GREEN BUILDING CONFERENCE
INNOVATIVE SOLUTIONS FOR A GREENER BUILT ENVIRONMENT

DOI: **10.5937/greenb26060B**
Research paper

ADVANCING CLIMATE-ADAPTIVE URBAN INTELLIGENCE: MACHINE LEARNING PREDICTION OF $PM_{2.5}$ DYNAMICS ACROSS THE BELGRADE METROPOLITAN AREA

Maja Brborić[1], Branka Nakomčić Smaragdakis[2], Miljan Šunjević[3], Vladimir Rajs[4], Sonja Dmitrašinović[5]

Abstract

This study analyses the seasonal and spatial dynamics of fine particulate matter ($PM_{2.5}$) across 13 low-cost sensor monitoring sites in the Belgrade metropolitan area over a 12-month period (15 April 2025 - 14 April 2026), divided into a non-heating season (NHS; 15 April - 14 October 2025) and a heating season (HS; 15 October 2025 - 14 April 2026). The area-averaged HS mean (32.5 ± 25.6 µg/m³) was 2.7 times higher than the NHS mean (11.9 ± 8.9 µg/m³), with December 2025 recording the peak monthly average of 43.4 µg/m³. The WHO 2021 daily $PM_{2.5}$ guideline (15 µg/m³) was exceeded on 75.5% of HS monitoring days. Strong spatial gradients were identified: Ritopek (42.5 µg/m³) and Zemun (41.8 µg/m³) recorded the highest HS means, while Beli Potok (23.6 µg/m³) was the least polluted site. Temperature was the strongest meteorological driver (Pearson r = −0.57 during HS). Four machine learning models were evaluated for $PM_{2.5}$ prediction; the best model, Random Forest augmented with site identity and autoregressive lag features, achieved R^2 = 0.680 (MAE = 7.24 µg/m³), a substantial improvement over meteorology-only approaches (R^2 = 0.552). *The implications for smart city air quality monitoring, climate-adapted urban planning and PM-rated ventilation in green buildings are discussed.*

Key words $PM_{2.5}$; machine learning; WHO exceedance; heating season; smart cities; green buildings

[1] PhD, Research associate, Faculty of Technical Sciences, Department of Environmental Engineering and Occupational Safety and Health, University of Novi Sad, Serbia, majabrboric@uns.ac.rs, ORCid 0009-0002-7669-9033

[2] PhD, Full professor, Faculty of Technical Sciences, Department of Environmental Engineering and Occupational Safety and Health, University of Novi Sad, Serbia, nakomcic@uns.ac.rs, ORCid 0000-0001-5754-2669

[3] PhD, Research associate, Faculty of Technical Sciences, Department of Architecture and Urban Planning, University of Novi Sad, Serbia, msunjevic@uns.ac.rs, ORCid 0000-0002-8125-2087

[4] PhD, Full professor, Faculty of Technical Sciences, Department of Energy, Electronics and Telecommunications, University of Novi Sad, Serbia, vladimir@uns.ac.rs, ORCid 0000-0003-4357-770X

[5] PhD, Research associate, Faculty of Technical Sciences, Department of Environmental Engineering and Occupational Safety and Health, University of Novi Sad, Serbia, dmitrasinovic@uns.ac.rs, ORCid 0000-0002-5686-4196

1. INTRODUCTION

Fine particulate matter ($PM_{2.5}$) is the leading environmental risk factor for human health globally, responsible for approximately 6.7 million premature deaths annually [1]. The WHO 2021 Air Quality Guidelines set an annual $PM_{2.5}$ target of 5 $\mu g/m^3$ [2], yet concentrations in Central and Eastern European (CEE) cities routinely exceed this threshold by factors of three to ten during winter months, driven primarily by residential solid-fuel combustion [3]. Serbia and the Western Balkans rank among the highest $PM_{2.5}$ burden areas in Europe, and Belgrade, with ~1.7 million inhabitants, complex orography and a large legacy thermal power plant, represents a particularly challenging urban air quality context [4].

The proliferation of low-cost IoT sensor networks, exemplified by the Klimerko open-data platform, now enables neighbourhood-scale continuous PM monitoring inaccessible to sparse regulatory networks [5, 6]. Combined with machine learning (ML) algorithms, these datasets support data-driven $PM_{2.5}$ prediction models that can serve as the algorithmic backbone of smart building ventilation control and real-time urban air quality management [7, 8]. Ensemble ML methods (Random Forest, Gradient Boosting) consistently outperform linear models for PM-meteorology relationships, and incorporating autoregressive lag features and site identity further improves predictive accuracy [9, 10].

This study pursues three objectives: (i) characterise seasonal and spatial $PM_{2.5}$ dynamics across 13 Belgrade sites over a full annual cycle; (ii) quantify WHO guideline exceedance frequency; and (iii) develop and compare ML models for $PM_{2.5}$ prediction, with implications for Smart and Climate-Adapted Cities (T06) and Green Buildings and Energy Efficiency (T02).

2. MATERIALS AND METHODS

2.1. Study Area and Air Quality Data

Belgrade (44.8°N, 20.5°E; 3,234 km^2) lies at the Sava–Danube confluence in north-central Serbia. Thirteen monitoring sites within the city's administrative boundaries were selected from the Klimerko network [5] based on data completeness (>150 valid daily records per seasonal sub-period): Beograd, Zemun, Batajnica, Barajevo, Obrenovac, Mladenovac, Jajinci, Kaluđerica, Ripanj, Ritopek, Beli Potok, Sremčica and Čukarica. Klimerko sensors (Plantower PMS7003 optical particle counters) report daily mean $PM_{2.5}$ under an open-data licence. The study period spans 15 April 2025 - 14 April 2026, divided into the NHS (183 days) and HS (182 days).

No formal cross-calibration of the Klimerko PMS7003 sensors against co-located reference-grade instruments was performed in this study, as verified SEPA reference data for the study period are not yet publicly available for download. Previous independent studies in Serbian urban environments have demonstrated strong correlation between Klimerko sensors and co-located SEPA Grimm EDM180 reference monitors (R^2 = 0.879 for PM2.5 in Belgrade [2]), though uncalibrated devices are known

to overestimate PM2.5 at relative humidity above 70% due to hygroscopic aerosol growth [11]. Stojanović et al. [12] reported acceptable agreement between sensors of the same type and SEPA stations across 15 Serbian municipalities after co-location calibration (PM2.5 RMSE = 6.50 μg/m³). In the present study, data were used without correction; absolute PM2.5 values should therefore be interpreted with caution, while relative spatial and temporal patterns remain robust.

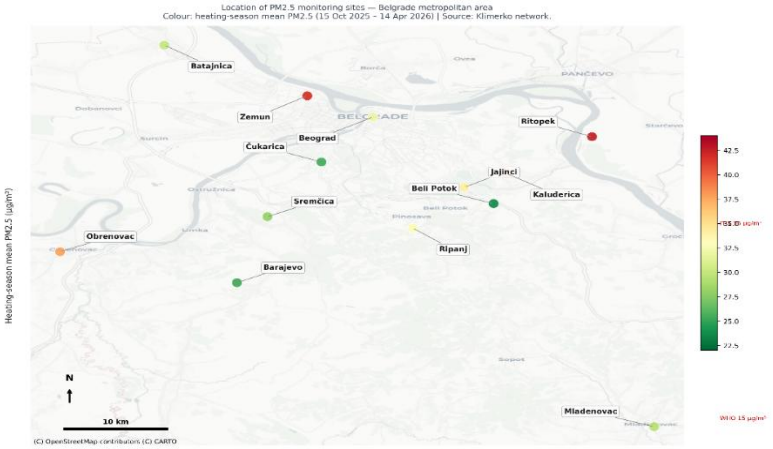


Figure 1. Map of $PM_{2.5}$ monitoring sites in the Belgrade metropolitan area

2.2. Meteorological Data

Daily meteorological observations for 13 sites were obtained from the Visual Crossing Weather API: temperature (°C), relative humidity (%), wind speed (km/h), sea-level pressure (hPa), cloud cover (%), precipitation (mm), dew point (°C), visibility (km) and solar radiation (W/m²). Merged $PM_{2.5}$–meteorology records yielded 4,588 site-days after quality screening.

2.3. Statistical and Machine Learning Analysis

Bivariate $PM_{2.5}$-meteorology relationships were assessed using the Pearson correlation coefficient computed separately for each season. WHO exceedance frequency was calculated as the percentage of site-days with $PM_{2.5} > 15$ μg/m³ [2]. Four supervised regression models were trained for $PM_{2.5}$ prediction: (i) Linear Regression, (ii) Ridge Regression (α = 1.0), (iii) Random Forest (RF; 200 trees, depth 12) and (iv) Gradient Boosting (GB; 200 estimators, LR = 0.05). Three progressive feature sets were evaluated: (a) 12 meteorological + temporal features; (b) adding a site identity encoding; and (c) additionally adding three autoregressive lag features ($PM_{2.5}$ at t−1, t−2, t−3) and a 7-day rolling mean. All models were evaluated by 5-fold cross-validation (R^2, MAE, RMSE). Analyses used Python 3.12 / scikit-learn 1.8 [13]. Pairwise Pearson correlations among meteorological predictors revealed several strong associations (temperature–dew point: r = 0.880; temperature–solar radiation: r = 0.809; relative humidity–solar radiation: r = −0.749), reflecting the physical co-occurrence of these variables during winter anticyclonic episodes. For the ensemble methods, predictor multicollinearity does not bias predictions but may distribute feature importance across correlated variables [14].

3. RESULTS AND DISCUSSIONS

3.1. Seasonal and Spatial PM2.5 Dynamics

The monthly time series (Figure 2a) reveals a sharp seasonal cycle across all 13 sites. During the NHS, area-mean $PM_{2.5}$ remained stable and low (10.1–13.2 μg/m³), near or below the WHO 2021 annual guideline. An abrupt transition occurred in October 2025 (18.9 μg/m³), with concentrations escalating to peak monthly averages of 43.4 and 42.6 μg/m³ in December 2025 and January 2026, respectively, nearly threefold exceedance of the WHO guideline. The HS mean (32.5 ± 25.6 μg/m³) was 2.7 times higher than the NHS mean (11.9 ± 8.9 μg/m³). The large HS standard deviation reflects day-to-day variability driven by synoptic patterns: anticyclonic blocking events with temperature inversions produce multi-day $PM_{2.5}$ episodes up to 250 μg/m³, while cyclonic conditions temporarily reset concentrations. This seasonal amplification is consistent with observations in similar CEE cities (Sofia, Bucharest, Warsaw) [3, 15, 16].

Considerable spatial heterogeneity was observed (Figure 2b). During the HS, site means ranged from 23.6 μg/m³ (Beli Potok) to 42.5 μg/m³ (Ritopek), a near-twofold intra-urban gradient. Ritopek's elevated values reflect its position in a narrow Danube valley that promotes nocturnal cold-air drainage and temperature inversions trapping combustion products. Zemun and Kaluđerica rank second and third, driven by dense low-rise residential heating in peri-urban settlements. Obrenovac records the highest NHS mean (25.5 μg/m³) attributable to the year-round operation of the Nikola Tesla thermal power plant (TENT A+B), the largest coal-fired facility in the Western Balkans (~3–7 km from the sensor).

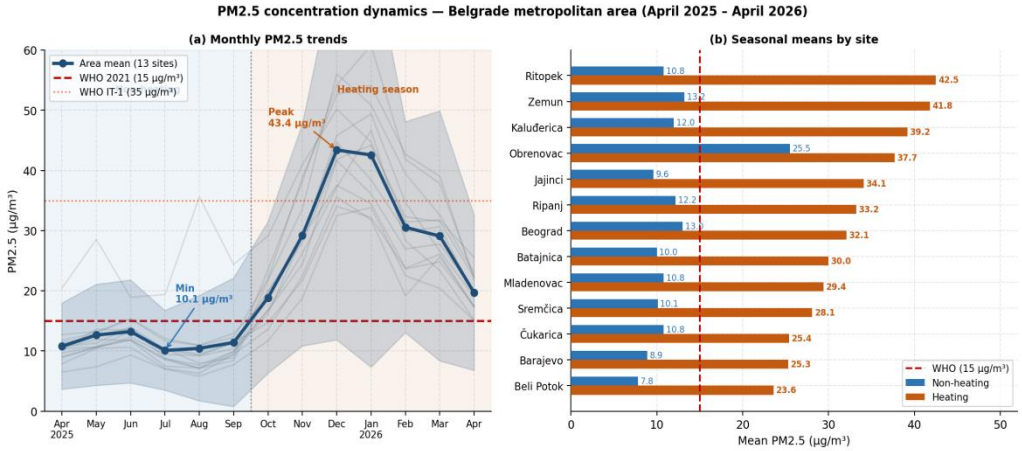


Figure 2. (a) Monthly $PM_{2.5}$ trends: grey lines = individual sites; dark line = 13-site area mean ±1 SD (shaded). Dashed red: WHO 2021 annual guideline (15 μg/m³); dotted orange: WHO IT-1 (35 μg/m³). (b) Seasonal mean PM2.5 by site, sorted by heating-season mean

3.2. WHO Guideline Exceedances

The WHO 2021 $PM_{2.5}$ guideline (15 μg/m³) was exceeded on 24.9% of NHS site-days but on 75.5% of HS site-days. The spatio-temporal exceedance pattern (Figure 3b)

reveals near-universal guideline violation during December 2025 and January 2026: most sites recorded >90% of days above the threshold, with Ritopek, Zemun and Kaluđerica reaching 100% in December. By contrast, July and August 2025 showed exceedance rates below 10% at the majority of sites, a window of relative compliance. The HS exceedance rate of 75.5% is broadly comparable to Bucharest (~70%) and Warsaw (65–70%), but substantially lower than Kraków (>85%), where basin topography compounds the coal-heating effect [16, 17]. It far exceeds London (<5%) and Munich (<8%), illustrating the scale of the regulatory gap between CEE and Western European cities [3].

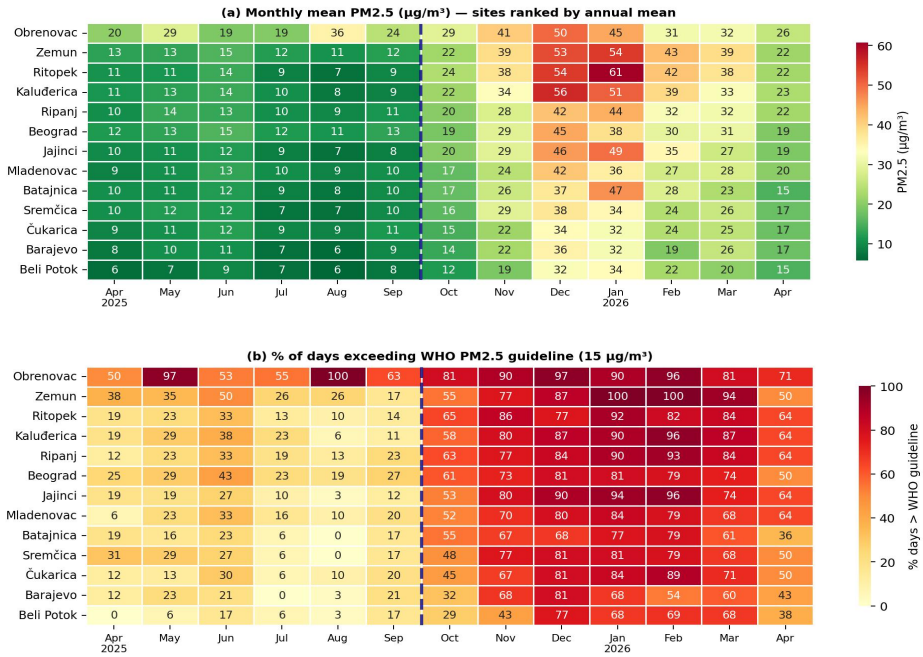


Figure 3. (a) Monthly mean $PM_{2.5}$ (µg/m³) by site and month. Sites ranked by annual mean (descending). Colour: green (low) → red (high). (b) Percentage of days exceeding the WHO $PM_{2.5}$ guideline (15 µg/m³) by site and month. Dashed blue line separates the two seasons

3.3. Meteorological Drivers of PM2.5

Pearson correlation analysis (Figure 4a) confirms temperature as the dominant negative driver of $PM_{2.5}$ during the HS (r = −0.57), reflecting the non-linear coupling between ambient temperature, residential heating demand and atmospheric stability. Solar radiation (r = −0.50) acts as a proxy for mixing layer development. Sea-level pressure (r = +0.29) and relative humidity (r = +0.31) show positive HS correlations consistent with anticyclonic blocking and hygroscopic aerosol growth, respectively [18]. Wind speed (r = −0.27) reflects dilution by ventilation. These meteorological archetypes, low temperature, high pressure, low wind, high humidity, constitute the dominant synoptic configuration for severe $PM_{2.5}$ episodes in the Sava-Danube basin [18], and are particularly frequent from December to February.

3.4. Machine Learning Prediction of PM2.5

3.4.1. Model performance

The 5-fold cross-validation results (Table 1, Figure 4b) demonstrate a clear hierarchy of model complexity and performance. Linear and Ridge Regression (R^2 = 0.369) capture only the linear components of $PM_{2.5}$–meteorology relationships. Adding site identity as a categorical encoding (RF + site ID) raises R^2 to 0.611, confirming that baseline spatial differences in $PM_{2.5}$ levels, spanning nearly 19 µg/m³ between sites during the HS, constitute a substantial predictable signal absent from the original feature set. The addition of autoregressive lag features (PM2.5 at t−1, t−2, t−3, and a 7-day rolling mean) further improves performance to R^2 = 0.680 (MAE = 7.24 µg/m³, RMSE = 12.30 µg/m³) - a 23% gain over the meteorology-only baseline. The lag features encode the autocorrelation of multi-day pollution episodes driven by persistent anticyclonic weather. Gradient Boosting with the same feature set achieves R^2 = 0.671, marginally below Random Forest; the latter is therefore selected as the preferred model. These R^2 values are consistent with literature on meteorology-only ML models for CEE urban $PM_{2.5}$: Kim et al. [10] reported R^2 = 0.48–0.56 for Seoul, while Zamani Joharestani et al. [9] obtained R^2 = 0.60–0.73 with additional satellite aerosol optical depth inputs.

Table 1. Predictive performance of ML models for daily $PM_{2.5}$ (5-fold cross-validation)

Models	Feature set	R^2	±SD	MAE (µg/m³)	RMSE (µg/m³)
Linear Regression	Meteo+time	0.379	0.024	11.28	17.17
Ridge Regression	Meteo+time	0.379	0.024	11.28	17.17
Random Forest	Meteo+time	0.552	0.032	8.33	14.59
Random Forest	+ site ID	0.621	0.028	7.89	13.44
Random Forest ✓ best	+ site ID + lags	0.680	0.045	7.24	12.30
Gradient Boosting	+ site ID + lags	0.671	0.044	7.50	12.48

MAE = Mean Absolute Error; RMSE = Root Mean Square Error. Green row = best model

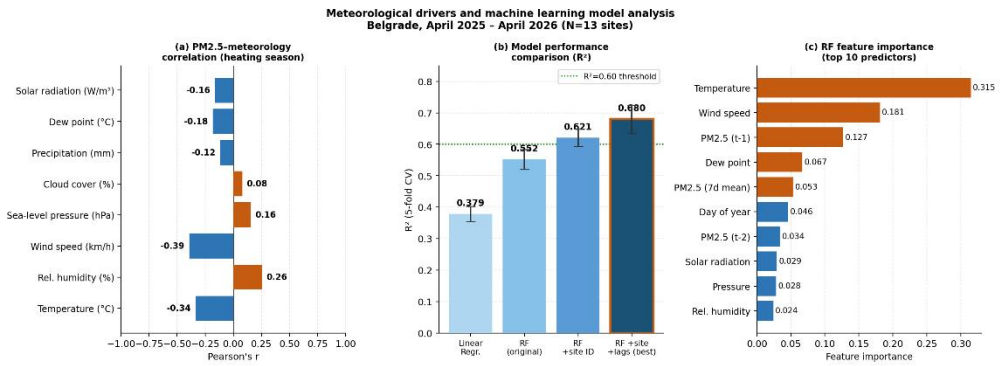


Figure 4. (a) $PM_{2.5}$–meteorology Pearson correlations during the heating season. (b) R^2 progression across model configurations (error bars: CV SD; orange outline: best model). (c) Top-10 feature importances for the best RF model

3.4.2. Feature importance and prediction quality

Feature importance analysis (Figure 4c) reveals that temperature (0.245) and wind speed (0.174) are the leading meteorological predictors, followed closely by the previous-day $PM_{2.5}$ lag (0.174), confirming that episode persistence is as informative as instantaneous meteorological state. The 7-day rolling mean $PM_{2.5}$ (0.084) captures the multi-day accumulation dynamics of anticyclonic episodes. Month and day-of-year together contribute ~15%, encoding the seasonal heating cycle. Site identity, while modest in raw importance, is essential for capturing baseline spatial differences in exposure levels. It should be noted that strong correlations among meteorological predictors (temperature–solar radiation: r = 0.809; relative humidity–solar radiation: r = −0.749) may cause the model to distribute importance scores across correlated features; the combined contribution of the thermal-radiative predictor cluster to $PM_{2.5}$ prediction therefore likely exceeds what individual importance values suggest [14].

Figure 5 (left) presents the scatter of observed versus predicted $PM_{2.5}$ on the 20% holdout test set (R^2 = 0.735, MAE = 6.36 μg/m³). The model tracks the time-series dynamics of the heating season peak well (Figure 5, right), capturing week-to-week fluctuations between anticyclonic accumulation episodes and cyclonic clearance events. Systematic underestimation occurs at the most extreme concentrations (>150 μg/m³), a known limitation of ensemble averaging methods [9]. Future integration of boundary-layer height observations and traffic intensity data could address the remaining residual variance.

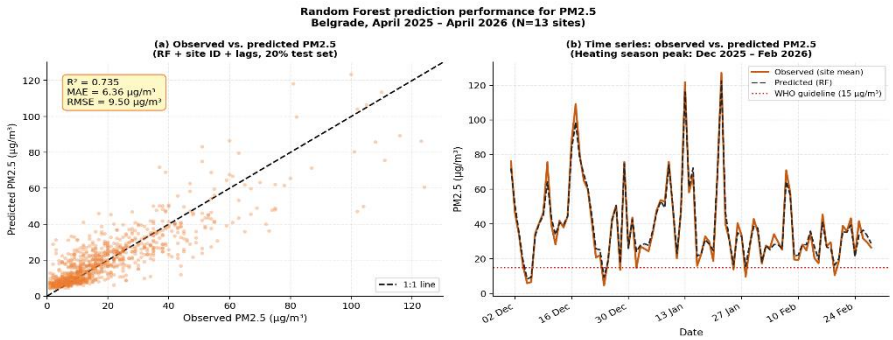


Figure 5. (a) Observed vs. predicted PM2.5 on the independent test set (Random Forest + site ID + lags; N ≈ 918 site-days, 13 sites). (b) Time-series comparison for the heating season peak (December 2025 – February 2026). Shaded area: residuals; dotted red: WHO guideline (15 μg/m³)

3.5. Implications for Smart Cities and Green Buildings

The findings carry direct and actionable implications across three thematic domains of Green Building 2026. (i) Smart Cities and Real-Time Management: the Klimerko sensor layer, combined with the RF prediction model developed here, constitutes the infrastructure backbone for real-time $PM_{2.5}$ dashboards and 24–72 h pollution episode forecasting using publicly available meteorological products (ECMWF, ALADIN). Such forecasts could trigger pre-emptive interventions, temporary traffic restrictions, adaptive public transport provision, heating fuel transition advisories, consistent with

smart city digital twin frameworks [7]. (ii) Climate Adaptation: the 2.7-fold HS amplification of $PM_{2.5}$ documents the air quality co-penalty of solid-fuel space heating. Replacing coal and wood combustion with heat pumps or district heating is projected to reduce residential $PM_{2.5}$ contributions by 60–80% [3], simultaneously advancing climate decarbonisation targets under the EU Green Deal. Continuous monitoring networks such as Klimerko will be essential for evaluating actual air quality co-benefits as building energy renovation programmes scale up. (iii) Green Building Ventilation: the sustained HS exceedance rate (75.5% of days above 15 μg/m³) establishes a robust empirical basis for mandatory mechanical ventilation with PM-rated filtration (ISO e$PM_{2.5}$ ≥60%, EN ISO 16890) in new and renovated buildings in Belgrade. Current Serbian building regulations do not explicitly require PM-class filtration, a gap increasingly at odds with EN 16798-3 and ASHRAE 62.1-2022. Given indoor/outdoor $PM_{2.5}$ penetration efficiencies of 50–80% in unfiltered buildings [19], residents in high-exceedance zones (Ritopek, Zemun) face annual indoor $PM_{2.5}$ exposures of 20–34 μg/m³, four to seven times the WHO annual guideline. The spatial exceedance maps developed here should be incorporated into site environmental assessments within BREEAM and LEED certification processes for Belgrade.

4. CONCLUSION

One full annual cycle of $PM_{2.5}$ monitoring across 13 sites in the Belgrade metropolitan area reveals a city operating in two fundamentally different air quality regimes. During the non-heating season, concentrations remain close to or below the WHO 2021 annual guideline of 15 μg/m³, confirming that the warm-season baseline $PM_{2.5}$ burden in Belgrade is broadly manageable and comparable to moderately polluted mid-sized European cities. The heating season tells a starkly different story: a near-instantaneous transition in October, a 2.7-fold amplification of the area mean to 32.5 μg/m³, and peak monthly averages approaching 43 μg/m³ in December and January. On three out of every four heating-season days, the WHO guideline was exceeded across the entire monitoring network. These are not marginal violations, they represent a structurally embedded public health problem rooted in the building sector's dependence on solid-fuel combustion.

The spatial analysis adds an important dimension to this picture. Even within a single city, $PM_{2.5}$ exposure during the heating season varies by nearly a factor of two between monitoring sites, shaped by topographic channelling of cold air (Ritopek, Kaluđerica), the density of low-rise residential heating in peri-urban districts (Zemun), and the year-round industrial signature of the Nikola Tesla thermal power plant in Obrenovac, which uniquely elevates non-heating-season concentrations and demands source-specific rather than seasonally uniform policy responses. This intra-urban heterogeneity has direct consequences for building design: a ventilation standard appropriate for Beli Potok is wholly inadequate for Ritopek or Zemun.

The meteorological analysis confirms that the most severe pollution episodes are the product of synoptic convergence, low temperature and wind speed, elevated pressure and humidity acting simultaneously to suppress the atmospheric boundary

layer and concentrate combustion emissions. This meteorological fingerprint is highly predictable, and it is precisely this predictability that the machine learning framework developed here exploits. By incorporating site identity and autoregressive lag features alongside meteorological predictors, the Random Forest model captures the day-to-day dynamics of multi-day accumulation episodes with sufficient fidelity for operational deployment in smart city air quality management systems.

Taken together, these results frame Belgrade's $PM_{2.5}$ challenge as simultaneously a climate problem, a building energy problem and a smart city governance problem. The heating-season pollution regime documented here will not be resolved by monitoring or modelling alone, it requires accelerated fuel switching and deep energy renovation of the residential building stock, transitioning households away from solid fuels toward electrified heating supplied by decarbonised grids. The air quality co-benefits of such a transition, projected at 60–80% reductions in residential $PM_{2.5}$ contributions [3], would transform the exceedance maps presented in this study and bring Belgrade's winter air quality within reach of WHO guideline compliance. Until that transition is complete, the findings presented here provide the empirical foundation for two complementary near-term interventions: mandatory PM-rated mechanical ventilation (EN ISO 16890, $ePM_{2.5}$ ≥60%) in new and renovated buildings across all high-exceedance zones, and deployment of the ML prediction model as a real-time forecasting layer within Belgrade's emerging smart city digital infrastructure, enabling pre-emptive building management responses, citizen exposure alerts and data-driven policy decisions triggered by forecast pollution episodes.

Future work should extend this framework in two directions: upward, through integration with mesoscale atmospheric models and satellite aerosol retrievals to improve episode prediction at extreme concentrations; and downward, through hourly temporal resolution and expanded sensor coverage to resolve the diurnal heating and traffic cycles that drive within-day exposure variability and inform the next generation of building ventilation control standards.

ACKNOWLEDGMENT

This research has been supported by the Ministry of Science, Technological Development and Innovation (No. 451-03-33/2026-03/ 200156), Faculty of Technical Sciences (No.115001-3394/1), HORIZON-MSCA-2021-SE-01, REMARKABLE (No. 101086387), and by the Autonomous Province of Vojvodina (No. 003870771 2025 09418 003 000 000 001 and 002497912 2026 09418 002 000 000 001 04 006).

LITERATURE

[1] WHO. Global Health Observatory: Ambient air pollution. World Health Organization, Geneva, 2024.

[2] WHO. WHO Global Air Quality Guidelines: PM2.5, PM10, O_3, NO_2, SO_2 and CO. WHO Press, Geneva, 2021. ISBN 978-92-4-003422-8.

[3] EEA. Air Quality in Europe 2023. EEA Report No 7/2023. European Environment Agency, Copenhagen, 2023.

[4] Chatoutsidou, S.E.; Lehtomäki, H.; Almeida, S.M.; Eleftheriadis, K.; Hänninen, O.; Lazaridis, M. Indoor particulate matter (PM) pollution: Scientific knowledge and policy implications. Atmosphere 2019, 10(2), 96. https://doi.org/10.3390/atmos10020096

[5] Božilov, A.V.; Tasić, V.M.; Mišić, N.Z.; Lazović, I.M.; Topalović, D.B.; Živković, N.V.; Mirkov, N.S. Civil air quality monitoring as an alternative and supplement to the national air quality monitoring network. Thermal Science 2023, 27(3B), 2255–2263. https://doi.org/10.2298/TSCI220303103B.

[6] Morawska, L.; Thai, P.K.; Liu, X.; Asumadu-Sakyi, A.; Ayoko, G.; et al. Applications of low-cost sensing technologies for air quality monitoring and exposure assessment: How far have they gone? Environment International 2018, 116, 286–299. https://doi.org/10.1016/j.envint.2018.04.018.

[7] Tamrakar, G.; Sharma, R.; Rohilla, S. Smart IoT-based air quality monitoring and alert system for urban environments. International Journal of Environmental Sciences 2025, 11(2), 628–633. https://doi.org/10.64252/hdrg5v49.

[8] Morawska, L.; Ayoko, G.A.; Bae, G.N.; Buonanno,et al. Airborne particles in indoor environment of homes, schools, offices and aged care facilities: The main routes of exposure. Environment International 2017, 108, 75–83. https://doi.org/10.1016/j.envint.2017.07.025.

[9] Zamani Joharestani, M.; Cao, C.; Ni, X.; Bashir, B.; Talebiesfandarani, S. PM2.5 prediction based on Random Forest, XGBoost, and deep learning using multisource remote sensing data. Atmosphere 2019, 10(7), 373. https://doi.org/10.3390/atmos10070373.

[10] Siam, M.A.H.; Jarif, M.I.A.; Rahin, T.A. Machine learning approaches for PM2.5 prediction: A comparative study. International Journal of Latest Technology in Engineering, Management & Applied Science 2025, XIV(XII). https://doi.org/10.51583/IJLTEMAS.2025.1412000075.

[11] Jayaratne, R. et al. The influence of humidity on the performance of a low-cost air particle mass sensor. Aerosol Science and Technology 2018, 52(9), 928–938. https://doi.org/10.1080/02786826.2018.1455924

[12] Stojanović, D.B. et al. Data evaluation of a low-cost sensor network for atmospheric particulate matter monitoring in 15 municipalities in Serbia. Sensors 2024, 24(13), 4052. https://doi.org/10.3390/s24134052

[13] Pedregosa, F.; Varoquaux, G.; Gramfort, A.; Michel, V.; et al. Scikit-learn: Machine learning in Python. Journal of Machine Learning Research 2011, 12, 2825–2830.

[14] Dormann, C.F.; Elith, J.; Bacher, S.; et al. Collinearity: a review of methods to deal with it and a simulation study evaluating their performance. Ecography 2013, 36, 27–46. https://doi.org/10.1111/j.1600-0587.2012.07348.x

[15] Stefanova, M.S. Analysis of concentration of PM10 on the territory of the city of Sofia (Bulgaria) for the period 2017–2020. Agricultural Sciences 2024, 16(41). https://doi.org/10.22620/agrisci.2024.41.011.

[16] Juda-Rezler, K.; Reizer, M.; Maciejewska, K.; Błaszczak, B.; Klejnowski, K. Characterization of atmospheric PM2.5 sources at a Central European urban background site. Science of the Total Environment 2020, 713, 136729. https://doi.org/10.1016/j.scitotenv.2020.136729.

[17] Błaszczak, B.; Widziewicz-Rzońca, K.; Zioła, N.; Klejnowski, K.; Juda-Rezler, K. Chemical characteristics of fine particulate matter in Poland in relation with data from selected rural and urban background stations in Europe. Applied Sciences 2019, 9(1), 98. https://doi.org/10.3390/app9010098.

[18] Shen, F.; Ge, X.; Hu, J.; Nie, D.; Tian, L.; Chen, M. Air pollution characteristics and health risks in Henan Province, China. Environmental Research 2017, 156, 625–634. https://doi.org/10.1016/j.envres.2017.04.026.

[19] Chen, C.; Zhao, B. Review of relationship between indoor and outdoor particles: I/O ratio, infiltration factor and penetration factor. Atmospheric Environment 2011, 45(2), 275–288. https://doi.org/10.1016/j.atmosenv.2010.09.048.