text{m}^3$) are below the annual average in IS-2 ($27.57 \mu\text{g}/\text{m}^3$).

Ensemble and CHIMERE simulated similar annual mean concentrations of PM_{2.5} (13.15 and $13.56 \mu\text{g}/\text{m}^3$, respectively), both of which are below the annual mean in IS-2 ($15.52 \mu\text{g}/\text{m}^3$) (Table 5).

Table 5. Annual Statistical Performance Indicators of the Ensemble and Chimere Model (2024)

Data source	Mean, μg/m³	Coef. Pearson	Mean Bias, μg/m³	MAE μg/m³	RMSE μg/m³	Standard deviation μg/m³		cRMSD μg/m³	cRMSDN
						σ _O	σ _M		
PM _{2.5}									
ENSEMBLE	13.15	0.68	-2.35	5.37	7.22	-	6.79	6.82	0.73
CHIMERE	13.56	0.65	-1.96	5.58	7.52	-	7.46	7.26	0.78
IS-2	15.52	-	-	-	-	9.35	-	-	-
PM ₁₀									
ENSEMBLE	16.31	0.60	-11.26	12.97	16.50	-	8.05	12.06	0.80
CHIMERE	21.2	0.64	-6.37	10.07	13.12	-	9.99	11.46	0.76
IS-2	27.57	-	-	-	-	14.99	-	-	-

An analysis of the Taylor plot (Figure 6a) of daily PM₁₀ concentrations, normalized to σ_0 and based on 353 days of data, and the statistical indicators in Table 5 shows that:

Ensemble obtained a normalized standard deviation of 0.54 and a correlation coefficient of 0.6, indicating underestimation of variability and moderate correlation with the measured data. In contrast, the CHIMERE model showed a normalized standard deviation of approximately 0.66, which is 34% lower than the observations and closer to the reference value. It also showed a correlation coefficient of 0.64 compared to the observations. This suggests that the CHIMERE model slightly better represents the temporal variations in PM₁₀ concentrations than Ensemble. However, the errors are much larger than those for PM_{2.5}, especially for Ensemble (bias = $-11.26 \mu\text{g}/\text{m}^3$; RMSE = $16.50 \mu\text{g}/\text{m}^3$). CHIMERE has smaller errors (bias = $-6.37 \mu\text{g}/\text{m}^3$; RMSE = $13.12 \mu\text{g}/\text{m}^3$), indicating relatively better performance. The RMSD values confirm this trend, being lower for CHIMERE than for Ensemble. In conclusion, CHIMERE is superior to Ensemble for PM₁₀. The analysis shows moderate agreement with the observations and underestimation in both models.

For PM_{2.5}, analysis of the Taylor diagram (Figure 6b), normalized to σ_0 and based on 356 days of data, and the statistical indicators in Table 5, shows that both models moderately reproduce and underestimate the daily pattern fidelity.

CHIMERE has an R of 0.65, a relative standard deviation of $\sigma = 0.80$ (20% lower than the observations), and a cRMSDN of 0.78. In absolute units, CHIMERE obtains an RMSE of $7.52 \mu\text{g}/\text{m}^3$, a σ_M of $7.46 \mu\text{g}/\text{m}^3$, and an average annual bias of $-1.96 \mu\text{g}/\text{m}^3$.

ENSEMBLE obtains R=0.68, $\sigma=0.73$ (27% lower than the observed variability), and cRMSDN=0.73. Its RMSE is $7.22 \mu\text{g}/\text{m}^3$, and its σ_M is $6.79 \mu\text{g}/\text{m}^3$.

The differences are small but consistent. Ensemble has a higher correlation and slightly lower pattern (cRMSD) and total (RMSE) errors, indicating slightly superior performance. While the correlations are statistically significant, the cRMSDN values (0.7–0.8) indicate amplitude errors.

The variability indicators (cRMSD and cRMSDN) demonstrate comparable abilities of the two models to reproduce the observed variation, with Ensemble showing slight superiority.

In conclusion, Ensemble is superior to CHIMERE in the case of PM_{2.5}, but both could benefit from correcting seasonal variability (Figure 6).

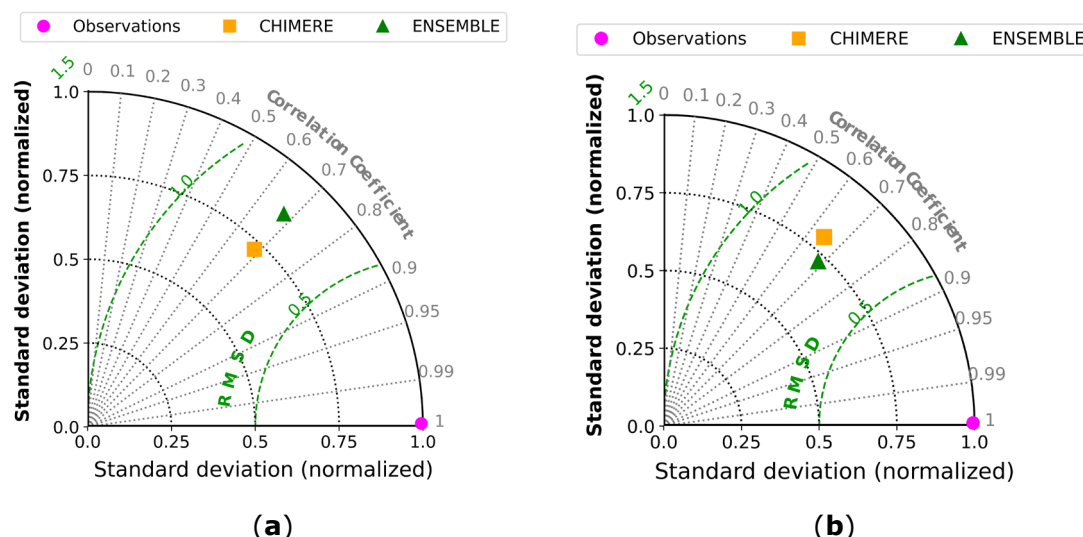


Figure 6. Taylor diagrams of daily concentrations (normalized) predicted by Chimere and Ensemble versus reference station IS-2 (01.01. - 31.12.2024): (a)PM₁₀; (b)PM_{2.5}.

4. Discussion

The results of this study are consistent with previous research, confirming the ability of the CHIMERE and Ensemble models to reproduce general trends, as well as their limitations in representing daily maximum values.

Regarding PM₁₀, both models underestimated the concentrations observed at the IS-2, though the intensity varied by season.

The multi-model ensemble exhibited higher negative biases (-8.5 to -19.0 $\mu\text{g}/\text{m}^3$) than CHIMERE (-1.4 to -10.1 $\mu\text{g}/\text{m}^3$), suggesting greater underestimation by the multi-model mean. While this method flattened the daily maximum PM₁₀ concentrations, the underestimation persisted, particularly from May to August, when the RMSE ranged from 12 to 22 $\mu\text{g}/\text{m}^3$ for Ensemble and from 8 to 19 $\mu\text{g}/\text{m}^3$ for CHIMERE.

The Pearson correlation coefficient showed good to very good performance in January–April, July, and October for Ensemble and January, April, September–November ($R > 0.7$). The strongest correlations were recorded in April for CHIMERE ($R > 0.9$) and in November for Ensemble, indicating maximum performance.

In May and July, however, correlations were almost absent, particularly for Ensemble ($R=0.16$ in May), suggesting limitations in representing dispersion processes and contributions from local sources. CHIMERE showed lower biases and more stable correlations. However, in months with high concentrations (August and October), it underestimated concentrations by -14.9 $\mu\text{g}/\text{m}^3$ and -10.1 $\mu\text{g}/\text{m}^3$, respectively. Although Ensemble reduced errors in the cold months, it amplified underestimations in the warm months. This confirms the results of European multi-model studies that highlighted the difficulty of reproducing PM₁₀ pollution episodes (Sartelet et al., 2007; Stern et al., 2008).

In conclusion, for PM₁₀ in Iași in 2024, the CHIMERE model provided better results than the multi-model ensemble, with lower biases and RMSE values. Both models confirmed the literature's reported trend of underestimating concentrations, particularly in the summer when resuspension processes and traffic emissions are challenging to represent at the regional modeling scale.

The map from April 1, 2024, was included not only to show the daily limit value exceeded for PM₁₀, but also to verify how the CHIMERE model reproduces the spatial distribution of pollutants. The visual representation allowed the observation of the spread of Saharan dust transport at the regional level and confirmed that the episode was much

larger than that captured by the urban background station's local measurements. Comparing this map with ground observations underscores the importance of dispersion models, as they provide the spatial information necessary to interpret exceedances and comprehend the atmospheric processes responsible for them. Thus, the map served as more than just an illustration; it was also used as an additional analysis tool to verify the accuracy of the CHIMERE simulations and to highlight the role of natural sources in the pollution episode.

CHIMERE and Ensemble had similar and different results at the IS-2 urban background station.

During the cold months, both models recorded high correlations ($R > 0.8$), confirming their ability to reproduce the variability of daily concentrations under stable weather conditions and increased residential emissions. During these periods, the biases were low: between -1.3 and $-4.3 \mu\text{g}/\text{m}^3$ for the Ensemble model and between -2.3 and $-3.9 \mu\text{g}/\text{m}^3$ for the CHIMERE model. However, the CHIMERE model showed lower absolute errors ($\text{MAE} = 3\text{--}5 \mu\text{g}/\text{m}^3$) compared to the Ensemble model ($\text{MAE} = 5\text{--}8 \mu\text{g}/\text{m}^3$), indicating a more accurate representation of concentrations by the CHIMERE model.

The largest discrepancies were recorded in May–June, with both models showing low correlations ($R < 0.2$). CHIMERE showed moderate biases (-2.9 and $-3.7 \mu\text{g}/\text{m}^3$), while ENSEMBLE showed a more pronounced underestimation, confirming observations from other European regions regarding the difficulty of CTMs to represent photochemical processes and local sources in summer (Stern et al., 2008; Sartelet et al., 2007).

In December, both models overestimated concentrations, but with different intensities ($+8.2 \mu\text{g}/\text{m}^3$ for CHIMERE and $+6.9 \mu\text{g}/\text{m}^3$ for ENSEMBLE). This differed from the models reported in the CAMS service (Marécal et al., 2015), where winter biases were negative, indicating local peculiarities. In 2024, CHIMERE had lower biases and lower RMSE errors for $\text{PM}_{2.5}$, while ENSEMBLE achieved slightly better correlations in the cold months, with the exception of December. Thus, the two approaches can be considered complementary: ENSEMBLE better reproduced daily variability in stagnant atmospheric conditions, while CHIMERE offered more stable performance and lower absolute error. For both $\text{PM}_{2.5}$ and PM_{10} , the models showed better results in the cold season (except for December), when atmospheric conditions were stable and residential emissions were dominant.

During the summer months, both models significantly underestimated concentrations, reflecting the challenges of representing photochemical processes, resuspension, and local sources, as documented in the European literature (De Meij et al., 2009). CHIMERE generally had lower biases and smaller absolute errors, while Ensemble had higher correlations in the cold months but accentuated underestimation during the warm period.

For 2024, results show Ensemble performs slightly better than CHIMERE for $\text{PM}_{2.5}$ in terms of correlation and average errors. This suggests that the Ensemble approach, which integrates multiple simulations, reduces the uncertainties associated with individual predictions and provides more robust estimates of $\text{PM}_{2.5}$ concentrations.

In contrast, for PM_{10} , the situation is reversed. CHIMERE performs better, with significantly lower errors and slightly higher correlations. The Ensemble's high negative bias indicates a systematic underestimation of PM_{10} concentrations, which could be due to limitations in representing coarse particle sources or insufficient capture of physicochemical processes by the Ensemble's components.

These results are confirmed by the literature and show that ensemble models tend to be more accurate at estimating $\text{PM}_{2.5}$ but may have difficulty reproducing PM_{10} concentrations, where meteorological factors and local sources play a more important role. These models can be considered complementary.

Taylor diagrams confirm these differences. For PM_{10} , variability is underestimated, critical episodes are not reproduced, and the forecasting ability is reduced. For $\text{PM}_{2.5}$, performance is slightly superior. Ensemble maintains a more stable correlation, and CHIMERE better reproduces the standard deviation.

However, the study has limitations. The analysis is based on a single urban background station, which may influence the assessment of performance at the regional level.

Overall, the results demonstrate the usefulness of the transport chemistry models, CHIMERE and Ensemble, for forecasting PM₁₀ and PM_{2.5} concentrations.

5. Conclusions

Reanalysis and forecast models, such as CAMS, enable the creation of accurate global maps of PM_{2.5} and PM₁₀, including in areas without monitoring stations (Chianese et al., 2018).

This study analyzed the performance of the CHIMERE and Ensemble CAMS models for PM₁₀ and PM_{2.5} concentrations in Iași in 2024. Both models underestimated the observed values but managed to capture seasonal variability and general trends.

For PM₁₀, CHIMERE showed a lower annual bias ($-6.37 \mu\text{g}/\text{m}^3$ compared to $-11.26 \mu\text{g}/\text{m}^3$ for Ensemble) and a lower RMSE ($13.1 \mu\text{g}/\text{m}^3$ compared to $16.5 \mu\text{g}/\text{m}^3$), indicating better performance, especially in the cold season. In contrast, for PM_{2.5}, Ensemble was superior, with an RMSE of $7.22 \mu\text{g}/\text{m}^3$ and a more stable correlation throughout the year, compared to $7.52 \mu\text{g}/\text{m}^3$ for CHIMERE.

Thus, CHIMERE is more accurate for episodes of high pollution and in cold months, while Ensemble is more suitable for analyzing general trends and annual variability.

The complementary use of the two models, together with in-situ observations, is essential for calibration and for increasing predictive performance. The results confirm their usefulness in forecasting PM₁₀ and PM_{2.5} concentrations and in assessing compliance with the new limit values set by Directive (EU) 2024/2881.

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